"ANTECEDENTS TO CONSUMER BEHAVIOUR TOWARDS M-COMMERCE: AN EMPIRICAL STUDY"

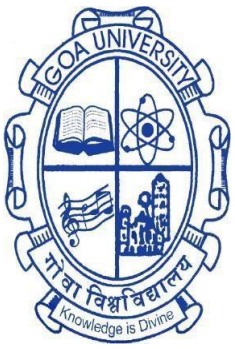
A THESIS SUBMITTED IN PARTIAL FULFILLMENT FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

in Commerce

IN THE GOA BUSINESS SCHOOL

GOA UNIVERSITY



By

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September 2025

DECLARATION

I, Roopa Arvind Acharya hereby declare that this thesis represents work which has been carried out by me and that it has not been submitted, either in part or full, to any other University or Institution for the award of any research degree.

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CERTIFICATE

I hereby certify that the above Declaration of the candidate, name of the candidate is true and the work carried out under my supervision.

Prof. (Dr.) Achut P. Pednekar

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ACKNOWLEDEMENT

As I reflect on my academic journey, I am deeply humbled by the kindness and goodwill extended to me at every stage. It is indeed a privilege to acknowledge all those whose contributions have played an instrumental role in shaping my research and in helping me reach this milestone of my life.

At the very outset, I bow my head in gratitude to the God for granting me good health, inner strength, resilience, and spiritual guidance throughout the course of my doctoral studies. His blessings sustained me in moments of challenge, uncertainty, and self-doubt, and His grace enabled me to persist with determination. Without His divine support, this journey would not have been possible.

I am profoundly indebted to my esteemed research guide, Prof. Achut P. Pednekar, whose invaluable mentorship has been the cornerstone of this work. From the very day of my registration, he has been a constant source of inspiration. His untiring support, patience, constructive criticism, and faith in my abilities provided me with clarity and direction at every step. I owe the successful completion of this thesis to his dedicated supervision and advice.

I wish to record my sincere appreciation to Prof. Filipe Rodrigues e'Melo**,** whose motivation and encouragement consistently inspired me to put forth my best efforts. I am equally grateful to Prof. Nilesh Borde**,** who, despite his demanding schedule, generously shared his expertise and guided me with valuable insights and suggestions. His intellectual guidance was instrumental in refining my study, and I hold his contribution in the highest regard. I also wish to thank the Principal and administrative staff of my research centre at Sant Sohirobanath Ambiye, Government College, Pernem and Goa Business School, administrative staff at Goa University specially Ms. Aditi for their cooperation and support in completing administrative procedures smoothly .I also wish to extend my gratitude to the distinguished experts who participated in the scale development process by providing their expert ratings, and to the respondents who took part in the qualitative study**.** Their contribution of time and effort was vital to the

empirical foundation of this research. I acknowledge their willingness to share their perspectives, which significantly enriched the study and helped me achieve the objectives of this thesis.

My heartfelt thanks go to Prof. Sandesh Dessai, Librarian, Goa University, and Dr. Nandkishor Bandekar, Assistant Librarian, Goa University, for their cooperation and assistance during my numerous visits to the university library. I am also grateful to the office staff of the Goa Business School, Goa University, for their constant cooperation and support during the administrative processes.

Special appreciation is due to Dr. Bhavesh Vanpariya and Ms. Nidhi Gajera, whose insightful guidance on academic writing and data analysis helped me with the necessary tools to organize my research more effectively. Their readiness to engage in meaningful discussions and to offer assistance whenever sought greatly helped my work. Their contribution has been invaluable in enhancing the quality of this thesis.

I also remain indebted to Mr. Vishal Gaonkar, Dr. Suraj Velip, Dr. Virendra Amonkar, and Dr. Sadanand Gaonkar for their constant encouragement and willingness to extend support whenever required. My heartfelt thanks are also due to my fellow research scholars, Shri Jayesh Mayekar and Mr. Yogeshwar Bhosle, whose academic companionship and constructive feedback made my research journey personally enriching.

I extend my deep gratitude to Mr. Virendra (Videsh) Dessai, Chairman of Cuncolim Education Society, and to all the members of the Management for their cooperation in sanctioning my study leave, which enabled me to pursue and complete my doctoral studies in a timely manner. I am equally thankful to our former Principal, Shri Laximan Naik, Prof. Sanjay Sawant Dessai, Dr. Sarala Ketegari, Prof. Avinash Raikar, and my Principal Prof. Brahma Edwin Barreto, whose consistent encouragement and moral support motivated me to register for Ph.D. and remain focused on my academic goals.

My sincere thanks are also due to all my colleagues and friends at C.E.S. College, and also to Assistant Professor Vibha Angle from Dempo College, for their cooperation, encouragement, and support throughout this journey. I am also grateful to the administrative staff of C.E.S. College, Cuncolim, who extended their assistance whenever required and helped me in fulfilling the necessary formalities with efficiency.

Beyond my academic circle, my deepest gratitude is reserved for my family**,** who have been the foundation of my strength. Whatever I am today is a reflection of their unconditional love, sacrifices, and firm belief in me.

I owe my achievements to the blessings and encouragement of my parents, Shri Arvind Acharya and Smt. Rekha Acharya**,** who have been my guiding light. Their moral support during this long journey of over six years gave me courage and determination when I needed it most.

I also wish to acknowledge the invaluable technical support extended by my nephew, Mr. Neel Prabhudesai**,** who stood by me until the final stages of thesis writing. I am equally grateful to my brother**,** Mr. Prasanna Acharya (I.A.S.)**,** and my sisters-in-law, Dr. Puja Acharya and Ms. Cristine Prabhudesai**,** as well as to Mr. Raj Prabhudesai and Ms. Isha Kurade, for their constant encouragement and Support.

My heartfelt thanks also go to my husband, Mr. Jitendra Prabhudesai**,** and my son, Mr. Deep Prabhudesai, for their patience, support, and sacrifices throughout my research journey.

Finally, I acknowledge with gratitude the contributions of numerous other individuals whose names may not find a place here but whose support, prayers, and encouragement have in some way contributed to the successful completion of this thesis. I sincerely pray that God bless them all abundantly. To each and every person who has supported me in this journey. **Thank You.**

DEDICATION

This thesis is dedicated with profound love and deepest gratitude to my beloved parents, Mr. Arvind S. Acharya and Mrs. Rekha A. Acharya. Their sacrifices, wisdom and constant faith in me have shaped my journey and given me the strength to pursue my aspirations.

This thesis is also dedicated to my dear son, Mr. Deep Prabhudesai, whose constant support has been an invaluable part of my research journey. I am deeply grateful for his thoughtful assistance in accompanying me to the Research Centre Pernem and Goa University, often driving me with patience and care. His timely help with various research-related tasks, including printing and other essential work, has made this journey smoother and less burdensome.

Beyond his practical support, his understanding, encouragement, and willingness to stand by me during challenging times have been a true source of strength. This achievement is as much his as it is mine, and I dedicate this work to him with heartfelt appreciation and love.

Antecedents to Consumer Behaviour towards M-Commerce:

An Empirical Study

By

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ABSTRACT

The rapid advancement of mobile technologies has significantly reshaped the domain of electronic commerce, leading to the emergence of mobile commerce (M-commerce) as a prominent channel for digital transactions. Although existing literature grounded in the Theory of Planned Behaviour (TPB) has highlighted the impact of factors such as attitude, perceived usefulness, ease of use, and trust on consumers' behavioural intentions towards mobile technologies, there remains a notable gap in comprehensive empirical investigations that specifically examine the antecedents of consumer behaviour within the M-commerce context. This study seeks to address this gap by empirically analysing the influence of core TPB constructs 'Attitude', 'Subjective Norms', and 'Perceived Behavioural Control on consumers' intentions towards mobile commerce and their actual mobile commerce purchase behaviour while shopping different categories of product.

This study investigated the antecedents of consumer behaviour towards mobile commerce (m-commerce) using the Theory of Planned Behaviour (TPB) as the conceptual framework. Based on structural equation modeling (SEM), the research validates the key TPB constructs Attitude, Subjective Norms, Perceived Behavioural. Control (PBC), and Intention to assess their influence on m-commerce adoption across diverse consumer segments.

The measurement model demonstrated strong validity, with significant factor loadings confirming construct reliability. Attitude emerged as a multidimensional construct, shaped by both positive aspects (e.g., convenience, user-friendliness) and negative concerns (e.g., safety, past experiences). Subjective Norms were largely influenced by peer and societal expectations, though some resistance due to negative social cues were evident. Perceived Behavioural Control showed limited influence, with ease of use and knowledge contributing positively but perceived risks negatively.

Demographic analysis revealed nuanced influences. Age, education, location, and marital status significantly impacted attitudes and intentions, with younger, urban, and more educated users showing greater adoption likelihood. Occupation influenced intention but not attitudes or subjective norms, while gender and income showed minimal effects. Importantly, non-adoption was strongly associated with lack of knowledge, negative attitudes, and low intention, highlighting barriers to digital inclusion.

SEM findings confirmed that Attitude and Subjective Norms are the strongest predictors of intention, whereas Perceived Behavioural Control had no significant effect on intention. Intention, in turn, significantly mediated the relationship between these antecedents and actual purchase behaviour, confirming its central role. The model displayed robust fit indices, validating its application to m-commerce research.

Overall, the findings reinforce the applicability of the TPB model in explaining m-commerce behaviour. The study highlights the dominance of consumer attitudes and social influence in shaping behavioural intentions, while also revealing demographic disparities. Strategic implications suggest the need for targeted awareness campaigns, user-centric design, and rural outreach to enhance m-commerce engagement across varied consumer groups.

Keywords: Electronic commerce, M-commerce, Attitude, Subjective Norms, Perceived Behavioural Control, Intention, Mobile commerce purchase behaviour

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CHAPTER-1
INTRODUCTION

1.1 INTRODUCTION:

Mobile commerce (m-commerce) in India has experienced rapid growth, transforming the way consumers shop and businesses operate. With the increasing penetration of smartphones and internet connectivity, m-commerce is poised to become the dominant force in the Indian e-commerce landscape. Unlike e-commerce, m-commerce offers the convenience of on-the-go shopping, personalized user experiences, and real-time access to products and services. However, consumer adoption is not solely determined by accessibility. Several other factors such as perceived usefulness, ease of use, trust and security concerns, significantly shape consumer intentions and actual usage (Jain et al., 2023). Moreover, younger consumers and digital natives show higher engagement with m-commerce due to their comfort with mobile technologies and demand for instant gratification (Gupta & Pathak, 2023). In contrast, resistance among older consumers and users in rural regions often stems from concerns about data privacy & lack of digital literacy (Kumar et al., 2019). Understanding these factors provide businesses with insights into how to tailor their M-commerce strategies effectively to meet consumer needs and preferences.

1.2 BACKGROUND OF THE STUDY:

Technology and innovation have become a significant part of our lives in recent years. Despite this fact several innovation-based technologies, businesses have never arrived at their fullest capacity due to lack of acceptance by users. Hence several researchers are working very hard over the years towards testing and proposing extended models of various technology adoption theories like, Theory of Reasoned action (TRA) (Fishbein and Ajzen, 1975), Technology Acceptance Model (TAM) (Davis, 1989), Diffusion of Innovation (DOI) (Rogers, 1962), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et.al,2003) and many others, in order to know the reasons behind acceptance of innovation by the consumers and also to know the factors determining behavioural intention towards adoption and use of technology.

This study aims to investigate both the reasons behind acceptance and rejection of use of mobile devices for shopping. The behavioural intention to use mobile commerce for shopping is the basic construct of this model. Chew (2006) defined behavioural intention as "the power of an individual's intention to perform a certain behaviour". In the context of

m-commerce, this construct can be described as an individual's intention to perform online shopping through mobile wireless devices (Yang, 2005).

Extensive research based on the review of literature, supports the notion that ultimate behaviour of consumers' is important for the survival of any business, which is 'adoption and use of mobile commerce'. The theory of planned behaviour (Ajzen,1991), is one of the preferred technology adoption theories for the research in social science as well as behavioural sciences. Hence researcher have decided to use it for predicting consumer behaviour towards m-commerce in the state of Goa. This study has been conducted primarily to test the usage behaviour of m-commerce applications by consumers for shopping.

This study integrates the Theory of Planned Behaviour with the study of consumer behaviour towards M-commerce, highlighting the theoretical underpinnings and empirical applications in understanding consumers' attitudes, subjective norms, and perceived behavioural control in adopting mobile commerce services for shopping .The Theory of Planned Behaviour (TPB), developed by Ajzen (1991), provides a robust framework for understanding and predicting human behaviour in various contexts, including consumer behaviour towards M-commerce. According to TPB, consumer behaviour is influenced by three primary factors: attitudes towards the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991).

Attitudes towards M-commerce refer to consumers' overall evaluation of engaging in mobile commerce activities such as purchasing goods or services through mobile applications. Positive attitudes towards M-commerce are likely to increase the intention to engage in such behaviours (Ajzen, 1991). For instance, if consumers perceive M-commerce as convenient, time-saving, and offering a wide variety of choices, their attitudes towards using M-commerce are likely to be favourable (Davis, 1989).

Subjective norms reflect the perceived social pressures and expectations that influence individuals' decisions to adopt M-commerce. This includes the influence of significant others, such as friends, family, and peers, who may encourage or discourage the use of mobile commerce services (Ajzen, 1991). Social influence plays a crucial role in shaping consumer behaviour, as individuals are likely to confirm to perceived norms regarding M-commerce usage (Venkatesh et al., 2003).

Perceived behavioural control refers to consumers' perceptions of their ability to successfully perform the behaviour of using m-commerce applications. Factors such as perceived ease of use, technical skills, and confidence in conducting secure transactions on mobile platforms influence perceived behavioural control (Ajzen, 1991; Gefen, 2003). Higher levels of perceived behavioural control enhance consumers' intention to adopt and use M-commerce services.

In the context of M-commerce, empirical studies grounded in TPB have shown that attitudes towards mobile technology, perceived usefulness, ease of use, and trust in mobile transactions significantly influence consumers' behavioural intentions (Venkatesh et al., 2003; Kim et al., 2008). For example, research indicates that consumers who perceive M-commerce as convenient and secure are more likely to develop positive attitudes and intentions towards using mobile commerce services (Kim et al., 2008).

Despite the theoretical insights provided by TPB, there remains a need for empirical research that applies this framework to investigate specific antecedents influencing consumer behaviour towards M-commerce comprehensively. This study aims to address this gap by examining the relationships between attitudes, subjective norms, perceived behavioural control, and consumer behaviour towards M-commerce, utilizing a quantitative research approach to gather and analyse data from a diverse sample of mobile users.

By applying TPB to the study of M-commerce, this research seeks to enhance our understanding of the psychological factors driving consumer adoption and usage of mobile commerce applications. The findings of this study are expected to provide valuable insights for businesses and policymakers aiming to optimize strategies for promoting M-commerce adoption and improving consumer engagement in mobile transactions.

1.3 THE E-COMMERCE INDUSTRY: A GLOBAL AND INDIAN PERSPECTIVE:

The e-commerce industry continues to evolve rapidly, driven by technological advancements and changing consumer preferences. Globally, regions like Asia-Pacific and North America lead the market, while India emerges as a significant player with immense growth potential. Businesses must stay alert, leveraging trends like mobile commerce, AI-driven personalization, and social commerce, while addressing challenges related to

logistics, infrastructure, and regulatory environments. By doing so, they can capitalize on the growing opportunities in the global and Indian e-commerce markets.

E-commerce has transformed consumer interactions with businesses by providing unmatched convenience and accessibility via electronic devices. Over the past decade, the global e-commerce sector has experienced significant growth, reshaping both consumer shopping behaviour and business operations. In 2023, global e-commerce sales reached approximately $5.8 trillion, accounting for nearly 20% of total retail sales worldwide (Statista, 2023). This growth is driven by increasing internet penetration, the proliferation of smartphones, and improvements in logistics and payment systems. The COVID-19 pandemic further accelerated e-commerce adoption, with more consumers turning to online shopping for convenience and safety**.**

Table 1.1: Recent Data and Projections of Global E-commerce Sales (2018-2025)

Year	**Sales (in Trillion USD)**
2018	2.8
2019	3.5
2020	4.2
2021	4.9
2022	5.2
2023	5.8
2024	6.5
2025	7.4

Source: IAMAI. (2023). Digital India and Mobile Commerce Report. Retrieved from IAMAI

In India, the e-commerce industry has experienced amazing growth, making it one of the fastest-growing e-commerce markets globally. In 2023, the Indian e-commerce market was valued at approximately $90 billion and is projected to reach $120 billion by 2025 (IBEF, 2023). This surge is attributed to a fast-growing net user base and increasing smartphone penetration (TRAI, 2023). Government initiatives like Digital India campaign and improvements in digital infrastructure have also played an important role in fostering this growth.

Table 1.2: Recent Data and Projections of Indian E-commerce Sales (2018-2025)

Year	Sales (in Billion USD)
2018	39
2019	51
2020	60
2021	67
2022	75
2023	90
2024	105
2025	120

Source: Statista. (2023). E-commerce market size in India. Retrieved from Statista

1.4 M-COMMERCE: AN INDIAN PERSPECTIVE:

Mobile commerce (m-commerce), has become an essential component of the e-commerce industry, driving significant changes in consumer behaviour and business strategies. With the explosion of smartphones and the increasing availability of high-speed internet, consumers now prefer to shop via mobile devices than ever before (Statista, 2023). This shift has compelled e-commerce platforms to optimize their interfaces for mobile use, enhancing user experiences through responsive design and mobile-specific features (Kumar & Mukherjee, 2022).

The growth of m-commerce is particularly noticeable in India, with mobile transactions accounting for nearly 60% of e-commerce sales, reflecting importance of mobile-first strategies in capturing the Indian market (Forrester, 2023). By 2023, India had one of the largest smartphone user bases globally, with more than 750 million users of smartphone,and this number is expected to surpass 1 billion by 2026 (Statista, 2023). This surge has made m-commerce a central factor of digital economy.

According to the Ministry of Electronics & Information Technology (MeitY, 2022), smartphone penetration in Goa is above the national average, yet there remain considerable differences in adoption of digital payment and m-commerce systems. Factors like socio-economic status, digital literacy, local business practices, and trust in mobile platforms can vary significantly, impacting the overall acceptance of m-commerce in the state of Goa. (Shirodkar et al., 2020).

Table 1.3: Recent Data and Projections of M-commerce Sales in India (2020-2025)

Year	Sales (in Billion USD)
2020	25
2021	30
2022	35
2023	40
2024	55
2025	75

Source: Statista. (2023)

1.5 MEANING OF M-COMMERCE:

Mobile commerce also known as m-commerce, involves using wireless handheld devices like cell phones and tablets to conduct commercial transactions online, including Mobile shopping (purchase and sale of products), Mobile Banking, Mobile Payments and Mobile Advertising.

1.6 DEFINITIONS OF M-COMMERCE:

1.6.1 “Mobile e-commerce, commonly referred to as m-commerce, is the ability to purchase goods anywhere through a wireless Internet-enabled devices.” **(Clarke)**

1.6.2 “M-commerce refers to any transaction of monetary value that is conducted through a mobile network, using devices such as mobile phones, pagers, personal digital assistants, or laptops.” **(Varshney & Vetter)**

1.7 CHALLENGES AND OPPORTUNITIES FOR M-COMMERCE IN INDIA:

The m-commerce industry in India is on a rapid growth trajectory, driven by increasing mobile internet penetration, the proliferation of mobile payment systems, and changing consumer behaviour. While there are challenges to address, the opportunities for growth are immense. Businesses that can effectively leverage technology, understand consumer preferences, and navigate logistical challenges will be well-positioned to succeed in this dynamic market.

1.7.1 Challenges for M-Commerce in India:

a. Logistics and Delivery Infrastructure: Despite improvements, logistics and delivery infrastructure remain a significant challenge for m-commerce in India, particularly in rural and remote areas. According to the Indian Logistics Report 2023, the logistics sector in India is expected to grow at a CAGR of 10.5% from 2020 to 2025. However, the average delivery time for rural areas is 2-3 days longer compared to urban areas.

Table 1.4: Average Delivery Time for M-commerce in India

Location	Average Delivery Time (Days)
Urban	2
Semi-Urban	3
Rural	5

Source: Indian Logistics Report 2023, KPMG.

Implication: Improving the logistics and delivery infrastructure is crucial for ensuring timely deliveries and enhancing customer satisfaction in rural and semi-urban areas.

b. Digital Literacy and Internet Penetration: While internet penetration is increasing, digital literacy remains low in certain segments of the population, particularly among older

adults and those in rural areas. As per the Internet and Mobile Association of India (IAMAI), the number of internet users in India reached 700 million in 2023. However, digital literacy in rural areas is only about 25%, compared to 61% in urban areas.

Table 1.5: Digital Literacy Rate in India

Area	Digital Literacy Rate (%)
Urban	61
Rural	25
National	38

Source: Internet and Mobile Association of India (IAMAI, 2023)

Implication: Enhancing digital literacy through educational programs and awareness campaigns is essential for increasing the adoption of m-commerce across all demographic segments.

c. Cybersecurity Concerns: Ensuring secure transactions and protecting consumer data are critical concerns that need continuous attention. According to the CERT-In (Indian Computer Emergency Response Team), there were over 1.16 million cybersecurity incidents in India in the year, 2022, a 20% increase from 2021.

Table 1.6: Cybersecurity Incidents in India (2020-2022)

Year	**Cybersecurity Incidents (Million)**
2020	0.93
2021	0.97
2022	1.16

Source: CERT-In (Indian Computer Emergency Response Team)

Implication: Investing in robust cybersecurity measures and educating consumers about safe online practices are crucial for building trust in m-commerce platforms.

1.7.2 Opportunities for M-Commerce in India:

a. Rural Market Penetration:

With the majority of India's population residing in rural areas, there is significant potential for m-commerce growth through targeted strategies and improved logistics. The rural e-commerce market in India is projected to 38 billion USD in 2028.

Table 1.7: Rural E-commerce Market Size Projection in India (2023-2028)

Year	Rural E-commerce Market Size (Billion USD)
2023	10
2024	13
2025	17
2026	22
2027	29
2028	38

Source: Statista, (2024)

Implication: Companies can tap into this vast market by developing localized strategies, improving rural connectivity, and creating mobile-friendly platforms that cater to the unique needs of rural consumers.

b. Rise of Mobile Payment Systems in India: The increasing adoption of mobile payment systems like UPI, Paytm, Google Pay, and PhonePe has facilitated the growth of m-commerce by simplifying transactions. UPI transactions reached a record high of 9.36 billion in December 2023, according to the National Payments Corporation of India (NPCI). The total value of UPI transactions for 2023 was approximately $1.8 trillion.

Table 1.8: UPI Transactions (Billion) in India

Year	UPI Transactions (Billion)	Total Transaction Value (Trillion USD)

2020	2.2	0.54
2021	3.8	0.93
2022	6.5	1.4
2023	9.36	1.8

Source: National Payments Corporation of India (NPCI).

Implication: The continued growth of mobile payment systems offers an opportunity for m-commerce platforms to enhance user experience by providing seamless and secure payment options, thus encouraging more consumers to use m-commerce for shopping.

c. AI and Personalization: Leveraging: Artificial Intelligence (AI) offering personalized shopping experiences can enhance customer satisfaction and drive sales. A report by McKinsey & Company indicates that companies using AI-driven personalization can achieve up to a 15% increase in sales. AI applications in m-commerce, such as chatbots and recommendation engines, are expected to grow by 25% annually in India through 2025.

Table 1.9: AI Applications Growth Rate Projection (%) In India

Year	**AI Applications Growth Rate (%)**
2020	10
2021	15
2022	20
2023	25
2024	25
2025	25

Source: McKinsey & Company. "AI-driven Personalization in E-commerce."

Implication: By integrating AI technologies, m-commerce platforms can provide tailored recommendations, personalized marketing, and efficient customer service, thereby improving user engagement and retention.

d. Augmented Reality (AR):

Augmented Reality (AR) can revolutionize the shopping experience, particularly in segments like fashion and home decor, by allowing customers to virtually try products before purchasing. According to a report by PwC, the AR market in India is projected to grow at a CAGR of 55% from 2023 to 2028.By 2028, AR is expected to influence up to $15 billion in m-commerce sales.

Table 1.10: AR Market Size Projections (Billion USD) in India

Year	AR Market Size (Billion USD)
2023	2
2024	3.5
2025	5
2026	7.8
2027	11.5
2028	15

Source: PwC. "Augmented Reality Market Projections for India."

Implication: Incorporating AR technology can enhance the shopping experience by providing interactive and immersive product demonstrations, which can increase consumer confidence and reduce return rates.

1.8 SIGNIFICANCE OF THE STUDY:

This study highlights the theoretical and practical significance of applying the Theory of Planned Behaviour to investigate consumer's behavioural intentions and its impact on actual usage behaviour in the context of M-commerce, emphasizing its relevance for business strategy, consumer education, and theoretical advancements in the field.

The Theory of Planned Behaviour (TPB), developed by Ajzen (1991), provides a structured framework for understanding and predicting consumer behaviour towards M-commerce. This theory suggests that consumer intentions and behaviours are influenced by three key factors: attitudes towards the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991).

1.8.1 Predictive Power of Attitudes, Subjective Norms, and Perceived Behavioural Control:

This study is significant as it applies TPB to investigate how attitudes towards M-commerce, subjective norms, and perceived behavioural control collectively influence consumers' intentions and actual behaviour towards using mobile commerce applications for shopping purpose. By empirically testing these relationships, the study aims to provide insights into which factors are most influential in shaping consumer adoption and usage of M-commerce applications (Ajzen, 1991; Venkatesh et al., 2003).

1.8.2 Practical Implications for Businesses and Policy Makers:

Understanding the factors influencing consumer behaviour towards M-commerce is crucial for businesses and policymakers. Insights gained from this study can help businesses design and implement effective marketing strategies that will adjust with consumers' attitudes and preferences towards mobile transactions (Gefen, 2003).

1.8.3 Contribution to Theoretical Advancement:

Empirical validation of TPB in the context of M-commerce contributes to theoretical advancements in consumer behaviour research. By testing TPB constructs in a specific domain like M-commerce, this study expands our understanding of how general theories of behaviour can be applied to contemporary technological contexts. Such advancements are essential for developing robust theoretical frameworks that can guide future research and practical applications in mobile commerce (Venkatesh et al., 2003).

1.8.4 Insights for Consumer Education and Trust Building:

The study's findings can also suggest initiatives aimed at educating consumers about the benefits and safety of M-commerce. By identifying factors that influence perceived behavioural control and trust in mobile transactions, policymakers can develop policies and

guidelines that promote consumer confidence in using mobile commerce platforms securely and effectively (Kim et al., 2008).

1.9 RESEARCH PROBLEM:

The rapid evolution of mobile technologies and the spread of smartphones have catalysed the emergence and growth of mobile commerce (m-commerce), creating significant changes in consumer purchasing behaviour. M-commerce, as a subset of e-commerce, allows consumers to engage in real-time transactions anytime and anywhere, offering unprecedented convenience and personalization (Chopdar & Sivakumar, 2024). However, despite the technological advancements and the increasing penetration of mobile internet, m-commerce adoption varies significantly across demographic segments. Many consumers remain hesitant or inconsistent in their usage of mobile platforms for shopping, suggesting that key behavioural antecedents are still not fully understood or optimized by businesses.

A critical research problem, therefore, lies in identifying and empirically examining the antecedents that shape consumer behaviour towards use of m-commerce for shopping. While numerous studies have attempted to apply frameworks such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Theory of Planned Behaviour (TPB) to understand technology adoption, there remains a research gap in contextualizing these frameworks specifically to mobile commerce with a consumer-centric lens (Zhou, 2013; Chong, 2013).

Hence, the core research problem is: "What are the key antecedents that influence consumer behaviour towards m-commerce, and how do these antecedents interact to impact their intention to adopt m-commerce applications for shopping"

1.10 THE SCOPE OF THE STUDY:

This study is set within the field of consumer behaviour and digital marketing, specifically focusing on Mobile Commerce (M-commerce). It aims to apply the Theory of Planned Behaviour (TPB) (Ajzen, 1991) to understand and predict consumer intentions and behaviours towards use of M-commerce applications for shopping. The scope of the study consists of theoretical scope, empirical scope, managerial and policy scope, and educational scope:

1.10.1 Theoretical Scope: The study applies TPB as its theoretical framework, which suggests that attitudes, subjective norms, and perceived behavioural control are central determinants of behavioural intention (Ajzen, 1991). By employing TPB, the study examines the cognitive and social factors influencing M-commerce adoption. (Mital et al., 2021).

1.10.2 Empirical Scope: The research will be empirical in nature, using quantitative methods to measure the strength and significance of the three TPB constructs in predicting consumer intention and behaviour. Data will be collected through structured surveys administered to users of smartphones across the state of Goa. Analytical tools like regression analysis and structural equation modelling (SEM) will be employed to establish relationships among variables (Dwivedi et al., 2020).

1.10.3 Managerial and Policy Scope: This study holds practical relevance for businesses, marketers, and policymakers by identifying the psychological and behavioural factors that affect M-commerce adoption. Businesses can leverage these insights to develop targeted marketing strategies, personalized mobile interfaces, and trust-building mechanisms. Moreover, the findings can guide policymakers in formulating digital literacy campaigns, data privacy frameworks, and consumer protection measures that enhance user confidence in mobile platforms (Shareef et al., 2021).

1.10.4 Educational Scope: The study also examines the role of **consumer education** in influencing trust and perceived behavioural control in M-commerce usage. It investigates how digital awareness, mobile literacy, and understanding of online transaction security can affect user attitudes and behavioural outcomes. This can contribute to designing effective educational interventions aimed at improving digital participation across different demographic segments of society (Nguyen et al., 2020).

1.11 PURPOSE OF THE STUDY:

The study aims to provide a comprehensive understanding of the factors influencing consumer intention and usage behaviour towards mobile commerce applications for shopping. By examining attitudes, subjective norms, and perceived behavioural control, the study seeks to contribute both theoretically and practically to the field of M-commerce research, offering insights that can inform business strategies and policy initiatives aimed at promoting the growth and acceptance of mobile commerce platforms.

The Theory of Planned Behaviour (TPB), developed by Ajzen (1991), provides a structured framework for understanding consumer behaviour, particularly in the context of decision-making processes related to technology adoption such as use of M-commerce for shopping. This study aims to explore and analyse the factors influencing consumer behaviour towards M-commerce through the lens of TPB, focusing on three primary constructs: attitudes towards M-commerce, subjective norms, and perceived behavioural control (Ajzen, 1991).

1.11.1 Attitudes towards M-Commerce:

The study will investigate how consumers' attitudes towards M-commerce influences their intentions and behaviours towards use of m-commerce for shopping. Attitudes include consumers' overall evaluations and perceptions of using mobile devices for m-commerce activities, such as purchasing goods or services using mobile devices. (Davis, 1989; Ajzen, 1991).

1.11.2 Subjective Norms:

The research will explore the influence of subjective norms on consumer behaviour towards M-commerce. Subjective norms refer to the perceived social pressures and expectations from significant others, including family, and peers, regarding the adoption and usage of M-commerce services. This study will analyse how social influences impact consumers' intentions and behaviours in adopting mobile commerce (Ajzen, 1991; Venkatesh et al., 2003).

1.11.3 Perceived Behavioural Control:

The study will assess consumers' perceived behavioural control over using M-commerce platforms. This construct includes factors such as perceived ease of use, technical skills, and confidence in conducting secure transactions via mobile devices independently. Understanding perceived behavioural control is crucial for predicting consumers' intentions and actual behaviours towards M-commerce adoption and usage (Ajzen, 1991; Gefen, 2003).

1.11.4 Methodological Approach:

To achieve its objectives, the study will employ a quantitative research methodology, involving survey instruments designed to measure attitudes, subjective norms, perceived behavioural control, and actual purchase behaviour towards m-commerce among a diverse sample of mobile users from the state of Goa. Statistical analyses such as regression analysis and structural equation modelling (SEM) will be used to examine the relationships between TPB constructs and consumer behaviour (Venkatesh et al., 2003; Kim et al., 2008).

1.12 RESEARCH QUESTIONS:

I. How do the respective measurement variables contribute to the relevance and validity of their latent constructs in the proposed model of the “Theory of Planned Behaviour"?

II. How do the constructs of “The Theory of Planned Behaviour” influence the intentions to use m-commerce among consumers?

III. How do the ‘Demographic Variables’ influence ‘Attitude’, ‘Subjective Norms’, ‘Perceived Behaviour Control’, and ‘Intention’ regarding the use of m-commerce among consumers?

IV. How does intention mediate the relationship between ‘Attitude’, ‘Subjective Norms’, ‘Perceived Behavioural Control’, and consumer behaviour towards purchasing specified products through m-commerce?

V. How does “The Theory of Planned Behaviour" explain the factors influencing consumers’ adoption of m-commerce, and whether the empirical evidence supports the validity of this conceptual model in this specific context?

VI. What are the factors influencing an individual's likelihood of non-adoption of m-commerce?

1.13 OBJECTIVES OF THE STUDY:

I. To evaluate the relevance and validity of the measurement variables to their respective latent constructs in the proposed structural model of the “Theory of Planned Behaviour”

II. To evaluate the significance and extent to which the constructs of the ‘Theory of Planned Behaviour’ influence the intentions to use mobile commerce.

III. To examine the impact of ‘Demographic Variables’ on consumers' ‘Attitude’, ‘Perceived Behaviour Control’, ‘Subjective Norms’ and ‘Intention’ to use m-commerce.

IV. To investigate the mediating role of 'Intention' in the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories, through m-commerce.

V. To validate the conceptual model based on "The Theory of Planned Behaviour".

VI. To identify and analyse the factors influencing an individual's likelihood of non-adoption of m-commerce.

1.14 ORGANISATION OF THE THESIS:

Chapter 1: Introduction: This chapter includes Introduction, Background of the study, The E-commerce Industry: A Global and Indian Perspective, M-commerce(m-commerce) An Indian Perspective, meaning and definitions of M-commerce, Challenges and Opportunities for M-Commerce in India, Significance of the Study, Research Problem, The scope of the Study, Purpose of the Study, Research Questions, Objectives of the study, Organization of the Thesis and Conclusions

Chapter 2: Literature Review: Introduction, Theoretical Background, Indian study on consumer behaviour, Impact of antecedents of planned behaviour: Indian study, Global Study on consumer behaviour, Impact of antecedents of planned behaviour: Global study, Research Gap, the logical explanation of each research question, research objective and research hypothesis development with supporting literature review and citations and Conclusions.

Chapter 3: Research Methodology: This chapter includes introduction, research methodology based on the research ONION, development of measurement instruments, Operational definitions, development of scale, Pilot Test, population, Unit of analysis, sampling and sample size, Statistical Test Used, Ethical Considerations of the study.

Chapter 4: Data Analysis and Interpretation: This chapter includes introduction, data screening, demographic profile of respondents, Descriptive Statistics, objectives and hypothesis testing, Conclusions

Chapter 5: Findings and Conclusions: This chapter includes: introduction, objective wise findings of the study, findings of demographic insights, implications for theory and practice, recommendations, limitations of the study, future research directions, summary of key contributions and conclusions.

1.15 CONCLUSIONS:

In conclusion, this chapter has provided the conceptual and theoretical foundation necessary for the research study. It has brought together insights from literature, industry reports, and theoretical frameworks to establish the relevance and necessity of exploring consumer behaviour towards m-commerce through the lens of the Theory of Planned Behaviour. With this groundwork laid, the subsequent chapters will focus on review of literature, research methodology, data analysis, and interpretation of findings to answer the research questions and fulfil the stated objectives of the study.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION:

The review of literature serves as a foundational pillar in any scholarly research. This chapter aims to critically synthesize existing scholarly contributions, identify gaps, and establish the theoretical framework necessary for the current study. A well-structured review of literature not only anchors the research within the broader academic discourse but also justifies the research questions and methodology adopted (Webster & Watson, 2002).

For this study, the review focuses on key themes such as consumer behaviour theories, e-commerce and mobile commerce trends, technological acceptance models, and strategic marketing practices. By analysing important works and contemporary studies, this chapter aims to map out the evolution of concepts and their application in various contexts.

Furthermore, this chapter critically examines both conceptual and empirical contributions, identifying methodological strengths and limitations that inform the design of the present study. Attention is also given to recent systematic and analytical reviews in the field of m-commerce to identify underexplored areas (Palmatier et al., 2018). In doing so, the review not only provides context for the study's hypotheses but also guides the development of a conceptual framework and operational variables. Ultimately, this chapter highlights the importance of revisiting existing theoretical constructs in light of current market realities and consumer expectations.

The chapter is organised under following sections:

- Theoretical Background
- Indian Study on Consumer Behaviour
- Impact of Antecedents of Planned Behaviour: Indian Study
- Global Study on Consumer Behaviour
- Impact of Antecedents of Planned Behaviour: Global Study
- Research Gaps Literature Review of Research Questions, Research Objectives, Hypothesis, Summary and Conclusions.

2.2 THEORETICAL BACKGROUND:

Consumer Behaviour Theories:

Understanding consumer behaviour has long been a focal point in marketing research, as it provides valuable insights into how individuals make purchasing decisions and respond to marketing stimuli. Over the decades, various theoretical frameworks have been developed to explain consumer decision-making processes. This section critically reviews major consumer behaviour theories that have significantly contributed to the academic and practical understanding of consumption patterns.

2.2.1 Traditional Economic and Psychological Foundations

Early conceptualizations of consumer behaviour were rooted in economic theory, particularly the notion of the rational consumer, who is assumed to make decisions based on utility maximization and cost-benefit analysis (Simon, 1955). However, this model was criticized for oversimplifying human behaviour and ignoring psychological and emotional factors. As a result, psychological models gained prominence, incorporating cognitive and affective processes into consumer decision-making.

The Stimulus-Organism-Response (S-O-R) Model (Mehrabian & Russell, 1974) introduced the role of internal states such as emotions and moods in mediating external stimuli (e.g., advertisements) and behavioural responses (e.g., purchase intentions). This model laid the foundation for more sophisticated psychological frameworks that consider both environmental and internal influences.

2.2.2 The Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (Fishbein & Ajzen, 1975) was one of the first models to formalize the role of attitudes and subjective norms in predicting behavioural intentions. TRA suggests that a consumer's behavioural intention is influenced by their attitude toward the behaviour and the perceived social pressure to perform it (subjective norm). These constructs together influence the intention to perform a behaviour, which is considered the immediate antecedent to actual behaviour. TRA assumes that if a person intends to perform a behaviour, they are likely to do so, provided they have the necessary resources and opportunities.

TRA has been widely adopted in marketing research to explain various consumer actions such as purchase intention, brand choice, online shopping, and technology adoption. Studies have found that attitudes and subjective norms consistently predict behavioural intentions across a variety of consumer contexts (Ryan & Bonfield, 1980; Miniard & Cohen, 1981). Similarly, in product innovation studies, researchers have employed TRA to understand how new product perceptions and social influence affect consumers' willingness to try innovations (Taylor & Todd, 1995). In digital marketing, TRA has been instrumental in understanding online purchase behaviour. For example, Lim et al. (2016) utilized TRA to study online shopping intentions and found that subjective norms, especially peer reviews and social media influence, strongly impact consumer intentions in e-commerce environments.

Despite its wide use, TRA has been critiqued for its inability to explain behaviours that are not under complete volitional control. Many consumer behaviours such as impulse buying or habitual consumption are not always deliberate or planned. As a response, Ajzen (1991) extended the model into the Theory of Planned Behaviour (TPB) by adding the perceived behavioural control (PBC) component to account for non-volitional factors.

Moreover, empirical studies have shown that TRA's explanatory power can be limited in contexts where external barriers, emotions, or situational constraints play a major role (Bagozzi & Yi, 1989).

2.2.3 The Theory of Planned Behaviour (TPB):

To address the limitations of TRA, Ajzen (1991) introduced the Theory of Planned Behaviour (TPB) by incorporating a third construct perceived behavioural control (PBC) which captures the individual's perception of ease or difficulty in performing a behaviour. TPB has been extensively used in marketing research to predict behaviours such as online shopping (Pavlou & Fygenson, 2006), green purchasing (Paul et al., 2016), and mobile commerce adoption (Yang, 2005). TPB's strength lies in its comprehensive structure and predictive validity, especially when combined with contextual or demographic mediators.

2.2.4 The Technology Acceptance Model (TAM) and Its Extensions:

Originally developed in the context of information systems, the Technology Acceptance Model (TAM) by Davis (1989) has gained widespread adoption in marketing, particularly in digital environments. TAM suggests that perceived usefulness and perceived ease of use are the primary predictors of technology adoption behaviour. The model has been extended into TAM2, TAM3, and eventually integrated into the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003).

These models are particularly useful in understanding consumer behaviour in tech-driven contexts such as e-commerce, mobile applications, and social media marketing. Nonetheless, critics argue that TAM and its variants often overlook emotional, cultural, and social influences (Bagozzi, 2007).

While TAM has contributed immensely to understanding user interaction with technology, its narrow focus on system-related beliefs limits its utility in diverse marketing contexts. The TPB, with its incorporation of subjective norms and perceived behavioural control, offers a more comprehensive, flexible, and empirically robust model.

2.3 INDIAN STUDY ON CONSUMER BEHAVIOUR:

The consumer landscape in urban India has undergone a significant transformation due to globalization, digitalization, and rising disposable income. A study by (Gupta and Verma ,2020) examined how lifestyle changes and digital access affect urban Indian consumers' decision-making processes. Their research focused on factors such as convenience, brand perception, and product innovation. The study revealed that urban consumers are highly influenced by digital advertisements and social media reviews, emphasizing the importance of digital touchpoints in consumer journeys. India’s cultural diversity plays a critical role in shaping consumer preferences. (Singh and Kaur ,2019) investigated how cultural values, traditions, and social norms influence buying behaviour across different Indian regions. The study employed a qualitative design through focus group discussions and found that collectivism, family influence, and religious beliefs significantly affect purchase decisions, especially in categories such as food, clothing, and lifestyle products. While urban markets have matured, rural India represents an evolving consumer segment. (Patil and Bansal ,2018) explored consumer behaviour in rural regions, focusing on awareness levels, purchasing power, and brand loyalty. The study concluded that rural consumers are increasingly aspirational, showing interest in branded products, but are constrained by limited income

and poor access to organized retail. The research highlights the need for affordable pricing and effective distribution networks to penetrate rural markets. The digital revolution has significantly influenced the buying behaviour of millennials and Gen Z in India. In a study conducted by (Sharma and Kapoor ,2021), the authors examined the role of social media platforms, influencers, and e-WOM (electronic word-of-mouth) in shaping young consumers' choices. The study used a quantitative approach with 500 college students in metropolitan cities. Results indicated that trust in influencers and peer recommendations had a significant impact on brand preferences and buying intentions. As environmental awareness grows, so does interest in sustainable consumption. (Mehta and Chatterjee ,2022) explored the emergence of green consumer behaviour in India by examining how eco-labels, environmental knowledge, and corporate social responsibility (CSR) practices influence buying behaviour. The research revealed a gap between consumer attitudes and actual green purchasing behaviour, often due to higher prices and limited availability of eco-friendly alternatives.

2.3.1 Consumer Behaviour and E-Commerce:

Trust and perceived risk are major determinants in online consumer behaviour. (Chauhan and Verma, 2018) explored how these two factors influence online purchase intentions among Indian consumers. Using a structured questionnaire survey with 400 respondents, the study revealed that concerns about data privacy, product authenticity, and payment security significantly shape trust and risk perceptions. Consumers with higher trust in the e-commerce platform showed greater intention to purchase online. Demographic variables such as age, income, education, and gender significantly influence online shopping behaviour in India. (Kanchan, Kumar, and Gupta,2015) investigated how these variables affect consumer attitudes and frequency of online purchases. The study found that young, educated, and urban consumers with moderate to high income were more likely to shop online. Gender differences also emerged, with males engaging more frequently in tech-based and high-value purchases. Website aesthetics, ease of navigation, loading speed, and product display are vital in influencing Indian consumer satisfaction and purchase behaviour. (Saxena and Khanna, 2019) evaluated the impact of website design on consumer engagement and loyalty in India’s online fashion retail segment. The study used SEM analysis and concluded that good website design leads to greater user trust, reduced bounce rates, and higher conversions. With the expansion of internet access and smartphone

penetration, consumers from Tier II and III cities in India have emerged as active participants in the e-commerce ecosystem. (Rao and Sinha, 2020) examined behavioural shifts among consumers in semi-urban and rural India. The study found that factors like COD (Cash on Delivery), regional language support, and local influencer marketing drive trust and adoption among this segment. Promotional strategies such as flash sales, discounts, cashback, and free delivery play a critical role in influencing impulsive buying behaviour among Indian online shoppers. (Mehta and Shah, 2021) conducted a quantitative study on the impact of online promotions on impulsive purchases, particularly during festive seasons. Their findings confirmed that time-limited deals and mobile app notifications significantly increased the frequency of unplanned purchases.

2.3.2 Consumer Behaviour and M-Commerce:

M-commerce adoption is closely linked to consumers' perceptions of ease of use and usefulness, as described by the Technology Acceptance Model (TAM). (Agarwal and Prasad, 2018) examined mobile shopping behaviour among urban Indian consumers and found that perceived ease of use and perceived usefulness were the two most significant predictors of mobile shopping adoption. Their quantitative study, conducted using a structured questionnaire, emphasized that user-friendly app interfaces and utility-driven features significantly influence consumer decision-making in the mobile environment. Trust is a critical determinant in shaping mobile shopping behaviour. (Bansal and Sharma, 2020) investigated the impact of trust, security, and privacy on Indian consumers' willingness to engage in m-commerce transactions. Their study revealed that perceived risk is a significant barrier, and consumers often hesitate to enter personal and financial information via mobile platforms. To mitigate these concerns, the authors recommended secure payment gateways and transparent return policies. Consumer lifestyle and demographic factors have a significant impact on m-commerce usage. In their study, (Kumar and Roy, 2019) analysed the influence of age, income, and lifestyle orientation on mobile shopping habits. They found that younger consumers (ages 18–35), particularly those with higher disposable incomes and tech-savvy lifestyles, are more likely to make frequent mobile purchases. Their findings support the importance of lifestyle segmentation in mobile marketing strategies. The quality of mobile applications significantly affects consumer engagement and loyalty. (Rana and Singh, 2021) explored how app design, ease of navigation, responsiveness, and personalized content influence repeat usage in the Indian m-commerce sector. Their structural equation modeling (SEM) analysis confirmed that mobile app quality directly enhances consumer

satisfaction and indirectly impacts continued purchasing behaviour. Promotional tools such as discounts, cashback offers, and flash sales are powerful motivators for consumer engagement in mobile commerce. (Deshmukh and Patel, 2022) conducted a mixed-method study to evaluate how such marketing strategies affect impulse buying and brand switching behaviour in m-commerce. Their findings showed that time-sensitive promotions and personalized notifications can trigger instant purchases, especially among young Indian consumers.

2.4 IMPACT OF ANTECEDENTS OF PLANNED BEHAVIOR:AN INDIAN STUDY:

Attitude toward behaviour is a key antecedent in the Theory of Planned Behaviour (TPB). In a study by (Ajzen and Fishbein, 2005), attitude was found to have a direct and significant influence on consumers' intentions to engage in online shopping. Positive evaluations of online buying (e.g., convenience, time-saving, and variety) lead to a stronger intention to shop online. This finding is supported by various marketing studies that align with the TPB model in explaining online consumer behaviour. Subjective norms refer to the perceived social pressure to perform or not perform a behaviour. (Armitage and Conner,2001) conducted a meta-analytic review of TPB studies and found that subjective norms significantly influence intention, particularly in collectivist cultures where social approval and family opinions play a dominant role. In the context of Indian consumers, the influence of family, friends, and social groups has been noted to be especially impactful in categories such as fashion, technology, and food. Perceived Behavioural Control (PBC) reflects an individual's perception of their ability to perform a behaviour. (Pavlou and Fygenson, 2006) applied the TPB model to e-commerce and found PBC to be a strong predictor of both intention and actual usage of mobile shopping. Factors such as internet literacy, mobile access, and ease of transaction influenced PBC levels. For marketing managers, enhancing the user's control over the buying process (e.g., through mobile UX and customer support) can positively impact outcomes. (Ajzen, 1991) emphasized that intention serves as a mediator between attitude, subjective norms, PBC, and actual behaviour. Several studies confirm that the predictive power of TPB depends on how strongly intention is formed by these antecedents. In marketing contexts such as environmental or ethical consumerism, although attitudes are favourable, unless PBC and subjective norms are also strong, actual purchase behaviour often does not occur—highlighting the mediating role of intention.

(Paul, Modi, and Patel ,2016) applied TPB to investigate Indian consumers' intentions toward buying green products. Their study revealed that attitude (e.g., environmental concern), subjective norms (peer influence), and PBC (availability and affordability of green products) all significantly contributed to purchase intention. Among these, attitude had the strongest influence. This suggests that pro-environmental marketing campaigns should not only raise awareness but also address perceived control and social desirability.

2.4.1 Study on Impact of Attitude Dimension of Planned Behaviour:

George and Kumar (2014). examined the influence of attitude on online purchase intention using TPB. Their study revealed that attitude was the most significant predictor among the three antecedents, especially among young urban consumers. The research showed that positive perceptions of convenience, time-saving, and value deals in e-commerce formed strong attitudes that translated into higher purchase intentions. (Yadav and Pathak, 2016) studied green consumer behaviour in India and found that attitude toward environmentally friendly products significantly affected consumer intention to buy them. Their study employed the TPB framework and demonstrated that consumers with positive environmental attitudes were more likely to express intention and follow through with purchasing green products. However, the attitude-behaviour gap was moderated by factors such as price and availability. (Venkatesh, Thong, and Xu, 2012) found that user attitude plays a pivotal role in mobile commerce adoption decisions. Positive attitudes toward using mobile apps for shopping—driven by perceived enjoyment, ease, and convenience—significantly influenced behavioural intentions. Marketers leveraging app design, personalization, and gamification strategies can therefore directly influence consumer attitudes and drive mobile commerce growth. (Bansal and Bharti, 2020) investigated the impact of consumer attitude toward social media advertisements on purchase intention in India. The study, grounded in the TPB framework, found that a positive attitude toward social media ads based on relevance, entertainment, and credibility—strongly influenced behavioural intention to engage with brands online. This highlights how digital marketers can shape consumer attitudes through targeted, value-driven ad content.

2.4.2 Impact of Subjective Norm Dimension of Planned Behaviour:

In a study on Indian e-commerce, (Sharma and Gupta, 2020) examined how subjective norms affect online buying intentions. They found that recommendations from family and

friends significantly influenced product choices, especially in the case of first-time online buyers. Peer influence was more pronounced among younger demographics, who rely heavily on reviews, social media, and influencer endorsements. This underscores the need for marketers to build trust and social validation through word-of-mouth and user-generated content. (Yadav and Pathak, 2016) investigated the role of subjective norms in promoting green purchasing behaviour among young Indian consumers. Their study revealed that peer and parental encouragement positively influenced intention to buy eco-friendly products. However, while subjective norm shaped intention, the actual purchase behaviour was still moderated by other factors like perceived behavioural control and product availability. (Patil and Rani, 2021) studied the acceptance of mobile wallets in India using the TPB framework. They found subjective norm to be a strong predictor of intention, particularly among users influenced by peer groups and social media trends. Social acceptance and normative beliefs about digital payment safety were crucial in encouraging users to adopt platforms like Paytm and Google Pay, particularly during and after the COVID-19 pandemic. (Saxena and Yadav, 2019) explored the impact of subjective norms on brand loyalty in the Indian fashion retail sector. Their findings indicated that consumers were significantly influenced by peer opinions and societal expectations regarding fashion choices, especially in metropolitan cities. The study suggested that brands should leverage influencer marketing and celebrity endorsements to align consumer identity with social approval, thus enhancing loyalty.

2.4.3 Study on Impact of Perceived Behavioural Control Dimension of Planned Behaviour:

Gupta and Arora (2017) studied online shopping behaviour in India and found that PBC was a significant predictor of online purchase intention, second only to attitude. Factors such as internet access, mobile phone usage proficiency, and secure payment options enhanced consumers' perceived control over online transactions. The study suggested that reducing technological and logistical barriers can increase consumers' online engagement and purchase frequency. (Zhou, 2011) investigated mobile commerce adoption in emerging markets using an extended TPB model. The study found that PBC had the strongest impact on consumer intention to adopt m-commerce, particularly due to its relationship with self-efficacy and facilitating conditions (like smartphone usability and mobile data access). The findings are particularly relevant in the Indian context, where mobile-based transactions are rapidly increasing but often constrained by network and payment infrastructure. (Paul,

Modi, and Patel, 2016) used TPB to investigate sustainable consumer behaviour in India. Their study highlighted PBC as a critical barrier to the adoption of sustainable products and practices, despite positive attitudes and social norms. High cost, lack of availability, and limited information reduced perceived control, weakening the link between intention and behaviour. The study recommended policy-level interventions to reduce these barriers and improve market accessibility. (Yadav and Pathak, 2016) examined the purchase intention of green products among Indian youth and found that PBC played a mediating role between intention and actual purchase behaviour. Although consumers had favourable attitudes and normative support, many did not purchase due to high prices and limited product availability. Enhancing consumer control (via affordability and accessibility) was identified as essential to translate positive intention into real buying behaviour.

2.5 GLOBAL STUDY ON CONSUMER BEHAVIOUR:

The digital revolution has profoundly transformed consumer behaviour across the globe, influencing how individuals search for, evaluate, and purchase products. With the proliferation of digital devices, internet accessibility, and interactive technologies, the decision-making journey of global consumers is increasingly shaped by online experiences, digital advertising, social media, and e-commerce platforms. According to (Cheung and Thadani ,2012), electronic word-of-mouth (e-WOM) has become a key factor influencing online consumer behaviour. Their comprehensive review found that consumers rely heavily on peer-generated content across global digital platforms such as Facebook, Twitter, and YouTube. e-WOM contributes significantly to trust formation, especially when brand communication is perceived as biased or untrustworthy. (Grewal, Roggeveen, and Nordfält ,2017) studied the impact of mobile technologies on in-store and online shopping across countries. Their research indicated that mobile apps and location-based services significantly affect consumer engagement, real-time decision-making, and impulse purchases. Globally, consumers now expect seamless integration between physical and digital retail experiences. (Park, Lee, and Han ,2007) demonstrated that online product reviews serve as influential decision aids for global consumers. Their research found that the quality and quantity of reviews significantly influence purchase intentions, particularly in high-involvement product categories. Review credibility and perceived helpfulness were shown to affect trust and buying behaviour across diverse consumer segments. (Arora et al. ,2008) emphasized the significance of digital personalization in enhancing consumer

satisfaction and loyalty. Their study across several Western markets highlighted that consumers respond positively to personalized emails, recommendations, and advertisements, which enhance perceived relevance and engagement. However, over-personalization may raise privacy concerns, especially in regions with strict data protection regulations. (Beldad, de Jong and Steehouder ,2010) explored how trust in online platforms is shaped across different cultures. Their findings reveal that perceived security, website usability, and reputation are central to digital trust. Trust-building mechanisms such as third-party certifications, clear privacy policies, and customer service transparency were particularly valued in both Western and Eastern consumer markets.

2.5.1 Consumer Behaviour and E-Commerce:

Trust remains a critical factor influencing consumer behaviour in e-commerce. (Gefen et al., 2003) found that perceived trust in online vendors significantly affects consumers' willingness to engage in e-commerce transactions. Elements like secure payment systems, privacy assurances, and positive reviews enhance trust and reduce perceived risk. The design and usability of an e-commerce platform play a pivotal role in shaping consumer behaviour. According to (Cyr et al., 2006), aesthetic appeal, navigation ease, and information quality on a website positively affect consumer satisfaction and purchase intentions. A user-friendly interface can reduce bounce rates and improve conversion. Social proof and peer influence drive online shopping decisions. (Chevalier and Mayzlin, 2006) illustrated how consumer-generated reviews on e-commerce platforms (e.g., Amazon) influence buyer behaviour, especially when the reviews are detailed and perceived as credible. This aligns with the rise of user-generated content in shaping online consumer perception. Mobile commerce (m-commerce) has revolutionized consumer behaviour by enabling real-time, location-independent shopping. (Yang, 2010) emphasized that convenience, personalization, and time-saving are key motivators for mobile shoppers. However, mobile app design and performance are crucial in ensuring a smooth user experience. Online consumers exhibit high price sensitivity due to the ease of price comparison. (Brynjolfsson and Smith, 2000) showed that digital markets have more price transparency, which compels consumers to seek value and compare alternatives. E-tailers respond with dynamic pricing, flash sales, and discount strategies to attract bargain-driven shoppers. Despite the growth in e-commerce, privacy concerns remain a significant deterrent. (Pavlou, 2003) argued that perceived privacy risks negatively affect consumer attitudes and online purchase intentions.

ensuring data security, transparent privacy policies, and ethical data use are essential for fostering consumer confidence.

2.5.2 Consumer Behaviour And M-Commerce:

According to the Technology Acceptance Model (TAM), perceived usefulness and ease of use are key predictors of consumer behaviour in mobile commerce. (Davis, 1989) originally introduced this model, and it has since been widely applied to m-commerce settings. Users are more likely to adopt mobile shopping apps if they find them efficient and simple to use. Research by (Zhang et al., 2012) highlighted that consumer attitudes shaped by personalization, entertainment, and utility significantly influence behavioural intentions toward m-commerce platforms. Positive consumer attitude toward mobile shopping apps increases the likelihood of repeated usage and brand loyalty. Trust and perceived security continue to be critical issues in mobile commerce. (Zhou, 2012) argued that trust in the mobile platform and vendor is a strong antecedent of purchase intention, especially when personal and financial data is involved. Enhancing data encryption and transparency builds consumer trust. Consumer motivations in m-commerce can be both hedonic (fun, enjoyment) and utilitarian (useful, efficient). A study by (Kim et al., 2007) showed that while utilitarian factors dominate initial adoption, hedonic factors play a key role in sustained engagement and loyalty to mobile commerce apps. Mobile application design quality significantly affects consumer satisfaction and loyalty. According to (Wang and Lin, 2012), intuitive navigation, aesthetic design, and responsiveness positively influence user perceptions and behaviour. A well-designed app improves the customer experience and purchase likelihood. Social influence through reviews, recommendations, and social media has a strong effect on mobile shopping. (Lu and Su, 2009) found that peer influence and online word-of-mouth shape perceptions of credibility and brand image, thus affecting mobile shopping behaviour.

2.6 IMPACT OF ANTECEDENTS OF PLANNED BEHAVIOUR: GLOBAL STUDY:

Attitude toward a behaviour is one of the strongest predictors of consumer intention in the Theory of Planned Behaviour. (Ajzen, 1991) emphasized that individuals evaluate the

outcomes of a behaviour before forming intentions. In marketing, favourable consumer attitudes toward a brand or product often led to a higher likelihood of purchase intention.

Subjective norms, or perceived social pressure, significantly impact consumers' behavioural intentions. According to (Fishbein and Ajzen, 2010), people are more likely to engage in a behaviour if they believe important others (family, peers, influencers) approve of it. This is particularly relevant in the context of social media marketing and peer-influenced purchase decisions.

Perceived Behavioural Control (PBC), which reflects the ease or difficulty of performing a behaviour, acts both as a direct and indirect predictor of consumer behaviour. (Armitage and Conner, 2001) noted that high PBC increases the likelihood of intention translating into action, especially in digital commerce, where ease of transaction matters.
(Taylor and Todd, 1995) extended TPB by incorporating e-commerce behaviours, finding that PBC (such as confidence in using technology) is a more significant determinant in online settings than in traditional settings. Their findings validate the flexibility of TPB across digital platforms in understanding online consumer behaviour.

Many studies have confirmed that the effect of TPB antecedents on actual behaviour is largely mediated by intention. A study by (George, 2004) in the online banking sector revealed that while attitude and PBC strongly influence intention, the actual behaviour depends on the stability of that intention over time. Culture can moderate the strength of TPB components. (Yousafzai et al., 2010) demonstrated that in collectivist cultures, subjective norms have a stronger effect than in individualist societies, where attitudes and PBC dominate. This has critical implications for global marketing strategies and behavioural prediction across cultures.

2.6.1 Impact of Attitude on behavioural intention:

Attitude as a core determinant in the Theory of Planned Behaviour (Ajzen, 1991) identified attitude as a key antecedent of behavioural intention in the Theory of Planned Behaviour (TPB). A positive attitude toward a product or behaviour increases the likelihood that consumers will intend to engage in related behaviour. This framework has become foundational in understanding consumer actions across various marketing contexts. According to (Keller, 1993), consumer attitudes significantly shape brand perception and brand equity. Positive attitudes toward a brand, driven by past experiences, advertising, or

word-of-mouth, create stronger brand associations, thereby increasing brand loyalty and long-term customer retention. In the e-commerce domain, (Pavlou, 2003) demonstrated that consumers' attitudes toward online transactions strongly affect their intention to purchase. A favourable attitude is influenced by website trustworthiness, ease of use, and perceived usefulness. Attitude plays a critical role in consumers' intention to purchase environmentally friendly products. According to (Chen and Chai, 2010), positive environmental attitudes significantly increase the likelihood of green product consumption. However, the attitude-behaviour gap may still occur due to price sensitivity and limited product availability. (Mitchell and Olson, 1981) distinguished between cognitive (rational) and affective (emotional) components of attitude in advertising. Both influences how consumers respond to marketing messages. Emotional appeals often produce stronger attitude change, which is essential for campaigns targeting lifestyle or identity-based products. Attitude formation is also subject to cultural context. (Wang and Lin, 2009) showed that in collectivist cultures, social conformity influences attitudes more than in individualist societies, where personal experience and values dominate. This has implications for global branding and segmentation strategies.

2.6.2 Impact of Subjective Norm on Behavioural Intention:

According to (Hansen et al., 2004), subjective norms significantly affect online consumer purchase intentions, especially when the product is socially visible or the consumer is uncertain. Positive social influence from peers and social media reinforces the consumer's intention to engage in online purchases. Subjective norms are particularly influential in green marketing and ethical consumption. (Dean et al., 2008) found that social norms strongly shape consumers' intentions to purchase organic food and eco-friendly products. Consumers are more likely to buy such products when they believe it is socially expected or valued in their community. (Yousafzai et al., 2010) observed that subjective norm has a stronger impact in collectivist cultures (e.g., India, China) than in individualistic ones (e.g., USA, UK). In collectivist settings, consumers are more motivated by social approval and conforming to group expectations when making purchasing decisions.

(Chu and Kim, 2011) showed that subjective norm plays a pivotal role in e WOM (electronic word-of-mouth) and brand advocacy on social media platforms. Consumers are more likely to share and endorse brands when they perceive that their peers approve or expect such engagement, making subjective norm a strategic variable in digital marketing. Research by (Conner and Armitage, 1998) suggested that subjective norm can moderate the gap between

intention and behaviour. For example, if a consumer intends to buy a health supplement but perceives disapproval from family or friends, the actual behaviour may be inhibited despite strong intention.

2.6.3 Impact of Perceived Behavioural Control on Behavioural Intention:

PBC has been found to influence sustainable behaviour such as buying eco-friendly products. (Vermeir and Verbeke, 2006) reported that consumers may hold favourable attitudes toward green products but only purchase them when they perceive behavioural control such as availability, affordability, and knowledge of use. In service marketing, (Taylor and Todd, 1995) found that PBC was especially important in predicting intentions to use self-service technologies. For example, consumers are more likely to use ATMs, kiosks, or online banking if they believe they are capable of doing so without assistance. Moderating Effect of PBC in the Intention-Behaviour Relationship (Armitage and Conner, 2001) conducted a meta-analysis and concluded that PBC moderates the relationship between intention and actual behaviour. Where perceived control is high, intentions are more likely to translate into actions. This insight is particularly valuable in designing marketing strategies for new product adoption.

2.7 RESEARCH GAP:

Despite the growing body of literature on m-commerce, several research gaps persist that warrant further investigation:

2.7.1 Gap1: Comprehensive Examination of Antecedents: There is a lack of integrated empirical model that consider a wide and multidimensional range of antecedents that influence consumer behaviour towards m-commerce.

While several studies have investigated individual predictors of m-commerce adoption such as perceived ease of use, trust, and security most research is fragmented, focusing on isolated variables or frameworks such as the Technology Acceptance Model (TAM) or Theory of Planned Behaviour (TPB). There is a noticeable lack of integrated models that simultaneously examine multiple categories of behavioural factors, in a unified framework.

For instance, (Chopdar and Sivakumar ,2019) integrated cultural values and perceived risk into mobile app usage behaviour, but did not include technological or hedonic factors. Similarly, (Liébana-Cabanillas et al. 2014) incorporated machine learning and structural equation modelling but focused more on user intention, leaving out interpersonal influences like subjective norms or peer recommendations.

This gap in holistic modelling limits our understanding of how these antecedents interact with one another. A comprehensive examination is essential to design well-rounded strategies for consumer engagement and long-term retention in m-commerce.

2.7.2 Gap 2: Behavioural Intention versus Actual Usage: There is a critical gap in distinguishing and empirically validating the relationship between behavioural intention and actual usage behaviour in the context of m-commerce, leading to limitations in predicting consumer conversion and retention.

Most empirical research on m-commerce continues to emphasize behavioural intention as a proxy for actual consumer behaviour. However, behavioural intention does not always translate into actual usage, especially in m-commerce, where external factors may hinder execution.

Studies like (Zhou ,2013 and Chong ,2013) have applied models like TPB and UTAUT to predict intention but did not measure actual purchase data. This results in a conceptual gap between what consumers intend to do and what they actually do. This also raises concerns about the validity of findings in real-world application, especially when businesses rely on behavioural data for strategy and personalization.

Addressing these research gaps will provide a deeper understanding of the antecedents to consumer behaviour towards m-commerce in Goa. This study aims to fill these gaps by conducting a comprehensive empirical investigation, considering regional specificities, a wide range of antecedents, the gap between behavioural intention and actual usage, the influence of attitude, perceived behavioural control and subjective norms on intentions and behaviour of consumers towards m-commerce. Such an investigation will contribute to the existing body of knowledge and provide valuable insights for stakeholders in the m-commerce ecosystem in Goa.

2.8 LITERATURE REVIEW OF RESEARCH QUESTIONS, RESEARCH OBJECTIVES AND HYPOTHESIS:

2.8.1 Research Question, Objective and Hypothesis 1:

Background of Research Question 1:

Understanding consumer behaviour involves analyzing various constructs such as Attitude, Perceived Behavioural Control (PBC), Subjective Norms (SN), and Intention, which are

central to predicting consumer intentions and actions as per the “Theory of Planned Behaviour". This literature review explores how specific measurement variables contribute to these constructs within the context of consumer behaviour in Goa.

Attitude: Attitude refers to consumers' overall evaluation or affective response towards a product, service, or brand (Ajzen & Fishbein, 1980). Measurement variables that contribute to attitude typically include affective, cognitive, and conative components (Fishbein & Ajzen, 1975). For instance, affective variables may assess consumers' emotional responses, while cognitive variables evaluate their beliefs and perceptions about a product's attributes (Eagly & Chaiken, 1993). Research has shown that these components collectively influence consumers' overall attitude formation and subsequent behavioural intentions (Ajzen, 1991).

Perceived Behavioural Control (PBC): PBC refers to consumers' perceptions of the ease or difficulty of performing a behaviour (Ajzen, 1991). Measurement variables contributing to PBC include self-efficacy, perceived resources, and perceived barriers (Ajzen, 2002). For example, consumers' confidence in their ability to afford a product or their perception of external obstacles can significantly influence their perceived control over purchasing decisions (Bandura, 1986). Understanding these variables helps predict consumers' ability to enact their intentions effectively (Ajzen, 1991).

Subjective Norms (SN): SN reflects consumers' perceptions of social pressures or expectations regarding a specific behaviour (Ajzen, 1991). Measurement variables contributing to SN include normative beliefs and motivation to comply (Fishbein & Ajzen, 1975). For instance, consumers' beliefs about the opinions of significant others and their motivation to conform to those expectations play a crucial role in shaping their behavioural intentions (Ajzen, 1991). Research indicates that SN significantly influences consumers' decisions by integrating social influences into their decision-making process (Kaplan & Graziano, 2009).

Intention: Intention represents consumers' readiness to perform a specific behaviour and is a direct precursor to actual behaviour (Ajzen, 1991). Measurement variables contributing to intention typically include attitude towards the behaviour, PBC, and SN (Ajzen, 1991). For example, a positive attitude towards a product, combined with a strong belief in one's ability to purchase it (PBC) and a perceived social expectation to do so (SN), increases the likelihood of forming a strong intention to purchase (Ajzen, 1991). Intention is considered a critical determinant of actual consumer behaviour across various contexts (Ajzen, 1991).

Research Question 1: How do the respective measurement variables contribute to the relevance and validity of their latent constructs in the proposed model of the "Theory of Planned Behaviour"?

The measurement variables associated with 'Attitude', 'Perceived Behavioural Control', 'Subjective Norms', and 'Intention' are important in understanding and predicting consumer behaviour in Goa. By examining these constructs and their respective measurement variables, researchers can develop comprehensive structural models that explain the factors influencing consumer decision-making processes in this specific region. Based on this argument, researcher developed the following objective and hypothesis to be studied.

Background of Research Objective 1:

Numerous existing studies provide a comprehensive analysis of measurement variables contributing to TPB constructs in m-commerce. (Ajzen, I. 1991). (Gefen et al. 2003) found 'Trust' to be a significant predictor of attitudes toward online commerce. In m-commerce, trust includes security and privacy measures, shaping users' positive or negative attitudes. (Taylor and Todd ,1995) found that, Self-efficacy, or the user's 'Confidence' in performing tasks on a mobile platform, strongly predicts PBC. High self-efficacy is linked to greater control and intention to adopt m-commerce. (Fishbein and Ajzen ,1975), this foundational work highlights those normative beliefs, such as approval from family and peers, shape subjective norms. For m-commerce, peer recommendations and family encouragement are critical normative measures. (Bhattacharjee ,2001) concluded that the post-adoption context, user satisfaction with prior m-commerce transactions can influence intention, which aligns with attitudinal feedback loops, where satisfaction reinforces positive attitudes. (Pavlou and Fygenson,2006) argued that perceived risk negatively affects attitudes toward m-commerce. Consumers wary of fraud or data breaches are less likely to form positive attitudes toward such platforms. (Luarn and Lin ,2005) found that monetary costs, such as transaction fees, negatively influence intention by affecting attitudes. When perceived costs outweigh benefits, users are less likely to adopt m- commerce. (Liébana-Cabanillas et al. 2014) revealed that perceived enjoyment enhances attitudes toward m-commerce, especially in entertainment-based applications. Platforms emphasizing user enjoyment are more likely to gain adoption. (Zhou et al. 2012) demonstrated that trust mediates the relationship between PBC and intention. Users who trust the platform perceive fewer obstacles in engaging with m-commerce. (Mallat,2007) emphasized the importance of contextual control variables,

such as the ability to perform transactions “on-the-go.”. Study found that, for m-commerce, mobility is a vital factor which enhances PBC. (Kim et al. ,2010) opined that, social influence, including opinions shared on social media, enhances subjective norms and younger users are particularly influenced by this variable when considering m-commerce adoption. (Chong, 2013) investigated that, personal innovativeness, a consumer trait, significantly contributes to attitudes toward m-commerce and innovative users are more open to adopting new platforms, creating a positive influence on attitude. (Zhou ,2013) found that Compatibility between m-commerce and users’ existing habits positively affects attitudes, especially when the m-commerce platform aligns with daily routines and expectations. (Slade et al. 2015) found that mobile literacy, or users’ ability to navigate mobile interfaces, strongly predicts PBC. Users with high mobile literacy perceive fewer barriers to adopting m-commerce. (Hajli ,2014) investigated that electronic Word of Mouth (eWOM) significantly shapes SNs and Positive reviews and recommendations enhance consumer perceptions of social approval for m-commerce platforms. (Chang et al. 2012) study revealed that, habitual behaviours, such as using smartphones for tasks, contribute to intention indirectly by influencing attitudes and SNs. (Mathieson, 1991) found that high-quality relevant information on m-commerce platforms enhances users' attitudes by reducing uncertainty and perceived risk. (Zhou and Wang ,2010) opined that, Concerns over privacy strongly mediates relationship between trust and attitude. Platforms addressing privacy concerns create more positive user attitudes.

Objective 1: To evaluate the relevance and validity of the measurement variables to their respective latent constructs in the proposed structural model of the “Theory of Planned Behaviour”

The objective of this study is to examine how each measurement variable included in the conceptual model influences and contributes to the latent constructs of Attitude, Perceived Behavioural Control (PBC), Subjective Norms, and Intention within the proposed structural equation model (SEM). The study aims to assess the strength and significance of these relationships, thereby validating the measurement model and providing insights into the determinants of behavioural intentions related to the studied phenomenon.

Key Components of the Objective:

Measurement Variables: To identify and analyze each measurement variable specified in the conceptual model. These variables serve as indicators or proxies for the underlying

constructs of Attitude, Perceived Behavioural Control, Subjective Norms, and Intention.

Contribution to Constructs: To evaluate the extent to which each measurement variable contributes to the variance of the respective constructs (Attitude, PBC, Subjective Norms, Intention) within the SEM framework. This involves examining the factor loadings or path coefficients between the measurement variables and their corresponding latent constructs.

Validation of Structural Model: To validate the proposed structural model by confirming that all measurement variables significantly contribute to the specified constructs. This validation ensures the reliability and validity of the measurement model, supporting the overall theoretical framework and providing a basis for interpreting the relationships between variables.

Implications: To discuss the implications of the findings for theory and practice. Understanding how these measurement variables influence attitudes, perceived control, social norms, and behavioural intentions can inform strategies for promoting desired behaviours or outcomes in relevant contexts.

By pursuing this objective, the study aims to advance understanding of the complex interrelationships between variables and contribute valuable insights to the field of consumer behaviour, and help:

- To validate the measurement model of the Theory of Planned Behaviour (TPB) by examining the relationships between measurement variables and latent constructs (Attitude, Subjective Norms, Perceived Behavioural Control, and Behavioural Intention) among individuals in Goa.

- To investigate the impact of the Theory of Planned Behaviour (TPB) constructs (Attitude, Subjective Norms, and Perceived Behavioural Control) on the buying intentions towards mobile commerce.

Based on the objective following hypothesis has been framed:

Hypothesis-1:

H1: The measurement variables are relevant and valid to their respective latent constructs in the proposed structural model of the "Theory of Planned Behaviour"

Sub-hypothesis:

H1a: All measurement variables are relevant and valid to the 'Attitude' construct in the proposed structural model of the "Theory of Planned Behaviour".

H1b: All measurement variables are relevant and valid to the 'Perceived Behavioural Control' construct in the proposed structural model of the "Theory of Planned Behaviour".

H1c: All measurement variables are relevant and valid to the 'Subjective Norms' construct in the proposed structural model of the "Theory of Planned Behaviour".

H1d: All measurement variables are relevant and valid to the 'Mobile Commerce Intention' construct in the proposed structural model of the "Theory of Planned Behaviour".

H1e: Measurement model is having goodness-of-fit indices.

Explanation:

This hypothesis suggests that each measurement variable included in the TPB model effectively measures and contributes to its corresponding latent construct: Attitude, Subjective Norms, Perceived Behavioural Control, and Behavioural Intention. In TPB, these constructs represent key determinants influencing individuals' intentions and behaviours.

2.8.2 Research Question, Objective and Hypothesis 2:

Background of Research Question 2:

Understanding consumer behaviour through the lens of the Theory of Planned Behaviour (TPB) provides insights into how attitudes, subjective norms, and perceived behavioural control influence buying intentions. This literature review synthesizes existing research to explore these relationships specifically within the context of consumers in Goa.

Attitude: Attitude in the context of TPB refers to consumers' overall evaluation or affective response towards purchasing a product or service (Ajzen, 1991). Positive attitudes are associated with favourable beliefs about the product's features, benefits, and quality (Fishbein & Ajzen, 1975). Research has consistently demonstrated that stronger positive attitudes towards a product or service correlate positively with higher buying intentions (Ajzen, 1991; Tarkiainen & Sundqvist, 2005). For example, consumers in Goa may develop positive attitudes towards products that are culturally relevant or align with their lifestyle preferences, influencing their intention to purchase (Verlegh & Steenkamp, 1999).

Subjective Norms: Subjective norms refer to consumers' perceptions of social pressures or expectations regarding purchasing behaviour (Ajzen, 1991). These norms are shaped by the

beliefs about what significant others think they should do and the motivation to comply with those opinions (Fishbein & Ajzen, 1975). In Goa, where social networks and cultural influences play significant roles in consumer decision-making, subjective norms can exert a strong influence on buying intentions (Kaplan & Graziano, 2009). For instance, recommendations from family members, peers, or opinion leaders within the Goan community can impact consumers' intentions to purchase specific products or brands (Ajzen, 1991; Verplanken & Holland, 2002).

Perceived Behavioural Control (PBC): Perceived behavioural control reflects consumers' beliefs about the ease or difficulty of performing the purchasing behaviour (Ajzen, 1991). Factors influencing PBC include perceived resources, skills, and situational constraints (Ajzen, 2002). In Goa, where economic conditions and accessibility to products and services vary, PBC becomes crucial in determining buying intentions (Ajzen, 1991; Venkatesh & Davis, 2000). Higher levels of perceived control over the purchasing process increase the likelihood that consumers will translate their intentions into actual purchases (Ajzen, 1991; Taylor & Todd, 1995).

Integration of Constructs and Buying Intention: The TPB suggests that attitudes, subjective norms, and PBC collectively determine individuals' intentions to engage in specific behaviours, including purchasing decisions (Ajzen, 1991). Studies have consistently shown that stronger positive attitudes, perceived social pressures, and greater perceived control over the buying process led to higher buying intentions (Ajzen, 1991; Venkatesh & Morris, 2000). In Goa, where consumer behaviour is influenced by cultural values, social norms, and economic factors, understanding these relationships is essential for marketers and policymakers aiming to predict and influence consumer decisions (Ajzen, 1991; Trafimow et al., 2002).

Research Question 2: How do the constructs of "The Theory of Planned Behaviour" influence the intentions to use m-commerce among consumers?

The constructs of the Theory of Planned Behaviour attitude, subjective norms, and perceived behavioural control play significant roles in shaping buying intentions among consumers in Goa. By examining these constructs, researchers can develop targeted strategies to enhance consumer engagement and satisfaction in this unique cultural context. Based on the given understanding, researcher has framed the following objective and hypothesis to be studied.

Background of Research Objective 2:

Some of the previous studies demonstrate the applicability of TPB to m-commerce, highlighting the dynamic interaction of attitudes, subjective norms, and perceived behavioural control in driving consumer behaviour. (Ajzen, I.1991) theory provides the foundation for understanding human intentions and behaviour. The TPB identifies attitudes, subjective norms, and perceived behavioural control (PBC) as predictors of intention. This framework is applicable in analysing consumer adoption of m-commerce. (Yang ,2012) investigated young consumers' intention to adopt mobile shopping using TPB. It revealed that attitudes and perceived ease of use significantly enhance intention, while subjective norms had a moderate effect. Findings suggest that positive attitudes toward convenience and security drive m-commerce adoption. (Chong et al. 2013) integrated perceived risk into TPB to examine m-commerce adoption. Perceived behavioural control was significantly influenced by perceived risks like transaction safety. As per study findings perceived risk strengthens PBC and increases m-commerce intention. (Slade et al. 2015) studied m-commerce with a focus on mobile payment systems. Subjective norms played a critical role, especially in collectivist cultures, where peer and family recommendations significantly influenced intention and found that social influence enhances subjective norms and purchase intention in mobile payments. (Kim et al. 2010) analysed attitudes toward m-commerce platforms, emphasizing usability, interface design, and personalization and found that positive user experiences significantly shaped attitudes and purchase intentions. (Nysveen et al. ,2005) extended the Theory of Planned Behaviour (TPB) by incorporating perceived ease of use and enjoyment as key factors influencing perceived behavioural control (PBC). Their findings highlighted the significance of these constructs in the context of mobile application-based shopping, demonstrating that ease of use has a positive impact on perceived behavioural control in m-commerce. (Gefen et al.2003) studied the mediating role of trust in m-commerce adoption. Trust was found to positively influence all TPB constructs, particularly attitudes and PBC and also enhances consumer intention to adopt m-commerce. (Ghazali et al. 2018) explored how app features influence attitudes and perceived behavioural control, in m-commerce. Features like seamless navigation, responsive design, and speed were significant contributors to attitudes. Study found that ‘m-commerce App quality’ positively influences attitudes and perceived behavioural control. (Dahlberg et al. 2008) examined the effect of PBC in the adoption of mobile payment systems, a critical component of m-commerce. The study found that PBC significantly impacts intention, influenced by transaction simplicity and simplified payment systems enhance PBC. (Shin and Kang ,2016) analysed cultural differences in TPB’s application to m-commerce

adoption. Subjective norms were found more critical in Asian cultures than in Western cultures. (Limayem et al. 2007) extended TPB by including habit as a predictor. Habit strongly influenced purchase intentions in mobile shopping contexts, particularly for frequent users and as per study findings, it also moderates the influence of TPB constructs.

Objective 2: To evaluate the significance and extent to which the constructs of the 'Theory of Planned Behaviour' influence the intentions to use mobile commerce.

The Theory of Planned Behaviour (TPB), developed by Ajzen in 1985, is a widely recognized psychological theory that predicts deliberate behaviour based on three key constructs: attitude, subjective norm, and perceived behavioural control. These constructs collectively shape an individual's behavioural intentions, which are strong predictors of actual behaviour.

Relevance to the Context of Goa

Goa, a prominent tourist destination in India, has a unique consumer market. Understanding the buying intentions of consumers in Goa, therefore, requires a tailored approach that considers these distinct sociocultural dynamics. The TPB provides a comprehensive framework for this purpose, allowing for the examination of external influences shaping consumer behaviour. This research aims to explore how these TPB constructs impact consumers' intentions to engage with m-commerce in Goa, a region with unique characteristics and a growing digital landscape.

Research Hypothesis-2:

H2: Theory of Planned Behaviour constructs significantly influence the intentions to use m-commerce.

Sub-hypothesis:

H2a: Attitude towards mobile commerce significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that a positive attitude towards using mobile commerce (e.g., perception of convenience, trustworthiness of mobile platforms) leads to a higher intention to make purchases via mobile devices.

H2b: Subjective norms significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that perceived social influences regarding mobile commerce usage (e.g., recommendations from friends, social media influencers) affect consumers' intention to engage in mobile commerce transactions.

H2c: Perceived behavioural control significantly influences the intentions to use m-commerce.

Explanation: This hypothesis proposes that consumers' perception of their ability to control and use mobile commerce applications (e.g., ease of use, technical skills required) impacts their intention to purchase goods or services via mobile devices.

H2d: Attitude, subjective norms, and perceived behavioural control significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that all three constructs, attitude, subjective norms, and perceived behavioural control, collectively influence consumers' buying intention in the context of mobile commerce.

2.8.3 Research Question, Objective and Hypothesis-3

Background of Research Question 3:

Understanding the demographic profile of respondents is crucial in various fields of research, including marketing, social sciences and education. This literature review explores the significance of demographic profiling and its implications for research outcomes:

Demographic segmentation continues to serve as a fundamental component of e-marketing strategies due to its effectiveness in guiding resource allocation, message customization, and market targeting (Kotler & Armstrong, 2016). By categorizing consumers based on variables such as age, gender, income, education level, and geographic location, marketers can design more personalized campaigns that resonate with specific audience groups (Schiffman & Wisenblit, 2019). For instance, age-based segmentation often helps tailor content and platform choice, while income segmentation influences product pricing strategies and promotional offers.

Despite its widespread application, the predictive power of demographic segmentation in explaining or influencing actual online consumer behaviour is not always robust. Its

effectiveness varies significantly depending on contextual factors, such as cultural background, digital literacy, and regional market maturity (Sheth, 2021). Moreover, the relationship between demographic variables and consumer decision-making is often complex and nonlinear, requiring sophisticated modeling techniques such as multivariate analysis, structural equation modeling, or machine learning algorithms to capture the nuances of consumer behaviour accurately (Harris & Goode, 2010; Pappas, 2016). As a result, while demographic segmentation offers a starting point for strategy formulation, its explanatory strength is greatly enhanced when combined with psychographic, behavioral, and technographic data in integrated marketing models (Wedel & Kamakura, 2012). Based on the given logical support, we have developed the following objective to be studied.

Research Question 3: How do the 'Demographic Variables' influence 'Attitude', 'Subjective Norms', 'Perceived Behaviour Control', and 'Intention' regarding the use of m-commerce among consumers?

Background of Research Objective 3:

Previous studies highlight the importance of demographic variables in shaping TPB constructs in m-commerce adoption. (Kim et al. 2010) highlighted the impact of age on PBC, showing that older users struggle with complex mobile applications, reducing their intention to use m-commerce. Despite favourable attitudes, the lack of perceived control over technology hinders adoption. Accessible design, including larger fonts, simplified navigation, and voice-activated commands, significantly improves PBC for older users. (Karjaluoto et al. 2007) examined the role of trust in m-commerce adoption, noting that older users place greater emphasis on trust than younger ones. For older adults, trust was a critical determinant of attitudes and SNs, moderating the relationship between PBC and intention. Younger consumers, however, relied more on peer recommendations. (Chong,2013) analysed the role of age in shaping mobile shopping behaviours, particularly attitudes and PBC. The findings discovered that young consumers are more likely to accept m-commerce, driven by their familiarity and comfort with mobile devices. Older adults, however, demonstrated lower PBC due to challenges with technology usability and security concerns. Despite favourable attitudes, the reduced sense of control hindered their intention to adopt. (Kumar and Mukherjee,2018) focused on millennials, emphasizing their openness to adopting m-commerce due to favourable attitudes toward technology. Millennials valued convenience, customization, and quick service, which positively influenced their intention.

Additionally, peer influence was a significant factor in shaping SNs among this demographic. (Riquelme and Rios ,2010) explored gender differences in trust and perceived risk in mobile shopping adoption. They found that women are more sensitive to security and trust concerns than men, directly impacting their attitudes and intention to adopt m-commerce. (Gefen and Straub,1997) explored how gender influences technology adoption by examining PBC and perceived ease of use. Women were found to rely more on external system support to feel confident using technology, highlighting the significance of PBC. Men, on the other hand, exhibited higher intrinsic confidence in navigating technology, translating to higher PBC with less reliance on system support. (Slade et al. 2015) investigated the influence of socioeconomic status on subjective norms in mobile payment adoption. They found that lower-income groups are more influenced by recommendations from peers, family, and community, as trust in technology is lower within this demographic. These social endorsements compensate for the lack of personal experience with mobile payments. (Hanafizadeh et al. 2014) explored how educational attainment affects attitudes toward mobile banking, a critical aspect of m-commerce. study found that consumers with higher educational levels are associated with stronger positive attitudes, as educated individuals better understand the benefits and risks associated with mobile transactions. This understanding fosters trust and reduces anxiety, which are key components of attitudes and intention. (Hofstede, 2001) emphasized the role of collectivist vs. individualist cultures in shaping subjective norms (SNs). In collectivist cultures, SNs are stronger as individuals are heavily influenced by societal expectations, family recommendations, and peer behaviour. These norms significantly drive m-commerce adoption in such societies. Conversely, in individualist cultures, attitudes and PBC play a more prominent role in shaping intention. (Zhou et al. 2012) examined gender differences in attitudes toward mobile shopping. Women demonstrated a stronger preference for secure and trustworthy platforms, which significantly influenced their attitudes. Men, on the other hand, were less concerned about security and more influenced by the platform's functionality and speed. (Cheung et al. 2012) examined the role of peer pressure in SNs for younger consumers. Their study discovered that younger demographics are more susceptible to peer influence, with recommendations from friends and influencers heavily driving their m-commerce intentions. (Cheung et al. 2012) analyzed the role of peer influence and electronic word of mouth (eWOM) in shaping subjective norms (SNs) for younger demographics. Younger users rely more on social recommendations and peer reviews when deciding to adopt m-commerce platforms. Positive eWOM significantly increased SNs, leading to higher intention to adopt. (Taylor and Todd

,1995) investigated how education level enhances PBC by improving technological self-efficacy. Educated users were more confident in their ability to navigate m-commerce platforms, leading to higher adoption intentions. (Davis et al. 1989) found that demographics like education significantly moderate ease of use. Educated individuals exhibit positive attitudes toward m-commerce due to their ability to navigate complex interfaces. (Barnes and Scornavacca, 2004) investigated the role of income levels in determining PBC for m-commerce. Wealthier individuals showed higher PBC due to access to advanced mobile devices and reliable internet connections. Lower-income groups faced technological barriers, reducing their perceived control over the adoption process (Pavlou ,2003) analysed the interplay between culture and perceived risk in shaping m-commerce intention. In collectivist cultures, SNs play a dominant role as users look to trusted peers for recommendations. Individualist cultures, however, focus more on attitudes and personal control over the process (PBC). (Choi et al. 2008) investigated gender-specific differences in SNs and PBC and found that women were more influenced by social proof (e.g., friend recommendations), while men were more self-reliant in making decisions. This aligns with the stronger effect of SNs on female users and higher intrinsic PBC in male users. (Liébana-Cabanillas et al. 2014) analysed the impact of geographical location on m-commerce adoption. Urban consumers exhibited higher PBC due to better access to infrastructure and technology, while rural users struggled with limited resources, affecting their PBC and intention.

Objective 3: To examine the impact of 'Demographic Variables' on consumers' 'Attitude', 'Perceived Behaviour Control', 'Subjective Norms' and 'Intention' to use m-commerce.

Studying the objective of describing the demographic characteristics of individuals in Goa who use smartphone is important for several reasons:

Understanding User Profiles: It provides insights into who is currently using mobile commerce services in Goa. By identifying demographic characteristics such as age, gender, education level, occupation, income, and location, researchers can create detailed user profiles. This understanding helps in targeting and tailoring mobile commerce platforms, services, and marketing strategies to better meet the needs and preferences of different demographic segments.

Market Segmentation: Demographic profiling allows for segmentation of the market based on user characteristics. This segmentation helps businesses and policymakers understand the diversity within the mobile commerce user base in Goa. It enables them to differentiate their offerings and develop targeted approaches for engaging specific demographic groups more effectively.

Predicting Adoption Trends: By studying demographic characteristics, researchers can predict future trends in mobile commerce adoption and usage patterns in Goa. For instance, understanding which age groups or income brackets are more likely to adopt mobile commerce can inform strategic planning and resource allocation for businesses and policymakers.

Policy Formulation: Demographic insights can inform policy decisions related to mobile commerce infrastructure, regulations, and incentives. For example, policies aimed at improving digital literacy or expanding mobile network coverage can be targeted based on demographic data to maximize impact and accessibility.

Comparative Analysis: Comparative analysis across different demographic groups allows for a deeper understanding of disparities in mobile commerce adoption and usage. It helps identify barriers or facilitators specific to certain demographic segments, guiding efforts to promote more equitable access and usage of mobile commerce services.

Academic Research: This objective provides a foundational dataset for academic research on mobile commerce behaviors and trends in Goa. Researchers can use demographic data to investigate broader questions related to consumer behavior, technology adoption, socio-economic impacts, and digital inclusion.

Business Strategy: Businesses can use demographic insights to refine their product offerings, user experience design, pricing strategies, and customer support initiatives. Understanding the demographic profile of mobile commerce users helps businesses align their strategies with the preferences and needs of their target audience.

Hypothesis-3:

H3: Demographic variables significantly influence consumers' attitudes, Perceived Behaviour Control, Subjective Norms and intention towards m-commerce.

Sub-Hypotheses:

H3a: There is no statistically significant difference between male and female consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3b: There is no statistically significant difference between Area of Location of consumers and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3c: There is no statistically significant difference between 'Marital Status' of consumers and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3d: There is no statistically significant difference between consumers 'Age' and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3e: There is no statistically significant difference between 'Educational level' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3f: There is no statistically significant difference between 'Occupation' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3g: There is no statistically significant difference between 'Monthly Family Income' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Explanation: By exploring these hypotheses and objectives, the research will provide a comprehensive understanding of how demographic factors shape the adoption and usage of m-commerce, offering valuable insights for businesses and policymakers aiming to enhance m-commerce experiences and adoption rates.

2.8.4 Research Question, Objective and Hypothesis-4

Background of Research Question-4:

Understanding the dynamics of '**Intention'** as a mediator between attitude, subjective norms, perceived behavioural control (PBC), and consumer behaviour in mobile commerce is essential for comprehending the decision-making processes of consumers in Goa. This literature review synthesizes relevant studies to explain these relationships.

Attitude and Intention: Attitude towards mobile commerce influences consumers' intentions to purchase products through this platform. Positive attitudes, characterized by favourable evaluations of mobile commerce (Ajzen, 1991), are likely to increase the intention to engage in such behaviours (Taylor & Todd, 1995).

In Goa, where technological adoption varies across demographic groups, consumers with positive attitudes towards the convenience and accessibility of mobile commerce are more inclined to express intentions to buy products through this channel (Venkatesh et al., 2012). For instance, perceptions of ease of use and trust in mobile payment systems positively influence intention formation (Venkatesh & Davis, 2000).

Subjective Norms and Intention: Subjective norms reflect consumers' perceptions of social pressures or expectations regarding mobile commerce adoption (Ajzen, 1991). These norms are influenced by cultural factors, peer influence, and family expectations (Riquelme & Rios, 2010). In Goa, where social networks and communal ties play significant roles in decision-making, subjective norms can strengthen or weaken intentions to engage in mobile commerce (Kaplan & Graziano, 2009). Consumers who perceive strong social approval or encouragement from significant others are more likely to form intentions aligned with these norms (Ajzen, 1991).

Perceived Behavioural Control (PBC) and Intention: PBC refers to consumers' beliefs about their ability to perform mobile commerce activities effectively (Ajzen, 1991). Higher levels of PBC, driven by factors such as technological literacy, internet access, and financial resources, increase the likelihood of forming strong intentions (Venkatesh & Davis, 2000). In Goa, where digital infrastructure and technological readiness vary, perceived control over mobile commerce usage can significantly influence intention formation (Hernandez et al., 2009). Consumers who feel confident in taking independent decisions with regards to shopping using m-commerce are more likely to translate intentions into actual buying behaviour (Ajzen, 1991).

Intention as a Mediator in Consumer Behaviour: Intention mediates the relationship between attitude, subjective norms, perceived behavioural control, and actual consumer behaviour in mobile commerce (Ajzen, 1991). Strong intentions driven by positive attitudes, supportive subjective norms, and perceived control over actions lead to higher levels of engagement with mobile commerce platforms (Venkatesh & Morris, 2000). Studies suggest that intention plays a pivotal role in bridging cognitive processes (attitude and norms) with behavioural outcomes (Ajzen, 1991). In Goa, understanding how these constructs interact through intention helps marketers predict and influence consumer behaviours effectively (Venkatesh et al., 2012).

Research Question 4: How does intention mediate the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and consumer behaviour towards purchasing specified products through m-commerce?

Intention serves as a crucial mediator between attitude, subjective norms, perceived behavioural control, and M-commerce purchase behaviour in Goa. By examining these relationships, researchers can develop strategies to enhance consumer engagement and facilitate adoption of mobile commerce platforms in this dynamic market.

Background of Objective 4:

Extensive review of previous study describes the mediating role of 'Intention' in the relationship between 'Attitude', 'Subjective Norms (SN), Perceived Behavioural Control (PBC) and actual purchase behaviour across various product categories. (Ajzen ,1991) Ajzen's foundational study on the Theory of Planned Behaviour proposes that intention is a critical mediator between constructs (ATT, SNs, PBC) and actual behaviour. He argued that without intention, the effect of ATT, SNs, and PBC on APB is weakened. (Pavlou and Fygenson ,2006) this study extends TPB to electronic commerce, emphasizing the role of intention as a mediator in the purchase of electronic goods. Intention fully mediates ATT, SNs, and PBC, making it a necessary construct for translating attitudes into actions. (Mallat ,2007) investigated that, for stationery items and newspapers, mobility-related purchase behavioural control enhances intention, mediating actual purchase behaviour. (Cheung et al. 2012) study examined subjective norms (via electronic word of mouth) for purchasing products like books and stationery and fond that intention mediates the relationship between SNs and APB. (Gupta and Arora ,2017) study concluded that, for low-involvement products like groceries, PBC strongly influences intention, which acts as a significant mediator for APB in m-commerce. (Luarn and Lin ,2005) investigated, ATT to be a significant predictor of intention, fully mediating the relationship with actual purchase behaviour. Similar mechanisms apply to high-value categories like jewellery and healthcare products in m-commerce. (Taylor and Todd ,1995) findings suggest that PBC has both direct and mediated effects (via intention) on APB, with healthcare items showing the strongest mediation effect due to higher perceived risk. (Zhou and Wang ,2010) study reveals that, privacy concerns act as a barrier to ATT and SNs, mediated by intention for products like healthcare and medicines and strong intention reduces the adverse effects of perceived risks. (Mathieson ,1991) concluded that high-quality information on mobile platforms enhances attitude,

mediated by intention, for healthcare products. (Kim et al. 2010) found that social influence enhances intention, which mediates SNs and APB for grocery and healthcare items. (Chiu et al. 2005) study shows that for games and jewellery, hedonic attitudes strongly predict intention, which mediates the effect on actual purchase behaviour. (Riquelme and Rios, 2010) found that perceived risk negatively influences attitude but is mitigated by strong intentions for jewellery and home appliances. (Hajli ,2014) study concluded that subjective norms via social media positively influence intention, especially for fashion items like clothing and shoes, which in turn drives actual purchase behaviour. (Liébana-Cabanillas et al. 2014) opined that, compatibility with mobile platforms increases attitude towards m-commerce, leading to higher intention and subsequent purchase behaviour for categories like home and kitchen appliances (Chang et al. 2012) found that, habitual use of mobile devices influences intention, mediating 'Attitude' and 'PBC' for books and magazines. (Slade et al. ,2015) found that mobile literacy enhances purchase behavioural control, leading to higher intention and actual purchase behaviour for grocery purchases. (Chong ,2013) opined that personal innovativeness enhances attitude, increasing intention and actual purchase behaviour for electronics and games.

Objective 4: To investigate the mediating role of 'Intention' in the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories, through m-commerce.

The research objective focuses on investigating how intention mediates the relationships between attitude, subjective norms, perceived behavioural control (PBC), and actual purchasing behaviour across various product categories through mobile commerce in Goa. Here's an explanation of each component:

Attitude: This refers to consumers' overall evaluation or perception of mobile commerce as a platform for purchasing different product categories. Positive attitudes are likely to lead to favourable intentions and subsequent purchasing behaviours (Ajzen, 1991).

Subjective Norms: This reflects consumers' perceptions of social pressures or expectations regarding the use of mobile commerce for shopping. They include influences from family, friends, and other significant others in the Goan context (Fishbein & Ajzen, 1975).

Perceived Behavioural Control: PBC refers to consumers' beliefs about their ability to perform actions related to mobile commerce effectively. Factors influencing PBC include technological skills, ease of use of mobile platforms, and trust in online transactions (Venkatesh & Davis, 2000).

Intention as a Mediator: Intention mediates the relationships between 'Attitude', 'Subjective Norms', Perceived Behavioural Control, and actual purchasing 'Behaviour'. It represents consumers' readiness or willingness to engage in mobile commerce for purchasing specific product categories (Ajzen, 1991). Strong intentions, influenced by positive attitudes, supportive social norms, and perceived control, are expected to lead to actual buying behaviour in Goa's mobile commerce environment (Ajzen, 1991; Venkatesh et al., 2012).

Actual Purchasing Behaviour: This refers to the real-world actions of consumers in Goa, where they use mobile commerce platforms to purchase electronic products, sports items, clothing, shoes, jewelry, home and kitchen appliances, books, magazines, newspapers, healthcare products, medicines, stationary items, games, and groceries. The study aims to observe how actual behaviors correspond with consumers' intentions, attitudes, subjective norms, and perceived behavioural control.

Explanation: By exploring these relationships across a wide range of product categories, the research aims to provide insights into the decision-making processes of Goan consumers in adopting mobile commerce in purchasing different categories of products. It seeks to understand how cognitive factors (attitude, subjective norms, PBC) influence behavioural outcomes (intention and actual purchase behaviour), thereby contributing to the broader understanding of consumer behaviour in digital commerce contexts.

Hypothesis-4:

H4: 'Intention' mediates the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories through m-commerce.

Sub-Hypotheses:

H4a: Attitude positively influences the intention to purchase various products through mobile commerce.

H4b: Subjective norms positively influence the intention to purchase various products through mobile commerce.

H4c: Perceived behavioural control positively influences the intention to purchase various products through mobile commerce.

H4d: Intention positively influences consumer behaviour towards buying electronic products, sports items, clothing, shoes, jewellery, home and kitchen appliances, books, magazines, newspapers, healthcare and medicines, stationary items, games, and grocery products through mobile commerce.

H4e: Intention mediates the relationship between attitude and consumer behaviour towards purchasing various products through mobile commerce.

H4f: Intention mediates the relationship between subjective norms and consumer behaviour towards purchasing various products through mobile commerce.

H4g: Intention mediates the relationship between perceived behavioural control and consumer behaviour towards purchasing various products through mobile commerce.

Explanation: By exploring this hypothesis, study will examine the mediating role of *intention* in the Theory of Planned Behaviour (TPB) framework within the context of mobile commerce (m-commerce) purchase behaviour towards specified product categories. and also, will investigate, whether *intention* significantly mediates the effect of each antecedent on purchase behaviour towards specified product categories, thereby validating the central belief of TPB that behavioural intention is a key predictor of actual behaviour.

2.8.5 Research Question, Objective and Hypothesis-5

Background of Research Question-5:

The Theory of Planned Behaviour (TPB), proposed by Icek Ajzen (1991), has been widely utilized to understand and predict various behaviours, including technology adoption and usage. TPB suggests that an individual's intention to perform a specific behaviour is influenced by three key components: attitudes towards the behaviour, subjective norms, and perceived behavioural control. This literature review explores how TPB explains the factors influencing consumer adoption and usage of mobile commerce (m-commerce) and examines empirical evidence supporting the validity of this model in the specific context of Goa.

Attitude towards Mobile Commerce:

Attitude refers to the degree to which a person has a favourable or unfavourable evaluation of the behaviour in question. In the context of m-commerce, attitudes encompass positive or negative beliefs about using mobile platforms for shopping, such as convenience, time-saving, and access to a wide range of products, risky, time consuming etc. Several studies have highlighted the positive correlation between favourable attitudes and the intention to adopt m-commerce (Kim, Mirusmonov, & Lee, 2010; Yang, 2010).

For instance, (Kim et al. 2010) found that perceived usefulness and ease of use significantly impact consumers' attitudes towards m-commerce, which in turn influence their behavioural intentions. Similarly, studies specific to Indian contexts, such as that by Gupta and Arora (2017), have demonstrated that perceived advantages like convenience and availability of diverse products positively affect consumer attitudes towards m-commerce.

Subjective Norms:

Subjective norms refer to the perceived social pressure to perform or not to perform a particular behaviour. In the domain of m-commerce, this includes the influence of peers, family, and societal trends on an individual's decision to use mobile platforms for shopping. Empirical studies have shown that subjective norms play a significant role in shaping consumer intentions towards technology adoption (Taylor & Todd, 1995; Venkatesh & Davis, 2000).

Research by (Lu, Yao, and Yu ,2005) indicates that social influence is a critical factor in m-commerce adoption, especially in collectivist cultures like India, where societal approval and peer influence are highly valued.

Perceived Behavioural Control:

Perceived behavioural control refers to an individual's perception of their ability to perform a specific behaviour, considering facilitating conditions and obstacles. In the context of m-commerce, this includes factors such as technological literacy, freedom to access mobile devices. Studies have consistently shown that perceived ease of use and control over technology significantly influence adoption intentions (Mathieson, 1991; Venkatesh, Morris, Davis, & Davis, 2003).

For example, research by Chong (2013) on mobile commerce adoption in Malaysia highlights that perceived ease of use and self-efficacy are significant predictors of behavioural intention. Similarly, (Tan et.al ,2014) found that perceived behavioural control, including factors like mobile internet experience and facilitating conditions, significantly impacts m-commerce adoption in developing countries.

Empirical Evidence from Goa:

While specific studies on m-commerce adoption in Goa are limited, broader research on Indian m-commerce provides valuable insights. A study by (Kapoor et.al ,2014) on mobile commerce adoption in India emphasizes the role of consumer attitudes, social influence, and perceived behavioural control, aligning with the TPB framework.

Furthermore, regional studies, such as those by (Singh et.al, 2019), indicate that the proliferation of smartphones and improved internet connectivity in Goa have positively impacted m-commerce adoption. However, challenges such as digital literacy and trust in online transactions remain significant barriers, highlighting the need for targeted interventions to enhance perceived behavioural control among consumers.

Research Question 5: How does "The Theory of Planned Behaviour" explain the factors influencing consumers' adoption of m-commerce, and whether the empirical evidence supports the validity of this conceptual model in this specific context?

The Theory of Planned Behaviour provides a robust framework for understanding the factors influencing consumer adoption and usage of mobile commerce in Goa. Attitudes towards m-commerce, subjective norms, and perceived behavioural control are critical determinants of consumer intentions and behaviours. Empirical evidence from broader Indian contexts supports the validity of the TPB model, suggesting its applicability to the state of Goa.

Background of Objective 5:

Majority of previous studies provide detailed insights into how the 'TPB' has been applied, validated, and extended to understand the adoption of m-commerce. (Ajzen ,1991) Ajzen's pivotal work on TPB provides the theoretical foundation for studying consumer behaviour across a variety of domains, including mobile commerce. The study suggests that 'Attitude', 'SNs', and 'PBC' are key determinants of behavioural intention, which subsequently affects actual behaviour. (Taylor & Todd ,1995) validated the TPB in the context of information technology adoption by incorporating perceived ease of use and perceived usefulness. The TPB model is confirmed as an effective framework for predicting mobile commerce adoption, demonstrating the impact of attitudes, subjective norms, and PBC on consumers' intention to use m-commerce platforms. (Lu et al.,2014) applied the TPB framework to mobile commerce adoption and validated its relevance. Their study confirms that attitudes, subjective norms, and perceived behavioural control significantly influence the intention to use m-commerce, which subsequently drives actual use. The study also finds that these

factors vary based on demographic and technological factors. (Hsu et al.,2004) investigated the role of perceived risk in m-commerce adoption and validated the TPB model's applicability in the mobile context. Their findings suggest that perceived behavioural control, attitude, and subjective norms influence the decision to adopt m-commerce, with perception of risk moderating these relationships. (Al-Qeisi et al.,2014) study validates the TPB constructs in the context of mobile commerce adoption. As per the findings of the study, attitudes toward mobile shopping, subjective norms, and perceived behavioural control directly impact intention to use mobile commerce, with consumer habits playing a significant role in moderating these relationships. (Cheng et al. ,2015) extend the TPB framework to explore how subjective norms, attitudes, and perceived behavioural control shape consumers' intention to adopt mobile commerce. Study demonstrates that social influences and perceived behavioural control have a significant effect on the intention to use mobile commerce. (Pavlou & Fygenson ,2006) applied the TPB model in the context of e-commerce, validating its constructs in predicting the adoption of mobile commerce. The study found that social influence, attitude, and perceived control are essential in determining behavioural intentions toward using m-commerce platforms. (Lee et al. ,2011) applied the TPB model in the context of mobile commerce adoption and found that attitude, subjective norms, and perceived behavioural control significantly predict the intention to adopt mobile commerce. The study also finds that trust and security concerns moderate these relationships. (Zhou et al. ,2011) extend the Theory of Planned Behaviour to investigate how attitudes, subjective norms, and perceived behavioural control is affecting the intention to adopt mobile commerce. Their findings validate the TPB model in predicting consumer m-commerce behaviours for product categories such as electronics and clothing. (Wang et al. ,2010) explored the application of the TPB in predicting m-commerce adoption in the Chinese market. The study concluded that perceived behavioural control, subjective norms, and attitudes significantly influence consumer intention to use mobile shopping applications. (Park et al. ,2003) studied the role of subjective norms in predicting m-commerce adoption using the TPB model. As per the findings, the influence of family and friends significantly moderates the intention to use m-commerce, particularly in purchasing products like healthcare items. (Zhou ,2011) tested the applicability of Theory of Planned Behaviour in understanding the adoption of mobile commerce in China. The study validates the influence of attitudes, perceived behavioural control, and subjective norms in shaping purchase intentions in the mobile retail space. (Kim & Park ,2012) found that subjective norms and perceived behavioural control influence consumers' purchase intentions toward m-

commerce platforms. Study suggests that attitude towards mobile shopping directly affect purchase intentions for product categories like clothing and electronics. (Choi et al. ,2013) validates the TPB framework in predicting m-commerce adoption, highlighting that attitudes, subjective norms, and perceived behavioural control are critical in forming intention to use mobile shopping services. Study also explored how gender and income moderate these relationships. (Liu et al. ,2022) validates TPB in predicting mobile commerce adoption in the context of purchasing healthcare products. The study found that attitudes and subjective norms significantly affect purchase intentions, with perceived control playing a mediating role. (Riquelme ,2010) applied the 'TPB' to study the adoption of mobile commerce in the UAE, and validated that attitudes, subjective norms, and perceived behavioural control significantly influence intention to use m-commerce platforms for purchasing electronics and sports items. (Moon & Kim ,2001) validated the integration of TPB with the Technology Acceptance Model (TAM), and found that attitude and subjective norms influence mobile commerce adoption in a similar manner to traditional e-commerce. (Zhou et al. ,2011) extended the Theory of Planned Behaviour by incorporating trust and perceived risk as additional constructs and validated this model and showed that attitudes, perceived control, and subjective norms strongly influence m-commerce intentions. (Chiu et al. 2005) study focused on Taiwan's m-commerce adoption through TPB and validated that subjective norms, attitudes, and perceived behavioural control contribute significantly to m-commerce usage in various product categories like electronics and clothing.

Objective 5: To validate the conceptual model based on "The Theory of Planned Behaviour".

The objective involves a systematic approach to verifying the effectiveness and applicability of a conceptual model for the mobile commerce (m-commerce) industry in Goa, grounded in the Theory of Planned Behaviour (TPB). The TPB, developed by Icek Ajzen, is a psychological framework that predicts individual behaviour based on three key factors: attitudes, subjective norms, and perceived behavioral control. Here's a detailed breakdown of what this objective entails:

Conceptual Model Development:

- **Theory of Planned Behaviour (TPB):** The model is constructed using the TPB framework, which suggests that an individual's intention to perform a behaviour is

influenced by their attitude towards the behaviour, the subjective norms surrounding it, and their perceived control over performing the behaviour.

❖ **Application to M-commerce:** This model will be tailored to fit the specific context of m-commerce in the state of Goa, considering unique regional factors that might influence consumer behaviour, such as local culture, technological infrastructure and economic conditions.

❖ **Components of the Model:**

a. **Attitudes:** Consumer attitudes towards m-commerce, including their beliefs about the advantages and disadvantages of using mobile platforms for shopping.

b. **Subjective Norms:** The perceived social pressure to engage or not to engage in m-commerce, influenced by peers, family, and societal trends.

c. **Perceived Behavioural Control:** The perceived ease or difficulty of using m-commerce, considering factors such as technological literacy, access to mobile devices, and internet connectivity.

❖ **Validation Process:**

- **Empirical Testing:** The model will be validated through empirical research, involving the collection and analysis of data from consumers in Goa. Surveys and interviews may be used to gather relevant data.
- **Statistical Analysis:** Advanced statistical techniques, such as Structural Equation Modeling (SEM), will be employed to test the relationships between the constructs of the TPB and their influence on m-commerce adoption and usage.
- **Hypothesis Testing:** Specific hypotheses derived from the TPB will be tested to determine their validity in the context of Goa's m-commerce industry. For example, hypotheses might examine whether positive attitudes towards m-commerce significantly increase the intention to use it.

❖ **Contextual Considerations:**

- **Regional Specificity:** The validation process will consider the unique characteristics of consumers of Goa, such as demographic profile, economic conditions, and technological landscape, ensuring the model is contextually relevant.

❖ **Outcomes and Implications:**

- **Model Refinement:** Based on the validation results, the conceptual model may be refined to better reflect the realities of the Goan m-commerce market.

- **Strategic Insights:** The validated model will provide valuable insights for businesses and policymakers, helping them understand the key drivers of m-commerce adoption and how to leverage them effectively.

Hypothesis-5:

H5: The "Theory of Planned Behaviour" describes consumers 'Attitude ", 'Subjective Norms', and 'Perceived Behavioural Control', influencing consumers' intentions and behaviour towards adoption of m-commerce.

Explanation: By exploring this hypothesis, the study will contribute to the academic literature by demonstrating the applicability and robustness of the TPB in the context of m-commerce, potentially offering a framework that can be adapted to other regions and contexts.

2.8.6 Research Question, Objective and Hypothesis-6

Background of Research Question-6:

The rapid growth of mobile commerce (m-commerce) has transformed retail landscapes globally. However, despite the widespread adoption, a significant portion of the population remains hesitant or unwilling to engage with m-commerce. This literature review explores the factors influencing an individual's likelihood of never using m-commerce, focusing on knowledge, education level, area of location, occupation, monthly family income, perceived behavioural control, attitude, and subjective norms.

Knowledge and M-Commerce Usage:

Knowledge about m-commerce plays a critical role in its adoption. Consumers with a higher level of awareness and understanding of m-commerce are more likely to use it (Liébana-Cabanillas et al., 2014). Lack of knowledge can result in apprehension towards the technology, leading to non-use (Yang, 2010). For instance, consumers who are not familiar with the functionalities and benefits of m-commerce are less likely to trust and use it (Gefen, Karahanna, & Straub, 2003).

Educational Level:

Educational level is a significant predictor of technology adoption, including m-commerce. Higher educational levels are associated with greater technological literacy and the ability to understand and use new technologies (Venkatesh, Thong, & Xu, 2012). Studies have shown that individuals with higher education are more likely to adopt m-commerce due to their ability to navigate and understand the complexities of mobile applications (Riquelme

& Rios, 2010). Conversely, lower education levels may correlate with higher likelihoods of never using m-commerce.

Area of Location:

The area of location, such as urban versus rural settings, significantly impacts m-commerce adoption. Urban areas typically have better internet infrastructure and higher smartphone penetration rates, facilitating easier access to m-commerce (Wei et al., 2011). In contrast, rural areas may face challenges such as poor internet connectivity and limited access to technology, contributing to a lower likelihood of m-commerce use (Gong et.al 2013).

Occupation:

Occupation influences an individual's inclination to use m-commerce. Certain professions, particularly those involving technology and office work, may encourage the use of m-commerce due to higher exposure and familiarity with digital platforms (Hernandez, Jimenez, & Martin, 2009). Conversely, occupations that do not require regular use of technology may see a lower adoption rate of m-commerce (Luarn & Lin, 2005).

Monthly Family Income:

Monthly family income is a crucial determinant of m-commerce usage. Higher income levels provide greater access to necessary resources such as smartphones and internet services, which are prerequisites for m-commerce (Zhou, 2011). Lower-income households may prioritize essential expenditures over discretionary technology purchases, resulting in lower m-commerce usage (Xu & Gupta, 2009).

Attitude:

Attitude towards m-commerce significantly influences its adoption. Positive attitudes, shaped by perceptions of usefulness, ease of use, and trust in the technology, are strong predictors of m-commerce usage (Davis, Bagozzi, & Warshaw, 1989). Negative attitudes, often stemming from concerns about security and privacy, can deter individuals from using m-commerce (Kim, Ferrin, & Rao, 2008).

Subjective Norm:

Subjective norm, or the perceived social pressure to engage or not engage in a behaviour, also affects m-commerce adoption (Fishbein & Ajzen, 1975). If significant others (e.g., family, friends) use and endorse m-commerce, individuals are more likely to adopt it (Venkatesh & Davis, 2000). Conversely, if there is a lack of social endorsement or negative

perceptions about m-commerce within an individual's social circle, the likelihood of never using m-commerce increases (Yang & Forney, 2013).

Perceived Behavioural Control:

Perceived behavioural control refers to an individual's perception of their ability to perform a particular behaviour (Ajzen, 1991). In the context of m-commerce, higher perceived behavioural control can lead to increased usage as individuals feel more confident in their ability to navigate and use mobile platforms (Taylor & Todd, 1995). On the other hand, low perceived behavioural control can act as a barrier, leading to non-use (Pavlou & Fygenson, 2006).

Research Question 6. What are the factors influencing an individual's likelihood of non-adoption of m-commerce?

Understanding the factors influencing an individual's likelihood of never using m-commerce is critical for developing strategies to increase adoption rates. Knowledge, education level, area of location, occupation, monthly family income, perceived behavioural control, attitude, and subjective norm all play significant roles in shaping m-commerce usage behaviours. Addressing these factors through targeted education, improving infrastructure, and enhancing user confidence and attitudes towards m-commerce can help mitigate barriers and promote broader adoption.

Background of Objective 6:

Previous studies have investigated various factors influencing an individual's likelihood of never using m-commerce, with a focus on knowledge, education level, area of location, occupation, monthly family income, 'PBC', 'Attitude', and 'SNs' and shown how these factors interact to influence whether individuals will adopt or avoid using mobile commerce in future. (Ajzen ,1991) Ajzen's work on the 'TPB' argued that an individual's 'Attitude', 'SNs', and 'PBC' significantly impact their intention to adopt new technologies. Lack of positive attitude and insufficient perceived control may increase the likelihood of never using new technology. (Dube et al. ,2010) emphasized that 'PBC' is a major predictor of m-commerce adoption. A lack of confidence in using mobile technologies, combined with limited knowledge or low educational attainment, can make individuals more likely to avoid using m-commerce. (Lu et al.,2014) study highlights that knowledge of mobile technologies and positive attitudes towards online shopping significantly influence adoption. Lack of knowledge and negative attitudes towards mobile devices lead to a higher likelihood of

never adopting m-commerce, especially in regions with lower levels of digital literacy. (Kim et al. ,2010) found that digital literacy is an essential factor in the adoption of mobile commerce. Individuals with low digital literacy or those who lack knowledge about mobile technologies, especially in lower-income groups or rural areas, have a higher likelihood of never using m-commerce. (Shin ,2010) study explores how perceived risk (privacy concerns, security risk, etc.) and attitudes towards technology influence mobile commerce adoption. Individuals with negative attitudes or high perceptions of risk are more likely to avoid m-commerce and Education and income levels influence these perceptions. (Kim et.al, 2013) study reveals that social influence (subjective norm) and education are crucial factors influencing the adoption of m-commerce. Individuals in low-education or low-income groups, or those with negative attitudes, are more likely to avoid m-commerce adoption. (Hsu et al., 2004) examined how income levels, education, and subjective norms influence mobile commerce adoption. They suggest that low-income individuals, especially those in rural areas, are more likely to avoid using mobile commerce due to lower exposure to mobile technologies. (Chau & Lai ,2003) studied how education level is a critical determinant in the adoption of new technologies, including m-commerce and found that, Low education levels contribute to the lack of knowledge and the likelihood of avoiding m-commerce. (Molla & Licker ,2005) identified that subjective norms and perceived behavioural control play significant roles in m-commerce adoption. Individuals from lower-income backgrounds, especially those who are less educated, are more likely to avoid m-commerce adoption. (Hanafizadeh et al. ,2014) explored the barriers to m-commerce adoption, noting that lack of knowledge, education, and subjective norms are critical factors. People with limited knowledge of mobile technologies are more likely to avoid m-commerce, especially if they perceive it as difficult or unnecessary. (Beldad et al. ,2010) studied consumer behaviour in m-commerce and argued that low education, low income, and subjective norms influence consumer behaviour, making individuals in certain segments more likely to avoid m-commerce adoption. These individuals often lack the knowledge or support to make informed decisions. (Hsieh et al. ,2012) studied barriers to E-Commerce adoption and discussed how ‘PBC’ and ‘Attitude’ affect adoption, with low income, rural location, and education level being significant barriers to m-commerce use. (Fogg et al. ,2001) studied how perceived trustworthiness and subjective norms affect adoption decisions. They found that lack of trust, combined with negative social influences, contributes to avoidance of m-commerce in low-income or less educated groups. (Kumar et al. ,2019) focused on socioeconomic factors such as education, income, and location in determining m-commerce

adoption. Study concluded that people with lower levels of education and limited income are less likely to adopt m-commerce, particularly in rural or underdeveloped areas. (Chang et al. ,2010) examined how 'Attitudes' and 'SNs' affect mobile commerce adoption. They find that negative attitudes, especially in lower-income or less-educated groups, increase the likelihood of never using m-commerce. (Zhou ,2011) study identifies 'Attitude', 'PBC', and education as major barriers to m-commerce adoption and found that individuals with low income, staying in rural locations, and with negative attitudes are more likely to avoid m-commerce.

Objective 6: To identify and analyse the factors influencing an individual's likelihood of non-adoption of m-commerce.

The research aims to investigate into the multifaceted reasons behind why certain individuals are unlikely to engage in mobile commerce (m-commerce). The goal is to comprehensively identify and analyse specific factors that influence this likelihood, with a focused examination of the following variables: knowledge, education level, area of location, occupation, monthly family income, perceived behavioural control, attitude, and subjective norm. Each of these factors is essential for understanding the barriers to m-commerce adoption and for developing strategies to encourage broader usage.

Knowledge:

Objective: To investigate the influence of 'Knowledge' on the likelihood of non-adoption of m-commerce.

Explanation: Knowledge refers to the awareness and understanding of m-commerce functionalities and benefits. Lack of knowledge can lead to apprehension and mistrust, reducing the likelihood of usage. The research will explore the extent to which knowledge deficits contribute to non-use and identify ways to improve consumer education.

Educational Level:

Objective: To examine the influence of 'Educational Level' on the likelihood of non-adoption of m-commerce.

Explanation: Education level is a significant determinant of technology adoption. Higher education often correlates with better digital literacy and the ability to understand and navigate m-commerce platforms. This objective seeks to analyse the relationship between educational attainment and m-commerce usage.

Area of Location:

Objective: To determine the influence of 'Area of Location' on the likelihood of non-adoption of m-commerce.

Explanation: The geographic area, particularly urban versus rural settings, affects access to technological infrastructure. Urban areas typically offer better internet connectivity and higher smartphone penetration, facilitating m-commerce adoption, whereas rural areas may face infrastructural challenges that impede usage of m-commerce.

Occupation:

Objective: To examine the influence of 'Occupation' on the likelihood of non-adoption of m-commerce.

Explanation: Occupation affects exposure to and familiarity with digital technologies. Professions that involve regular use of technology may encourage m-commerce adoption, while others may not provide the same level of exposure or necessity. This objective aims to analyse these occupational differences and their impact on m-commerce use.

Monthly Family Income:

Objective: To determine the influence of 'Monthly Family Income' on the likelihood of non-adoption of m-commerce.

Explanation: Income levels influence access to m-commerce applications for shopping. Higher income may correlate with greater adoption, while lower income can be a barrier. The research will explore how financial constraints affect m-commerce engagement.

Attitude:

Objectives: To investigate the impact of consumers' 'Attitude' on the likelihood of non-adoption of m-commerce.

Explanation: Attitudes towards m-commerce, shaped by perceptions of usefulness, ease of use, and trust, significantly influence adoption. Positive attitudes enhance the likelihood of use, while negative attitudes deter it. The research aims to identify the components of negative attitude that most strongly affect m-commerce adoption.

Subjective Norm:

Objective: To determine the influence of 'Subjective Norms' on the likelihood of non-adoption of m-commerce.

Explanation: Subjective norms refer to the perceived social pressure to engage or not to engage in a specific behaviour. Social influences from family, friends, and peers can significantly impact m-commerce adoption. This objective seeks to understand the role of social pressures on individual decision to use or not to use m-commerce for shopping.

By systematically analysing these factors, the research aims to provide a holistic understanding of the barriers to m-commerce adoption. The insights gained will be valuable

for stakeholders, including policymakers, businesses, and technology developers, in creating targeted interventions to promote m-commerce usage among diverse consumer segments.

Perceived Behavioural Control:

Objective: To analyse how 'Perceived Behavioural Control' affects an individual's likelihood of non-adoption of m-commerce

Explanation: Perceived behavioural control involves the individual's perception of their ability to use m-commerce effectively. If individuals feel confident and capable of using m-commerce, they are more likely to adopt it. This objective focuses on understanding how perceived control influences behaviour of consumers.

Hypothesis-6:

H6: There is no significant association between an individual's 'Lack of knowledge', 'Education level', 'Area of location", 'Occupation', 'Monthly Family Income', 'Perceived Behaviour Control', 'Attitude', 'Subjective Norms', 'Intentions' and their likelihood of non-adoption of m-commerce.

Sub-Hypothesis:

H6a: There is no significant relationship between an individual's Lack of Knowledge and their likelihood of non-adoption of m-commerce.

H6b: There is no significant association between an individual's educational level and their likelihood of non-adoption of m-commerce.

H6c: There is no significant association between an individual's area of location and their likelihood of non-adoption of m-commerce.

H6d: There is no significant association between an individual's Marital Status and their likelihood of non-adoption of m-commerce.

H6e: There is no significant association between an individual's Occupation and their likelihood of non-adoption of m-commerce.

H6f: There is no significant association between an individual's Monthly Family Income and their likelihood of non-adoption of m-commerce.

H6g: There is no significant relationship between individuals, who have never used m-commerce, Perceived Behaviour Control, Attitude and Subjective norms.

Explanation: The research hypothesis is based on the assumption that there is no significant association between various individual characteristics and their likelihood of never using m-commerce. By breaking down the hypothesis into specific, measurable factors, the research aims to identify which, if any, of these factors are significantly associated with m-commerce usage patterns. Each objective is designed to isolate and examine one potential influencing factor, providing a comprehensive understanding of the barriers and facilitators to m-commerce adoption. This detailed analysis will help in developing targeted strategies to enhance m-commerce adoption across different demographic segments.

2.9 CONCLUSIONS:

In summary, this chapter has consolidated theoretical perspectives, empirical findings, and contextual insights into a clear framework for the study. It has established the relevance of the Theory of Planned Behaviour in examining consumer behaviour towards m-commerce, demonstrated the importance of considering Indian-specific contexts alongside global patterns, and identified critical research gaps that justify the present investigation. By systematically linking literature to research questions, objectives, and hypotheses, this chapter provides a strong foundation for the subsequent methodological design and empirical analysis.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTRODUCTION:

This chapter presents a comprehensive account of the research methodology adopted for the study. It begins by elaborating on the underlying research philosophy and approach, establishing a conceptual foundation for the investigation. Subsequently, the chapter describes the critical methodological procedures implemented throughout the research process. It further details the research design, strategic framework, time horizon, and methods employed for data collection, thereby offering a structured overview of the methodological framework.

In addition, the chapter discusses the design of the questionnaire, followed by the operational definitions and measurement of the key constructs namely, the independent, dependent, and mediating variables along with their respective sub-constructs. This aids in clarifying the conceptual and empirical parameters of the study. The instrument's preliminary evaluation through a pilot test is then presented to assess its validity and reliability.

The chapter also outlines the target population, sampling frame, sample size, and the sampling technique employed, forming the basis for the empirical data collection. Finally, ethical considerations related to the conduct of the research are examined to ensure adherence to academic and professional standards.

3.2 RESEARCH METHODOLOGY BASED ON THE RESEARCH ONION (Saunders et al., 2012):

The Research Onion model proposed by (Saunders, Lewis, and Thornhill ,2012) offers a structured approach to designing research methodology by guiding the researcher through six key layers: research philosophy, research approach, methodological choice, strategy, time horizon, and data collection methods. Each layer informs the next, ensuring methodological coherence and alignment with research objectives. The following sections describe each layer as applied in a marketing management context.

3.2.1 Research Philosophy:

Research philosophy refers to 'the underlying systems of beliefs and assumptions about knowledge development' (Saunders et al., 2016). There are five main philosophies: positivism, interpretivism, pragmatism, critical realism, and postmodernism (Saunders et al., 2016). The current study mainly adopts a positivist philosophy, which promotes an objective interpretation of reality and uses data from surveys and experiments (Gray, 2021).

In social science, most of the literature relies on two philosophies: positivism and interpretivism. Positivism philosophy is mainly linked with quantitative research using surveys or structured interviews. In contrast, interpretivism philosophy is primarily associated with qualitative research using surveys or structured interviews using observation or unstructured interviews (Lee & Lings, 2008). According to (Wahyuni ,2012), the essential fact supporting the positivist philosophy is that different studies would yield similar outcomes of a particular problem when they analyse a large sample employing a similar research method and statistical tests. Positivist research uses existing theories to develop hypotheses and collects observable data to investigate causal relationships between variables (Saunders et al., 2012). In the same vein, (Della Porta & Keating, 2008) noted that researchers set out with a hypothesis, collect data, and then identify whether or not the findings support the proposed hypothesis.

According to (Della Porta & Keating, 2008), the researcher and the subject are independent and objective in positivist philosophy. Therefore, the researcher is unbiased and does not influence the research subject.

The current study aims to investigate the role of antecedents to consumer behaviour towards M-Commerce through a survey questionnaire. In addition, the conceptual framework of this study will be examined based on an existing theory, 'Theory of Planned Behaviour'. Therefore, positivist philosophy is determined as the most appropriate paradigm to answer the questions of the study.

3.2.2 Research Approach:

Two prominent approaches to research are the inductive and deductive approaches (Saunders et al., 2016). The deductive approach is based on positivist philosophy and the quantitative methodology. It begins with reviewing the relevant literature and using existing theories to develop hypotheses. Following that, data are collected to test these hypotheses. The findings are used to support or refute the hypotheses, and the theories are revised accordingly (Bryman, 2001).

The inductive approach, on the other hand, is based on interpretivist philosophy and qualitative methodology. It aims to build theories from empirical observations and solid evidence, which can be generalised to the entire population (Bernard, 2013).

Since this study aims to identify the impact of Attitude, subjective norms and perceived behavioural control on intention and behaviour based on the positivist philosophy that intends to generalize the finding for a large population, the deductive approach is adopted to answer the questions of the current study based on statistical findings.

3.2.3 Research Design:

Researcher has used conclusive descriptive cross sectional one sample survey research design. In case of social researches, there are basically two types of fundamental questions that the researcher can ask. First question refers to the description of facts, "what is going on" and the second question is "why is it going on", which explains the reason. The factual research answering the question "Why" is called as Explanatory Research (De Vaus,2001).

The present study is descriptive in nature, which describes the behaviour of consumers towards use of mobile commerce for shopping. Study also attempts to identify the factors responsible for such behavioural intentions of consumers and its role as a mediator in determining such behaviour. The study empirically tests the relationship between important constructs, Based on TPB model, influencing the behavioural intentions of consumers towards use of m-commerce for shopping.

3.2.4 Research Strategy:

Different strategies for collecting empirical data include experiments, surveys, action research, case studies, grounded theory, and archival and ethnographic strategies (Saunders et al., 2009).

This study uses a structured survey questionnaire to collect quantitative data. This strategy is widely used in empirical research, allowing researchers to collect large amounts of data from a population (Bryman, 2001). Structured survey questionnaires typically consist

of closed-ended questions with pre-determined answer choices. This makes them easy to administer and score, and it allows researchers to compare responses from different participants (Saunders et al., 2016). Furthermore, the survey questionnaire will enable the researcher to collect the empirical data needed to examine the proposed conceptual framework quantitatively using descriptive and inferential statistics (Saunders et al., 2009).

3.2.5 Methodological Choice:

There are two main data collection methods: quantitative and qualitative. Quantitative research involves collecting and analysing numeric data, while qualitative research involves non-numeric data, such as text, images, or videos (Saunders et al., 2016).
The selection of the data collection method relies on the research questions being asked and the information needed to answer them. Quantitative research is often utilised to test hypotheses or estimate the relationship between constructs. Qualitative research is often employed to explore people's experiences and views or to comprehend the social and cultural contexts in which phenomena appear (Christensen, 2016).

In this study, the researcher is interested in investigating various types of association and relationship between construct. Therefore, the quantitative data collection method is the most appropriate for this study.

3.2.6 Time Horizon:

Time horizon determines the scope of research in terms of time.There are two types of studies based on the time frame in which data is collected: cross-sectional and longitudinal studies. In cross-sectional studies, researchers collect data at a single point in time to answer their research questions. In longitudinal studies, researchers collect data at different points in time to answer their research questions (Sekaran & Bougie, 2016).

This study employs a cross-sectional design to collect data. A cross-sectional design is the most appropriate for this study because it allows the researcher to collect data from a large sample of respondents at a particular time to investigate a specific relationship.

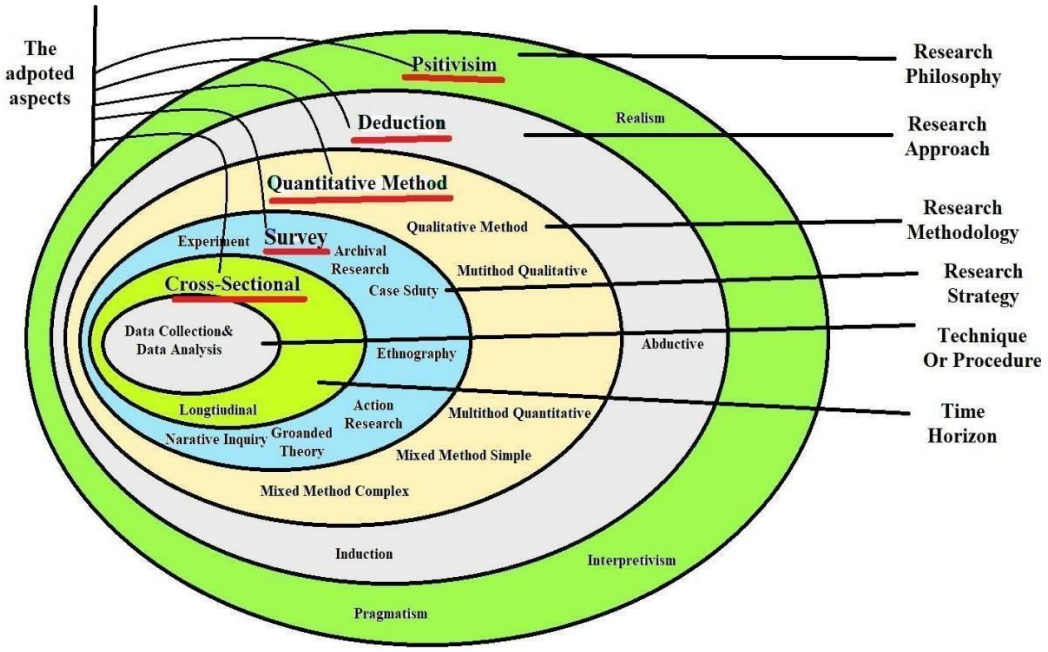


Figure 3.1: The research Onion

(Source: Saunders et al. 2012)

3.3 DEVELOPMENT OF MEASUREMENT INSTRUMENT:

A questionnaire (Measurement Instrument) refers to "a prepared set of questions (or measures) used by respondents or interviewers to record answers (data)" (Hair et al., 2019, p. 274).

According to Saunders et al., (2009), there are three types of questionnaires for conducting both qualitative and quantitative research: unstructured, semi-structured, and structured. Unstructured questionnaires support free answers where respondents are provided with open-ended questions and can offer broad views. This type of questionnaire is suitable for qualitative studies. Semi-structured questionnaires support both unrestricted and restricted answers where respondents are given open-ended and closed-ended questions. This type of questionnaire is suitable for mixed studies. The last type of questionnaire is the structured questionnaire. It only includes closed-ended questions where the respondents are given a set of answers from which they should select the most appropriate. This type of questionnaire is suitable for quantitative research (Hague & Jackson, 2002).

According to (Taylor-Powell & Marshall, 1998), a questionnaire incorporates four types of information that are "beliefs and thoughts, attitudes, knowledge, and attributes and

behaviour". Beliefs and thoughts refer to emotions of individuals, opinions, conclusions and views. The knowledge addresses the understanding of respondents about a specific issue. The behaviour relates to what respondents intend to do something, whether in the past or present. Last, attributes include personal demographic characteristics of the respondents, such as gender, age, education, area of location, occupation and income.

The widely employed rating scale is the Likert scale designed by Likert (1932), which is easy to understand and takes less time to answer (Shahin, 2011). It comprises several options per question. Scholars may use sequences of "strongly agree, agree, disagree, or strongly disagree" or other sequences such as poor, fair, good, poor, and outstanding (Alabi & Jelili, 2023; Heiberger et al., 2015). Dawes (2008) proposed that a five-point scale is appropriate for conducting structural equation modelling (SEM).

This study relies on positivist philosophy and quantitative method; hence, it adopts a closed-ended questionnaire (Collis & Hussey, 2009) based on five Likert scales as the most appropriate type to measure the three constructs related to the conceptual framework (Shahin, 2011).

The questionnaire is designed into six sections. The first section incorporates the demographic profile of the respondents, in order to make the respondent feel psychologically comfortable with the questionnaire (Sekaran & Bougie, 2016). The second section includes questions for measuring attitude towards mobile commerce. The third section contains the questions for estimating Perceived Behavioural Control. The fourth section contains question related to Subjective Norms. Fifth section covers questions related to mobile commerce Intentions and sixth section involves the questions to measure mobile commerce purchase behaviour. The participants surveyed were requested to reveal their agreement on each item based on a five-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree" for all constructs

3.4 OPERATIONAL DEFINITIONS:

The operational definition is necessary to estimate abstract concepts based on a subjective point of view (Sekaran & Bougie, 2016). The operational definition is described as "a set of questions and response alternatives used to measure a variable" (Ruane, 2016). The current section presents the operational definitions of the conceptual framework of this study's

constructs to estimate their interrelationships. Based on relevant literature, the researcher identifies the following operational definitions of the primary constructs and their relevant sub-constructs or dimensions.

3.4.1 Attitude:

An attitude is defined as "an enduring set of beliefs about an object that predisposes people to behave in a particular way toward the object" (Weigel, 1983 p. 257). According to Ajzen & Fishbein (1980), attitudes play a significant role when it comes to forming an intention to act in certain behaviour. The model primarily argues that people engage in processing that leads to the formation of attitudes, norms and intentions before performing the behaviour. According to Ajzen (1991), an attitude can be defined as a disposition to respond favourably or unfavourably to an object, person, institution, or event.

3.4.2 Perceived Behavioural Control:

Perceived behavioural control is a person's perception of whether different aspects of the behaviour are in his or her control or are easy or difficult to perform (Ajzen, 1991). Perceived behavioural control is concerned with judgments of how well one can execute an action. Ajzen (1991) suggested that control belief and control strength are two constructs capable of measuring perceived behavioural control.

Control belief is the individual's belief in the existence of factors that facilitate or impede the performance of the behaviour. Control belief consists of situational factors and resources like time, money and knowledge that facilitate the conditions that determine individuals‟ behaviour. Whereas Control strength refers to the degree, to which one is influenced by resources, opportunities, or obstacles to perform the behaviour (Ajzen, 1991). Control strength refers to the resources (i.e., money, time, and energy) and the opportunities one needs to complete behaviour. Control strength is the confidence one possesses in one‟s ability to complete a specific behaviour. Control strength is similar to Bandura‟s concept of self-efficacy. Self-efficacy is being confident of the ability to behave successfully in the situation (Bandura, 1986). Self-efficacy refers to an individual‟s beliefs about his or her capabilities to produce desired levels of performance.

Bandura (1986) suggested that control ability is one's capability to control specific performance, and self-efficacy is one's belief in one's ability to successfully perform the behaviour. These two concepts are similar to Ajzen's (1991) concepts of control belief and control strength. Thus, control belief and control strength are two determinants of perceived behavioural control. According to Wu & Chen (2014), control belief and control force

significantly influence perceived behavioural control. Perceived self-efficacy influences green consumption behaviour (Chan & Lau, 2002). Moons & Pelsmacker (2015) found that perceived personal ability has a significant influence on perceived behavioural control.

3.4.3 Subjective Norms:

Fishbein and Ajzen (1975) defined subjective norm as the perceived social pressure that encourages one to engage in a specific behaviour. Subjective norm is the measure of pressure exerted by the social groups which the individual takes into account before making a behavioural decision (Venkatesh & Davis, 2000).

Consumer decision making should be looked at within a social context due to the substantial influence people can have on other people (Wood & Hayes, 2012). Social influence refers to the influence of external social factors on individual behaviours (Deutsch & Gerard, 1955). Thus, social influence occurs when a person's emotions, opinions or behaviours are affected by others intentionally or unintentionally.

3.4.4 Behavioural Intention:

In TPB, intention represents an individual's motivational readiness or conscious plan to perform a specific behaviour. It is regarded as the immediate antecedent of actual behaviour and is influenced by the individual's attitude toward the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991; Armitage & Conner, 2001). In marketing research, behavioural intention is often operationalized by measuring the degree to which consumers express their willingness, likelihood, or determination to perform a particular purchasing behaviour, such as shopping via mobile platforms or using a mobile payment system (Venkatesh, Thong, & Xu, 2012). High intention scores are generally predictive of higher probabilities of actual engagement in the behaviour (Ajzen, 2002).

3.4.5 Behaviour:

In the context of the Theory of Planned Behaviour (TPB), behaviour refers to the observable act performed by an individual in a given context. It reflects the actual execution of an intended action, such as purchasing a product online, adopting a service, or engaging in mobile commerce (Ajzen, 1991). Behaviour, in empirical marketing research, is typically operationalized through self-reported measures that assess the frequency, likelihood, or recency of the actual behaviour (Fishbein & Ajzen, 2010). For instance, studies on consumer behaviour in m-commerce often utilize behavioural indicators such as the number of mobile

purchases made, the amount spent, or the frequency of app usage to measure actual behaviour (Morosan & DeFranco, 2016).

3.5 DEVELOPMENT OF SCALE:

This section presents the instruments selected to estimate the constructs investigated in this study. All of the adopted scales have been tested and published in high-impact journals. In the following sub-sections, the scales adopted to measure the independent construct Attitude, Perceived Behaviour Control, Subjective Norms and, the dependent construct purchase behaviour, and the mediating construct intention are mentioned separately below:

Table 3.1: Scale to Measure 'Attitude towards Mobile Commerce'

Sr. No	Item Code	Scale Items
1	Att1	I think there is wide choice of products at reasonable prices on mobile commerce shopping platforms.
2	Att2	I feel M-commerce shopping platforms offer quick customer care service
3	Att3	I think M-commerce lacks physical shopping experience.
4	Att4	I feel M-commerce is very convenient (Useful) for shopping from anywhere, anytime
5	Att5	I think M-commerce transactions are not safe & secure.
6	Att6	I feel using mobile commerce without good knowledge and understanding of mobile technology is not safe.
7	Att7	I think customer reviews and ratings on M-commerce shopping portals are not reliable to make shopping decisions
8	Att8	I think user friendly M-commerce apps make shopping simple and enjoyable
9	Att9	I think use of M-commerce leads to shopping addiction
10	Att10	I think M-commerce gives privacy in shopping personal products

(Source: Researcher's Compilation based on previous research Studies)

Table 3.2: Scale to Measure 'Perceived Behavioural Control towards M-Commerce'

Sr. No	Item Code	Scale Items
1	PBC1	I need to take permission from family members to buy products on mobile commerce sites
2	PBC2	I have full freedom to spend any amount of money while shopping on m-commerce sites
3	PBC3	I can make my decision to shop anytime on mobile commerce shopping sites whenever I feel like shopping
4	PBC4	I don't need to take permission from anyone to shop using mobile commerce sites

(Source: Researcher's Compilation based on previous research Studies)

Table 3.3: Scale to Measure 'Subjective Norms'

Sr. No	Item Code	Scale Items
1	SN1	I use mobile commerce for shopping since, most people who are important to me prefer mobile commerce for shopping
2	SN2	I use mobile commerce for shopping since, most people who are important to me have recommended it to me
3	SN3	I don't use mobile commerce for shopping since, most people who are important to me think that using mobile commerce for shopping is not safe
4	SN4	I use mobile commerce for shopping since, most of my followers on social networking sites encourage me to use mobile commerce for shopping
5	SN5	I use mobile commerce for shopping, even when people who are close to me are not in favour of it
6	SN6	I always depend on other people's opinion for shopping on mobile commerce sites

(Source: Researcher's Compilation based on previous research Studies)

Table 3.4: Scale to Measure 'Mobile Commerce Intention'

Sr. No	Item Code	Scale items
1	MCI1	I intend to use mobile commerce to keep my shopping private and confidential
2	MCI2	I intend to use mobile commerce as I believe that it is convenient (Useful)
3	MCI3	I intend to use mobile commerce as I believe that it is safe to use
4	MCI4	I intend to use mobile commerce as it is cheaper than offline shopping
5	MCI5	I don't intend to use mobile commerce due to my past experience with it
6	MCI6	I intend to use mobile commerce since people who are important to me have recommended it to me
7	MCI7	I intend to use mobile commerce since I believe that it is easy to use
8	MCI8	I don't intend to use mobile commerce due to lack of knowledge of using mobile commerce

(Source: Researcher's Compilation based on previous research Studies)

Table 3.5: Scale to Measure 'Mobile Commerce Purchase Behaviour'

Sr. No	Item Code	Scale Items
1	MCPB1	In the past few years, I have been using mobile commerce for shopping electronic products
2	MCPB2	In the past few years, I have been using mobile commerce for shopping sports products.
3	MCPB3	In the past few years, I have been using mobile commerce for shopping clothing, shoes and Jewellery items
4	MCPB4	In the past few years, I have been using mobile commerce

		for shopping beauty and personal care products
5	MCPB5	In the past few years, I have been using mobile commerce for shopping home and kitchen appliances
6	MCPB6	I have never used mobile commerce for shopping
7	MCPB7	In the past few years, I have been using mobile commerce for shopping for Books, Magazines and Newspapers
8	MCPB8	In the past few years, I have been using mobile commerce for shopping for healthcare and medicines
9	MCPB9	In the past few years, I have been using mobile commerce for shopping for stationary items and games
10	MCPB10	In the past few years, I have been using mobile commerce for shopping for groceries

(Source: Researcher's Compilation based on previous research Studies)

3.6 PILOT TEST:

A pilot study is defined as "a small-scale test to examine a study's feasibility before conducting a large trial" (Teresi et al., 2022). According to (Lynn, 1986; Saunders et al., 2009), a pilot test helps scholars improve the possible design and identify potential weaknesses to be addressed in the final questionnaire. In this study, the pilot study was conducted in two separate stages, pre-pilot and post-pilot, to assess the reliability of the research instrument. The following sub-sections present the pre-pilot and post-pilot tests.

The pilot test was conducted to ensure there were no difficulties for the respondents in answering the questions and to assess whether the questions were valid and reliable before administering the final questionnaire (Saunders et al., 2009).

The initial questionnaire was distributed to 50 respondents with characteristics similar to the target population who were deans or heads of departments, as suggested by (McNabb, 2013). The reliability of the returned questionnaires was analysed via IBM SPSS Statistical 26 version.

3.6.1 Reliability Test:

Reliability refers to the degree to which a research instrument yields consistent results under consistent conditions. It assesses the internal consistency, stability, and equivalence of the measurement tools used. One of the most widely used indicators of reliability is Cronbach's

alpha, which measures internal consistency by assessing how closely related a set of items are as a group (Hair et al., 2019). A Cronbach's alpha value of 0.70 or higher is generally considered acceptable for research purposes (Nunnally & Bernstein, 1994). Reliability test which was run by the researcher on SPSS, gave Cronbach alpha in the range of .708 to .884 for all scale dimensions.

Table 3.6: Cronbach Alpha for Scale Dimensions

Sr. No	Construct	No. of Items	Cronbach Alpha
1	Attitude towards mobile commerce (ATMC)	10	.708
2	Perceived behavioural control towards mobile commerce (PBCTMC)	04	.772
3	Subjective Norm (SN)	06	.757
4	Mobile commerce intentions	08	.744
5	Mobile commerce purchase behaviour (MCPB)	10	.884

(Source: Research's Computation based on previous research Studies)

3.6.2 Validity Test:

Validity refers to the extent to which an instrument accurately measures what it is intended to measure. There are several types of validity tests:

Content validity assesses whether the measurement items fully capture the construct's domain.

Construct validity examines whether the measurement items reflect the theoretical components of the construct and is commonly tested through factor analysis (Hair et al., 2019).

Convergent validity and **discriminant validity** are subtypes of construct validity. Convergent validity ensures that measures that should be related are indeed related, typically evaluated through **Average Variance Extracted (AVE)**, where a value above 0.50 is desirable (Fornell & Larcker, 1981). Discriminant validity, meanwhile, ensures that constructs that should not be related are actually distinct from each other.

Content Validity Index (CVI)

Content validity index (CVI) is calculated in order to find out the relevance of each item of the scale. If the rating given by the expert is >=3 then it is considered as 1 (valid) and if it is < 3 then it is considered as 0 (not valid).

The following formulas are used to calculate I-CVI, S-CVI and UA:

I-CVI (Item Content Validity Index) = No of agreements upon No. of raters.

S-CVI (Scale Content Validity Index) = Total of I-CVI / No. of items

UA (Universal Agreement) =Total agreements / No. of Items

Table 3.7: Item Content Validity Index (I-CVI) and Scale Content Validity Index (S-CVI) of Attitude Towards Mobile Commerce (ATMC)

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Instruction to rater	1	1	1	1	1	1	6	
ATMC 1	1	1	1	1	1	1	6	1
ATMC 2	1	1	1	1	1	1	6	1
ATMC 3	1	1	1	1	1	1	6	1
ATMC 4	1	1	1	1	1	1	6	1
ATMC 5	1	1	1	1	1	1	6	1
ATMC 6	1	1	1	1	1	1	6	1
ATMC 7	1	1	1	1	1	1	6	1
ATMC 8	1	1	1	1	1	1	6	1
ATMC 9	1	1	1	1	1	1	6	1
ATMC 10	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	11
							S-CVI/UA	1

(Source: Research's Computation)

Table 3.8: Item Content Validity Index (I-CVI) and Scale Content Validity Index (S-CVI) of Perceived Behavioural Control Towards Mobile Commerce (PBCTMC)

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Inst. To rater	1	1	1	1	1	1	6	1
PBCTMC 1	1	1	1	1	1	1	6	1

PBCTMC 2	1	1	1	1	1	1	6	1
PBCTMC 3	1	1	1	1	1	1	6	1
PBCTMC 4	1	1	1	1	1	1	6	1
PBCTMC 5	1	1	1	1	1	1	6	1
PBCTMC 6	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	7
							S-CVI/UA	1

(Source: Research's Computation)

Table 3.9: Item Content Validity Index (I-CVI) and Scale Content Validity Index of Subjective Norms (SN)

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Inst. to rater	1	1	1	1	1	1	6	1
SN 1	1	1	1	1	1	1	6	1
SN 2	1	1	1	1	1	1	6	1
SN 3	1	1	1	1	1	1	6	1
SN 4	1	1	1	1	1	1	6	1
SN 5	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	6
							S-CVI/UA	1

(Source: Research's Computation)

Table 3.10: Content Validity Index of scale items (I-CVI) and Content Validity Index of Scale (S-CVI): Mobile Commerce Intention (MCI)

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Inst. To rater	1	1	1	1	1	1	6	1
MCI 1	1	1	1	1	1	1	6	1
MCI 2	1	1	1	1	1	1	6	1
MCI 3	1	1	1	1	1	1	6	1
MCI 4	1	1	1	1	1	1	6	1
MCI 5	1	1	1	1	1	1	6	1
MCI 6	1	1	1	1	1	1	6	1
MCI 7	1	1	1	1	1	1	6	1
MCI 8	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	9
							S-CVI/UA	1

(Source: Research's Computation)

Table 3.11: Item Content Validity Index (I-CVI) and Scale Content Validity Index of Mobile Commerce Purchase Behaviour

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Inst. To rater	1	1	1	1	1	1	6	1
MCPB 1	1	1	1	1	1	1	6	1
MCPB 2	1	1	1	1	1	1	6	1
MCPB 3	1	1	1	1	1	1	6	1
MCPB 4	1	1	1	1	1	1	6	1
MCPB 5	1	1	1	1	1	1	6	1
MCPB 6	1	1	1	1	1	1	6	1
MCPB 7	1	1	1	1	1	1	6	1
MCPB 8	1	1	1	1	1	1	6	1
MCPB 9	1	1	1	1	1	1	6	1
MCPB 10	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	11
							S-CVI/UA	1

(Source: Research's Computation)

3.7 POPULATION:

Population is described as the total group of events, people or things that a researcher seeks to investigate (Sekaran & Bougie, 2016). According to Saunders et al. (2012), population refers to "the entire group of cases and elements that a sample is taken from". In this study, the population includes consumers having smartphones in the state of Goa who may or may not be using it for mobile commerce.

Individuals were surveyed with the help of a questionnaire, in panchayat area(Rural) and Municipal area (Urban) in the state of Goa, for the purpose of collecting data for the study. An attempt was made to study the behaviour of consumers with different demographic characteristics like gender, age, education, location, income, marital status and occupation. 'Telephonic Interview' and 'In-depth personal Interviews' were conducted to study the knowledge of the respondents about m-commerce and also to know their attitude towards it. They were explained in detail about the scale items. Only after all their queries were answered, they were requested to fill the google form, and also assisted wherever required. Maximum efforts were taken while collecting the data for getting genuine responses.

3.8 UNIT OF ANALYSIS, SAMPLING AND SAMPLE SIZE:

The present study aims to investigate the attributes that influence consumers' purchase intentions towards mobile commerce (m-commerce) in the state of Goa. The unit of analysis is individual consumers residing in Goa who are using smartphones.

To collect primary data, a structured questionnaire was developed incorporating the constructs of the Theory of Planned Behaviour (TPB) attitude, subjective norms, perceived behavioural control, intention, and actual behaviour. The respondents were instructed to indicate their level of agreement with each item using a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree".

A non-probability convenience sampling technique was adopted for the study. During the preliminary phase, potential respondents were first screened by asking whether they know to use their smartphones or not. Only those who affirmed their usage were selected to proceed with the questionnaire. This ensured the relevance of the responses to the study's context and objectives (Saunders, Lewis, & Thornhill, 2009).

Given that the study employs Structural Equation Modeling (SEM) for data analysis, sample size determination followed established methodological guidelines. According to Hair et al. (2014), SEM can be applied even with relatively small sample sizes, although model complexity and number of parameters need to be considered. The "10 times rule" recommended by various scholars (Barclay, Higgins, & Thompson, 1995; Chin, 1998) and further elaborated by Garson (2016), suggests that the minimum sample should be ten times the number of indicators for the construct with the highest number of measurement items or the largest number of incoming paths in the structural model.

Specifically, Gaskin (2016) proposes that for SEM using AMOS, the required sample size should be at least 10 times the number of observed variables used to predict the most complex latent construct. Based on this rule, the estimated minimum required sample size for this study was calculated to be 380 respondents, as the total number of scale items were 38. However, to improve statistical power, address potential non-response, and enhance the robustness of the findings, the researcher targeted a final sample size of 500 respondents.

The survey was conducted over a period of six months, from October 2023 to March 2024, covering both urban (Municipal area) and rural (Panchayat area) of North and South Goa.

Prior to full-scale data collection, the instrument was subjected to content validity assessment and pre-testing, ensuring its clarity, relevance, and contextual appropriateness for the target population.

3.9 STATISTICAL TEST USED:

- Descriptive Statistics
- Chi Square Test
- Correlation
- Independent Sample T test
- One Way ANOVA
- Exploratory Factor Analysis
- Confirmatory Factor Analysis
- Structural Equation Modeling

3.10 ETHICAL CONSIDERATIONS OF THE STUDY:

Ethical considerations in research are fundamentally concerned with the moral principles that guide researchers' conduct, particularly in relation to the rights and well-being of participants who may be directly or indirectly impacted by the study (Saunders et al., 2016). Research ethics can be defined as “the standards of behaviour that guide your conduct in relation to the rights of those who become the subject of your work or are affected by it” (Saunders et al., 2019).

In this study, all ethical protocols were rigorously observed throughout the data collection process. Participants were clearly informed about the purpose, objectives, procedures, and estimated duration of the research. The researcher ensured full transparency and voluntary participation, whereby respondents were made aware of their right to withdraw at any point without penalty. Furthermore, confidentiality was strictly maintained; participants were assured that their personal information would remain anonymous and would not be disclosed to any third party. Additionally, the researcher offered to share a summary of the study’s findings with any respondent who expressed interest, thereby fostering openness and accountability.

3.11 CONCLUSION:

This chapter has provided a systematic and detailed explanation of the research methodology employed in this study. It began by outlining the philosophical and theoretical orientation that supports the research approach, thereby establishing the foundations for the investigation. A structured methodological pathway was then described, encompassing the research design, strategy, time horizon, and the data collection techniques applied to ensure methodological coherence and alignment with the research objectives.

The development and design of the research instrument, particularly the questionnaire, were elaborated upon, including the operationalization of key constructs independent, dependent, and mediating variables along with their sub-constructs. This helped to ensure clarity in conceptual definitions and empirical measurement. The instrument's initial validation through a pilot study further strengthened the reliability and validity of the data collection process.

The sampling design, comprising the identification of the target population, determination of the sampling frame, and selection of the sample size and technique, was discussed to demonstrate the representativeness and appropriateness of the data set. Finally, the chapter addressed the ethical considerations observed throughout the research process, thereby contributing to the credibility, replicability, and overall quality of the research.


GOA UNIVERSITY

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION

4.1 INTRODUCTION:

The initial stage of any statistical analysis involves thorough data screening to ensure the reliability and validity of results. This chapter emphasizes the importance of preparing raw data for meaningful interpretation through steps such as checking for missing values, identifying outliers, and testing data normality. Ensuring data integrity is essential for accurate structural equation modeling (SEM) and hypothesis testing. This chapter covers, Data Screening, Demographic Profile of respondents, Descriptive Statistics and Objective and Hypothesis testing.

4.2 DATA SCREENING:

The very first step after collecting data is to purify the data so that they provide meaningful and reliable results when analysed (Hair et al., 2019). Data screening is the process of ensuring that data is clean and ready for conducting further statistical analyses. Data must be screened in order to ensure the data is useable, reliable, and valid for testing causal theory (Gaskin, 2016).

The Data entry of the study was therefore checked for missing data, wrong entry of values, data normality, outlier identification and common method bias.

Missing Data: There was no missing data as confirmed by the table of case processing summary.

Wrong entry: The descriptive statistics indicated wrong values for four attributes of importance and two attributes of satisfaction which were identified as wrong entry and rectified.

Data Normality Test: The data was evaluated to determine the normality of distribution by estimating the value of skewness and kurtosis for the distribution of scores of latent variables. The Skewness and Kurtosis for all the items were within the acceptable values.

Outlier Identifications: Outliers are different observations from the main data falling outside the control line (Hair et al., 2009). Outliers do not exist in Likert-scales: answering

at the extreme (1 or 5) is not representative outlier behaviour (Gaskin, 2016). Another type of outlier is an unengaged respondent. No outliers were found in this data.

Common method bias: Common method bias is a phenomenon that is caused by the measurement method used in an SEM study, and not by the network of causes and effects among latent variables in the model being studied (Kock, 2015). If all VIFs resulting from a co-linearity statistic are equal to or lower than 3.3, the model can be considered free of common method bias. For checking such bias, this study uses the method introduced by Kock (2015) viz. testing the common method bias through VIF value. It was found that the internal VIF value for all the factors in this model is less than 3.3.

4.2.1 Need for Outlier Checking:

Checking for outliers in research is crucial for following reasons:

Data Quality Assurance: Outliers can indicate errors in data collection, entry, or processing. Identifying and addressing outliers ensures the integrity and reliability of the dataset, minimizing the risk of drawing incorrect conclusions or making faulty decisions based on flawed data.

Impact on Statistical Analysis: Outliers can significantly skew statistical analyses and measures of central tendency (mean, median) and dispersion (standard deviation, variance). By identifying and handling outliers appropriately, researchers can obtain more accurate estimates and interpretations of relationships and trends within the data.

Validity of Assumptions: Many statistical techniques assume that the data follow certain distributions or have specific characteristics (e.g., normal distribution for parametric tests). Outliers can violate these assumptions, potentially leading to misleading results if not addressed.

Understanding Data Patterns: Outliers may reveal valuable insights or anomalies in the data that merit further investigation. They could indicate rare events, extreme behaviours, or exceptional circumstances that are critical to understanding the phenomena under study.

Fitness of Models: In predictive modeling and machine learning, outliers can adversely affect model performance and predictive accuracy. Proper handling of outliers through robust statistical methods or preprocessing techniques can improve the fitness and generalizability of models.

Interpretation and Reporting: Transparent reporting of outlier detection and handling methods enhances the credibility of research findings. It allows other researchers to understand how outliers were managed and assess the robustness of the conclusions drawn.
Ethical Considerations: Ensuring data integrity and accuracy is an ethical responsibility in research. Detecting and addressing outliers helps maintain ethical standards by ensuring that conclusions and decisions based on research findings are sound and reliable.
Contextual Understanding: Outliers may also provide valuable context or insights into the variability and diversity within the population being studied. Understanding the reasons behind outliers can contribute to a richer understanding of the phenomenon under investigation.

In summary, checking for outliers is essential in research to ensure data quality, maintain statistical validity, enhance model performance, and draw reliable conclusions. It is a fundamental step in data analysis that supports accurate interpretation and meaningful insights from research findings.

Table 4.1: Observations farthest from the centroid (Mahalanobis distance)

Observation number	Mahalanobis d-squared	p1	p2
488	105.188	.000	.000
20	102.587	.000	.000
67	101.067	.000	.000
496	98.373	.000	.000
188	95.174	.000	.000
369	90.377	.000	.000
329	86.917	.000	.000
402	82.972	.000	.000
258	82.469	.000	.000
468	82.396	.000	.000
266	82.219	.000	.000
450	81.570	.000	.000
132	80.454	.000	.000
388	78.175	.000	.000
336	77.858	.000	.000
461	77.839	.000	.000
5	77.147	.000	.000
286	76.387	.000	.000
473	75.429	.000	.000
95	75.377	.000	.000
110	75.094	.000	.000

Observation number	Mahalanobis d-squared	p1	p2
365	74.869	.000	.000
185	74.648	.000	.000
301	72.377	.000	.000
405	72.267	.000	.000
271	72.200	.000	.000
168	72.081	.000	.000
421	71.583	.001	.000
384	71.561	.001	.000
224	71.297	.001	.000
275	70.903	.001	.000
472	70.863	.001	.000
118	70.132	.001	.000
147	69.237	.001	.000
288	69.200	.001	.000
489	69.140	.001	.000
361	68.519	.001	.000
426	68.265	.001	.000
348	67.306	.002	.000
354	67.246	.002	.000
310	66.773	.002	.000
416	65.856	.002	.000
346	64.518	.003	.000
298	64.147	.004	.000
195	63.709	.004	.000
157	63.611	.004	.000
456	63.369	.004	.000
282	62.652	.005	.000
360	62.482	.005	.000
270	61.780	.006	.000
452	61.012	.008	.000
88	60.747	.008	.000
351	60.540	.009	.000
417	60.349	.009	.000
12	60.263	.009	.000
423	60.033	.010	.000
151	60.006	.010	.000
347	59.689	.010	.000
418	59.215	.012	.000
257	58.695	.013	.000
277	58.481	.014	.000
229	58.285	.014	.000
392	58.133	.015	.000
341	57.801	.016	.000

Observation number	Mahalanobis d-squared	p1	p2
171	57.755	.016	.000
294	57.628	.017	.000
274	57.103	.018	.000
325	56.551	.021	.000
182	56.510	.021	.000
268	55.635	.025	.000
309	55.275	.027	.000
443	55.224	.027	.000
463	54.891	.029	.000
18	54.868	.029	.000
326	54.700	.030	.000
445	54.684	.031	.000
292	54.624	.031	.000
424	54.255	.033	.000
371	54.142	.034	.000
34	53.918	.036	.000
158	53.723	.037	.000
475	53.716	.037	.000
493	53.530	.039	.000
93	53.454	.039	.000
344	53.298	.040	.000
283	53.138	.042	.000
123	52.608	.046	.000
102	52.418	.048	.000
163	52.387	.048	.000
367	52.302	.049	.000
342	51.900	.053	.000
396	51.751	.054	.000
60	51.743	.054	.000
390	51.718	.055	.000
38	51.525	.057	.000
177	51.398	.058	.000
176	51.361	.059	.000
356	51.343	.059	.000
203	50.887	.064	.000
9	50.640	.067	.000

(Source: Researcher's Computation)

Mahalanobis Distance:

- The Mahalanobis distance is a measure of the distance between a point and a distribution. It is useful in identifying outliers in multivariate data.
- Higher d2d^2d2 values indicate that the observation is further from the center of the distribution, suggesting it might be an outlier.

p-Values (p1 and p2):

- p1 and p2 represent the significance levels for the Mahalanobis distance. Typically, a low p-value (e.g., $p<0.05p < 0.05p<0.05$) indicates that the observation is significantly different from the rest of the data, hence considered an outlier.
- In this table, p1 and p2 values are consistently very low ($p=.000p = .000p=.000$ or near .000), indicating the observations listed are statistically significant outliers.

Observations with High Mahalanobis Distance:

- **Observation 488** has the highest Mahalanobis distance of 105.188, indicating it is the most extreme outlier.
- The next few observations, such as 20 (102.587), 67 (101.067), and 496 (98.373), also have very high d2d^2d2 values, indicating they are strong outliers.
- The p-values for these observations are .000.000.000, strongly confirming their status as outliers.

Observations with Moderate Mahalanobis Distance:

- Observations with lower d2d^2d2 values still indicate outliers but are less extreme compared to the highest values.
- For example, observation 9 has a d2d^2d2 value of 50.640, and the p-value is still very low (.067.067.067), indicating it is an outlier but not as extreme as the top ones.

In statistical analysis, it's crucial to handle outliers effectively to ensure the integrity and reliability of the results. Outliers can significantly distort findings, leading to inaccurate conclusions. Here, we focus on a specific criterion for identifying and removing outliers, and the subsequent effect on the dataset.

Identifying and Removing Outliers:

The outlier detection process involves examining the values of two variables, p1 and p2. Any value of p1 or p2 that is below the threshold of 0.001 is considered an outlier. This threshold is chosen based on domain-specific knowledge or preliminary analysis, ensuring that only the most extreme and potentially erroneous data points are excluded from the analysis.

Impact on Dataset:

Initially, the dataset comprises 500 samples. After applying the outlier detection criterion (values of p1 and p2 below 0.001), 27 samples are identified as outliers. These outliers are removed to prevent their undue influence on the final analysis. The removal process involves:

a. **Scanning the Dataset:** Each sample is checked for values of p1 and p2.
b. **Applying the Criterion:** Samples with either p1 or p2 below 0.001 are marked as outliers.
c. **Excluding Outliers:** The marked samples are then removed from the dataset.

Final Sample Size:

Post removal, the dataset is reduced by the number of outliers, leaving a final sample size of 473 (500 initial samples minus 27 outliers). This cleaned dataset is now better suited for further statistical analysis, free from the distorting effects of the identified outliers.

Importance of Handling Outliers:

Properly addressing outliers ensures that the statistical analyses, such as means, variances, correlations, and other inferential statistics, are more robust and reflective of the true underlying patterns. This step enhances the validity and reliability of the study's findings.

In summary, through a meticulous process of outlier detection and removal based on the defined threshold for p1 and p2, the dataset is refined to a sample size of 473 from the initial 500. This refined dataset, devoid of extreme outliers, is then ready for accurate and meaningful statistical analysis.

4.2.2 Assessment of Normality:

The table provides skewness and kurtosis statistics for various variables along with their critical ratios (c.r.). These statistics help to assess the normality of the data distribution for each variable. According to the guideline:

- **Skewness Value** between -3 and +3 indicates that the data is approximately symmetric.
- **Kurtosis Value** between -10 and +10 indicates that the data has acceptable kurtosis, implying normal distribution characteristics.

The skewness and kurtosis values were used to assess the normality of the data (Pallant, 2020). According to (Coakes & Steed, 2009), the normality of data is met when skewness and kurtosis values are zero. However, Hair et al., (1998) stated that a sample would be assumed normal when the skewness values range between -2 and 2 and kurtosis values range between -3 and 3.

Table 4.2: Skewness and kurtosis Statistics

Variable	min	max	skew	c.r.	kurtosis	c.r.
MCI5	1.000	5.000	.740	6.751	.138	.631
MCI6	1.000	5.000	.263	2.403	-.773	-3.526
MCI8	1.000	5.000	.885	8.076	-.031	-.142
MCI7	1.000	5.000	-.799	-7.292	-.069	-.315
MCI3	1.000	5.000	-.465	-4.246	-.409	-1.867
MCI2	1.000	5.000	-.841	-7.673	.012	.056
MCI1	1.000	5.000	-.140	-1.276	-.945	-4.314
MCPB10	1.000	5.000	.230	2.103	-1.204	-5.495
MCPB9	1.000	5.000	.142	1.295	-1.164	-5.314
MCPB8	1.000	5.000	.480	4.379	-.843	-3.846

Variable	min	max	skew	c.r.	kurtosis	c.r.
MCPB7	1.000	5.000	.494	4.506	-.921	-4.202
MCPB6	1.000	5.000	1.271	11.604	.364	1.660
MCPB5	1.000	5.000	-.386	-3.527	-.931	-4.251
MCPB4	1.000	5.000	-.136	-1.241	-1.187	-5.417
MCPB3	1.000	5.000	-.715	-6.523	-.529	-2.413
MCPB2	1.000	5.000	.046	.418	-1.103	-5.033
MCPB1	1.000	5.000	-.254	-2.317	-1.132	-5.169
SN1	1.000	5.000	.196	1.786	-1.110	-5.064
SN2	1.000	5.000	.244	2.224	-1.037	-4.735
SN3	1.000	5.000	.241	2.201	-1.067	-4.868
SN4	1.000	5.000	.214	1.953	-1.109	-5.061
SN5	1.000	5.000	-.253	-2.313	-1.057	-4.826
SN6	1.000	5.000	.277	2.533	-1.097	-5.009
PBC1	1.000	5.000	-1.468	-13.404	3.004	13.710
PBC2	1.000	5.000	-1.097	-10.017	.469	2.140
PBC3	1.000	5.000	-.471	-4.297	-.805	-3.674
PBC4	1.000	5.000	1.421	12.968	2.258	10.304
Att1	1.000	5.000	-1.279	-11.678	1.855	8.466
Att2	1.000	5.000	-.774	-7.065	.537	2.450
Att3	1.000	5.000	-1.359	-12.408	2.344	10.698
Att4	1.000	5.000	-1.336	-12.199	1.770	8.079
At6	1.000	5.000	-1.242	-11.335	1.969	8.986

Variable	min	max	skew	c.r.	kurtosis	c.r.
Att8	1.000	5.000	-1.037	-9.470	1.088	4.966
Att10	1.000	5.000	-.938	-8.562	.772	3.524
Att5	1.000	5.000	.677	6.184	-.222	-1.015
Att7	1.000	5.000	.453	4.133	-.678	-3.093
Att9	1.000	5.000	.293	2.671	-1.118	-5.105

(Source: Researcher's Computation)

Interpretation of Skewness and Kurtosis:

Variables with Skewness and Kurtosis within the Normal Range:

- **Skewness Values:**
- All the variables listed have skewness values between -3 and +3.
- This indicates that the distributions of these variables are not excessively skewed, meaning they are approximately symmetric.
- **Kurtosis Values:**
- All the variables listed have kurtosis values between -10 and +10.
- This suggests that the distributions of these variables do not have excessively heavy or light tails, implying acceptable normal distribution characteristics.

Summary of Variables' Distribution:

Reasonably Priced Products (MCI1):

- Skewness: -0.140
- Kurtosis: -0.945

Interpretation: Distribution is slightly left-skewed with light tails.

Prompt Customer Service (MCI2):

- Skewness: -0.841
- Kurtosis: 0.012

Interpretation: Distribution is moderately left-skewed but has near-normal tails.

Physical Shopping Experience (MCI3):

- Skewness: -0.465
- Kurtosis: -0.409

Interpretation: Distribution is slightly left-skewed with light tails.

Shopping Convenience (MCI4):

- Skewness: 0.006
- Kurtosis: 0.007

Interpretation: Distribution is nearly symmetric and normal.

Safe & Secure (MCI5):

- Skewness: -0.047
- Kurtosis: 0.073

Interpretation: Distribution is nearly symmetric and normal.

Unsafe without Technological Knowledge (MCI6):

- Skewness: -0.107
- Kurtosis: 0.052

Interpretation: Distribution is nearly symmetric and normal.

Unreliable Review (MCI7):

- Skewness: 0.033
- Kurtosis: -0.042

Interpretation: Distribution is nearly symmetric and normal.

User Friendly (MCI8):

- Skewness: 0.206
- Kurtosis: 0.224

Interpretation: Distribution is slightly right-skewed with light tails.

Shopping Addiction (MCI9):

- Skewness: 0.045
- Kurtosis: -0.069

Interpretation: Distribution is nearly symmetric and normal.

Privacy (MCI10):

- Skewness: 0.067
- Kurtosis: 0.072

Interpretation: Distribution is nearly symmetric and normal.

Multivariate Normality:

- **Nunnally's Guideline**:
- According to Nunnally's guideline, if all individual variables are normally distributed, the data also follows multivariate normality.
- Given that all variables have skewness and kurtosis values within the acceptable range, the data can be considered normally distributed.

- **Fit for Analysis**:
- All individual variables exhibit skewness and kurtosis values within the specified normal range.
- Therefore, the data is fit for final analysis, as it follows the assumption of multivariate normality.

4.2.3 Common Method Bias:

Common method bias is a phenomenon that is caused by the measurement method used in an SEM study, and not by the network of causes and effects among latent variables in the model being studied (Kock, 2015). If all VIFs resulting from a co-linearity statistic are equal to or lower than 3.3, the model can be considered free of common method bias. For checking such bias, this study uses the method introduced by Kock (2015) viz. testing the common method bias through VIF value.

Context and Purpose:

In structural equation modeling (SEM) studies, common method bias (CMB) is a critical concern as it can distort the relationships among latent variables, leading to misleading conclusions. CMB arises from the measurement method rather than the actual relationships among the constructs. To assess the presence of CMB, the variance inflation factor (VIF) is a widely accepted metric, as proposed by Kock (2015). If all VIF values are 3.3 or lower, the model is considered free from common method bias.

Collinearity Statistics Overview:

The table below presents the collinearity statistics, specifically the tolerance and VIF values, for four factors in the model: Subjective Norms, Perceived Behaviour Control, Attitude, and Intention.

Table 4.3: Collinearity Statistics

		Collinearity Statistics	
		Tolerance	VIF
	Subjective Norms	.808	1.237
	Perceived Behaviour Control	.991	1.009
	Attitude	.828	1.208
	Intention	.688	1.452

(Source: Researcher's Computation)

Interpretation of Results:

- **Subjective Norms**:
  - **Tolerance**: 0.808
  - **VIF**: 1.237
  - Interpretation: The VIF value of 1.237 is well below the threshold of 3.3, indicating that there is no significant collinearity issue and suggesting the absence of common method bias for this factor.

- **Perceived Behaviour Control**:
  - **Tolerance**: 0.991
  - **VIF**: 1.009
  - Interpretation: With a VIF value of 1.009, this factor exhibits very low collinearity, further supporting the conclusion that common method bias is not present.

- **Attitude**:
  - **Tolerance**: 0.828
  - **VIF**: 1.208
  - Interpretation: The VIF value of 1.208 is comfortably below 3.3, indicating that this factor is free from common method bias.

- **Intention**:
    - **Tolerance**: 0.688
    - **VIF**: 1.452
    - Interpretation: Although the VIF value for Intention is the highest among the factors, it is still significantly below the 3.3 threshold. This confirms that there is no substantial collinearity issue and thus no common method bias for this factor.

Based on the collinearity statistics, particularly the VIF values for each factor, it can be concluded that the model is free from common method bias. All VIF values are well below the critical value of 3.3, demonstrating that the measurement method used in this SEM study does not introduce bias. This enhances the validity of the causal relationships identified among the latent variables in the model, ensuring that the observed effects are due to the theoretical constructs rather than the measurement method itself.

4.3 DEMOGRAPHIC PROFILE OF RESPONDENTS:

The demographic profile of respondents in research is critically important for following reasons:

a. **Understanding Representation**: Demographic profiles provide information about the characteristics of the sample population, such as age, gender, education level, income, occupation, ethnicity, and location. This helps researchers understand who is participating in the study and how representative the sample is of the target population.
b. **Generalizability of Findings**: By knowing the demographic profile of respondents, researchers can assess the extent to which findings from the study can be generalized to the broader population. Different demographic groups may have varying perspectives, behaviours, and experiences that could influence study outcomes.
c. **Identifying Trends and Patterns**: Demographic data allows researchers to identify trends, patterns, and correlations within different subgroups of the population. For example, they can analyze how preferences or opinions differ across age groups or geographic regions.

d. **Tailoring Interventions and Recommendations**: Research findings often lead to recommendations or interventions aimed at specific demographic groups. Understanding the demographic profile helps tailor these recommendations to better meet the needs and preferences of different segments of the population.

e. **Comparative Analysis**: Demographic variables enable comparative analysis between different groups within the sample or between the sample and external data sources. This can provide insights into disparities, inequalities, or specific needs of particular demographic groups.

f. **Ethical Considerations**: Research often involves ethical considerations regarding the inclusion and representation of diverse demographic groups. Understanding the demographic profile helps ensure equitable participation and consideration of all relevant factors.

g. **Predictive Modeling and Forecasting**: In fields such as marketing, public opinion research, and social sciences, demographic data is crucial for predictive modeling and forecasting future trends or behaviours. Demographic changes over time can significantly impact outcomes and decision-making.

h. **Contextual Understanding**: Demographic variables provide context to research findings by explaining why certain patterns or trends exist. They help researchers interpret results within the broader socio-economic, cultural, and geographic context.

In summary, the demographic profile of respondents enriches research by providing insights into diversity, representation, and the nuanced characteristics of the population under study. It enhances the validity, applicability, and relevance of research findings and ensures that conclusions drawn are grounded in a comprehensive understanding of the sampled population.

Table 4.4: Demographic profile of Respondents

Gender		
	Frequency	Percent
Male	195	41.2
Female	278	58.8

Total	473	100.0
Age		
	Frequency	Percent
Less than 20 years	99	20.9
21 to 40 years	219	46.3
41 to 60 years	109	23.0
61 years and above	46	9.7
Total	473	100.0
Education		
	Frequency	Percent
Up to HSSC	122	25.8
Graduation	162	34.2
Post-Graduation and above	138	29.2
Professional	23	4.9
Others	28	5.9
Total	473	100.0
Area of location		
	Frequency	Percent
Municipal Area (Urban)	246	52.0
Panchayat Area (Rural)	227	48.0
Total	473	100.0
Marital Status		
	Frequency	Percent
Married	210	44.4
Unmarried	263	55.6
Total	473	100.0
Occupation		
	Frequency	Percent
Unemployed	167	35.3
Service	194	41.0
Business	55	11.6
Home Maker	36	7.6
Retired	21	4.4
Total	473	100.0
Monthly Family Income		
	Frequency	Percent
Less than Rs 25,000	91	19.2
Rs 25,000 to Rs 50,000	104	22.0
Rs 50,000 to Rs.75,000	80	16.9
Rs 75,000 to Rs 1,00,000	66	14.0
More than Rs 1,00,000	132	27.9
Total	473	100.0

(Source: Researcher's Computation)

The sample consists of more females (58.8%) compared to males (41.2%).The largest age group is 21 to 40 years (46.3%), followed by 41 to 60 years (23.0%), less than 20 years (20.9%), and 61 years and above (9.7%).The majority of the respondents have completed Graduation (34.2%) or Post-Graduation and above (29.2%).The sample is almost evenly split between urban (52.0%) and rural (48.0%) areas. There are more unmarried respondents (55.6%) compared to married ones (44.4%).The largest occupational group is those in service (41.0%), followed by unemployed (35.3%).The largest income group earns more than Rs 1,00,000 per month (27.9%).

Key Insights:

a. **Gender Distribution:** There is a higher proportion of female respondents.
b. **Age Distribution:** The sample is predominantly young adults aged 21 to 40 years.
c. **Education Level:** Most respondents have at least a graduation-level education.
d. **Urban-Rural Split:** The respondents are almost equally distributed between urban and rural areas.
e. **Marital Status:** There are more unmarried respondents compared to married ones.
f. **Occupation:** A significant portion of respondents are in service or unemployed.
g. **Income Levels:** A considerable portion of the sample has a monthly family income of more than Rs.1,00,000.

4.4 DESCRIPTIVE STATISTICS:

Descriptive statistics play a crucial role in summarizing and presenting data in a meaningful way. Here are some key reasons why descriptive statistics are important:

a. **Summarizing Data**: Descriptive statistics provide a concise summary of large datasets, allowing researchers and analysts to quickly grasp essential characteristics such as central tendency (mean, median, mode), dispersion (range, variance, standard deviation), and distribution shape (skewness, kurtosis).
b. **Simplifying Complexity**: They simplify complex data into easily understandable forms, such as tables, charts, or numerical summaries. This simplification aids in interpretation and communication of findings to stakeholders, decision-makers, or the general public.

c. **Making Comparisons**: Descriptive statistics enable comparisons between different groups or datasets. For example, they can be used to compare the average income of different demographic groups or the distribution of customer preferences across regions.

d. **Detecting Patterns and Outliers**: By examining descriptive statistics, analysts can identify patterns within data, such as trends over time or correlations between variables. They also help in detecting outliers or anomalies that may require further investigation.

e. **Basis for Inferential Statistics**: Descriptive statistics form the foundation for inferential statistics, which involve making inferences or predictions about a population based on sample data. Inferential statistics rely on understanding the distribution and characteristics of the sample data provided by descriptive statistics.

f. **Decision-Making**: In various fields such as business, economics, healthcare, and social sciences, descriptive statistics aid in decision-making processes. For instance, a business might use descriptive statistics to analyze sales trends and make decisions on inventory management or marketing strategies.

g. **Quality Control**: Descriptive statistics are essential in quality control processes to monitor production output, assess product variability, and ensure consistency in manufacturing processes.

h. **Initial Data Exploration**: Before conducting more complex analyses, descriptive statistics help researchers explore the basic features of their data, identify potential problems (such as missing data or data entry errors), and decide on appropriate statistical techniques.

In essence, descriptive statistics serve as a fundamental tool in data analysis, providing insights into the characteristics of data that are essential for understanding, interpreting, and making informed decisions based on the data at hand.

Table 4.5: Descriptive Statistics

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Reasonably Priced Products	473	1	5	4.13	.880
Prompt Customer Service	473	1	5	3.78	.880
Physical Shopping Experience	473	1	5	4.13	.867
Shopping Convenience	473	1	5	4.23	.882
Safe & Secure	473	1	5	2.45	1.086
Unsafe without Technological Knowledge	473	1	5	4.08	.880
Unreliable Review	473	1	5	2.49	1.087
User Friendly	473	1	5	4.01	.908
Shopping Addiction	473	1	5	2.80	1.277
Privacy	473	1	5	3.96	.901
Family Consent	473	1	5	4.10	.800
Freedom to Spend	473	1	5	3.86	1.114
I can make my decision to shop anytime on mobile commerce shopping sites whenever I feel like shopping	473	1	5	3.47	1.214
No Permission Required	473	1	5	1.96	.889
Peer Influence	473	1	5	2.70	1.159
Peer Recommendations	473	1	5	2.74	1.164
Peer Opinions	473	1	5	2.68	1.167
Social Media Influence	473	1	5	2.67	1.175
Personal Preference	473	1	5	3.21	1.145
External Influence	473	1	5	2.71	1.238
Private and Confidential	473	1	5	3.19	1.140
Convenience	473	1	5	3.76	1.084
Safety	473	1	5	3.40	1.039
Economical	473	1	5	3.64	1.115

Bad Past Experience	473	1	5	2.45	1.003
Recommendation	473	1	5	2.75	1.085
Ease of Use	473	1	5	3.66	1.095
Lack of Knowledge	473	1	5	2.35	1.196
Electronic products	473	1	5	3.20	1.261
Sports products	473	1	5	2.93	1.217
Clothing, Shoes and Jewellery items	473	1	5	3.52	1.235
Beauty and Personal care products	473	1	5	3.11	1.274
Home and Kitchen appliances	473	1	5	3.23	1.197
Never used m-commerce	473	1	5	2.02	1.303
Books, Magazines and Newspapers	473	1	5	2.58	1.231
Healthcare and medicines	473	1	5	2.54	1.200
Stationary items and games	473	1	5	2.84	1.247
Groceries	473	1	5	2.74	1.301

(Source: Researcher's Computation)

The table presents the descriptive statistics for various items related to m-commerce attitudes, behaviours, and preferences. Here's a detailed interpretation:

4.4.1 General Product Attributes:

Reasonably Priced Products (Mean = 4.13, SD = 0.880)

- Respondents generally agree that reasonably priced products are important in m-commerce.

Prompt Customer Service (Mean = 3.78, SD = 0.880)

- A moderate agreement that prompt customer service is important.

Physical Shopping Experience (Mean = 4.13, SD = 0.867)

- Indicates a strong preference for a good physical shopping experience online.

4.4.2 Shopping Experience and Security:

Shopping Convenience (Mean = 4.23, SD = 0.882)

- High agreement on the importance of shopping convenience.

Safe & Secure (Mean = 2.45, SD = 1.086)

- Respondents are less convinced about the safety and security of m-commerce.

Unsafe without Technological Knowledge (Mean = 4.08, SD = 0.880)

- A strong belief that lack of technological knowledge makes m-commerce unsafe.

4.4.3 Trust and User Experience:

Unreliable Review (Mean = 2.49, SD = 1.087)

- Agreement that unreliable reviews are a concern.

User Friendly (Mean = 4.01, SD = 0.908)

- Strong agreement that user-friendly interfaces are important.

Shopping Addiction (Mean = 2.80, SD = 1.277)

- A moderate concern about shopping addiction.

Privacy (Mean = 3.96, SD = 0.901)

- High concern for privacy in m-commerce.

4.4.4 Factors Influencing Purchase Decisions:

Family Consent (Mean = 4.10, SD = 0.800)

- Strong agreement that family consent is crucial.

Freedom to Spend (Mean = 3.86, SD = 1.114)

- Agreement on the freedom to spend as an important factor.

Decision Flexibility (Mean = 3.47, SD = 1.214)

- Respondents moderately agree that they can decide anytime to shop online.

No Permission Required (Mean = 1.96, SD = 0.889)

- Low agreement on the necessity of no permission to shop.

4.4.5 Social and Peer Influence:

Peer Influence (Mean = 2.70, SD = 1.159)

- Moderate influence of peers on shopping decisions.

Peer Recommendations (Mean = 2.74, SD = 1.164)

- Slightly higher agreement on the importance of peer recommendations.

Peer Opinions (Mean = 2.68, SD = 1.167)

- Minor influence of peer opinions.

Social Media Influence (Mean = 2.67, SD = 1.175)

- Little impact of social media on shopping decisions.

4.5 OBJECTIVES AND HYPOTHESIS TESTING:

4.5.1 Objective-1: To evaluate the relevance and validity of the measurement variables to their respective latent constructs in the proposed structural model of the "Theory of Planned Behaviour"

Hypothesis-1: The measurement variables are relevant and valid to their respective latent constructs in the proposed structural model of the "Theory of Planned Behaviour".

Construct testing in data analysis is crucial for several important reasons:

a. **Validation of Measurement Tools**: Construct testing helps validate the measurement instruments used to assess theoretical constructs or variables in a study. It ensures that the items or indicators effectively capture the intended concepts or attributes, confirming the validity of the operational definitions used in the research.
b. **Ensuring Conceptual Clarity**: It promotes clarity and precision in defining constructs. By testing constructs, researchers clarify the theoretical underpinnings and operational definitions of variables, ensuring that they accurately represent the concepts being studied.
c. **Enhancing Measurement Accuracy**: Construct testing improves the accuracy and reliability of measurements. It identifies and addresses potential sources of measurement error, such as ambiguous wording in survey items or inadequate operationalization of constructs, thereby enhancing the quality of data collected.
d. **Supporting Hypothesis Testing**: Valid constructs facilitate hypothesis testing and theory development. Researchers can confidently analyze relationships between variables or test theoretical propositions when constructs are well-defined and properly validated.
e. **Facilitating Comparative Research**: Validated constructs enable meaningful comparisons across studies, populations, or contexts. Researchers can replicate studies or conduct cross-cultural research with confidence, knowing that measurements are consistent and comparable.

f. **Informing Decision-Making**: Construct testing provides robust evidence for decision-making processes. In applied research and practical settings, validated constructs support evidence-based decision-making by providing reliable data on which decisions can be grounded.

g. **Improving Research Reproducibility**: Validated constructs contribute to research reproducibility and replicability. When measurement tools are rigorously tested and validated, other researchers can replicate the study with confidence, strengthening the reliability and generalizability of research findings.

h. **Guiding Construct Revision and Refinement**: Insights from construct testing inform iterative improvements in research design and measurement instruments. Researchers can refine constructs based on empirical evidence, enhancing the relevance and validity of future studies.

In summary, construct testing in data analysis plays a critical role in ensuring the validity, reliability, and robustness of research findings. It supports rigorous inquiry, theory development, and evidence-based decision-making across various disciplines and research contexts.

❖ **Testing of Measurement Construct: Attitude:**

H1a: All measurement variables are relevant and valid to the 'Attitude' construct in the proposed structural model of the "Theory of Planned Behaviour".

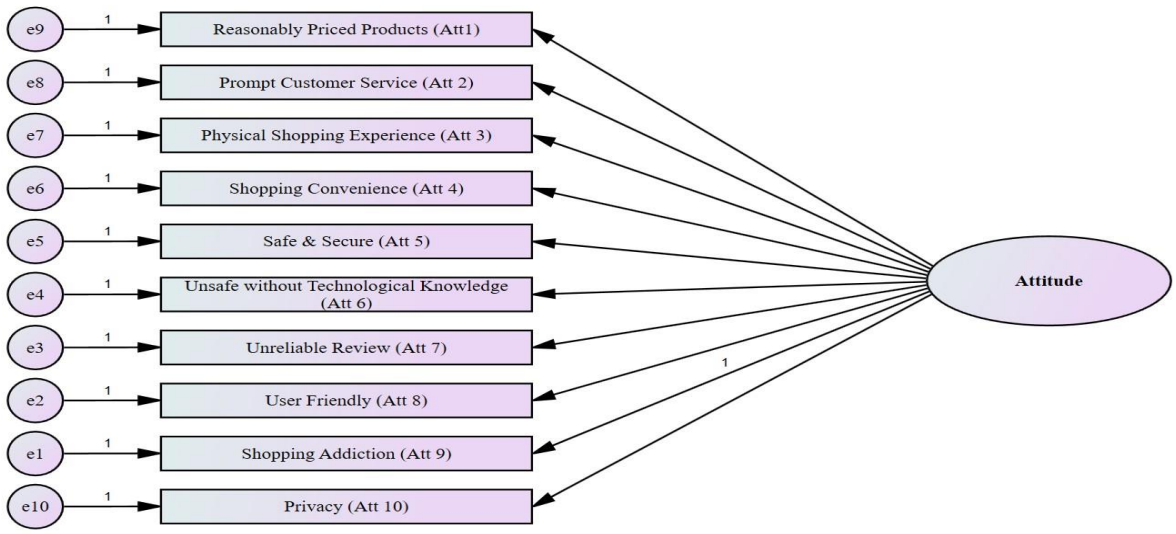


Figure 4.1: Measurement Model-Attitude

(Source: Researcher's compilation based on the original model of TPB)

This hypothesis suggests that each of the measurement variables included in the SEM model adequately measures or represents the Attitude construct. In SEM, measurement variables (also known as indicators or manifest variables) are observed variables that reflect underlying constructs (latent variables). This hypothesis implies that the chosen indicators are valid and reliable measures of the Attitude construct, and collectively they contribute meaningfully to the overall measurement model.

In SEM analysis, such hypotheses are tested by examining the standardized factor loadings (also called path coefficients) between the latent Attitude construct and its corresponding measurement variables. Significant factor loadings indicate that the measurement variables are statistically related to the latent construct, supporting the validity of the measurement model.

Table 4.6: Significance of Attributes of Attitude

			Estimate	S.E.	C.R.	P	Label
Att9	<---	Attitude	1.000				
Att8	<---	Attitude	-1.901	.282	-6.743	0.00	Significant
Att7	<---	Attitude	1.054	.194	5.430	0.00	Significant
At6	<---	Attitude	-.985	.171	-5.762	0.00	Significant
Att5	<---	Attitude	1.415	.233	6.071	0.00	Significant
Att4	<---	Attitude	-1.897	.280	-6.768	0.00	Significant
Att3	<---	Attitude	-.873	.158	-5.522	0.00	Significant
Att2	<---	Attitude	-1.652	.249	-6.626	0.00	Significant
Att1	<---	Attitude	-1.742	.261	-6.685	0.00	Significant
Att10	<---	Attitude	-1.531	.236	-6.501	0.00	Significant

(Source: Researcher's Computation)

The table provided represents the results of a regression analysis within a structural equation modeling (SEM) context, showing how the latent factor "Attitude" influences each of the observed variables (Att1 through Att10). Here is a detailed interpretation of the regression weights:

Column Descriptions:

a. **Estimate**:

- The regression weight indicates the strength and direction of the relationship between the latent factor (Attitude) and each observed variable (Att1 to Att10).

b. **S.E. (Standard Error)**:

- This represents the standard error of the regression weight, reflecting the variability or precision of the estimate.

c. **C.R. (Critical Ratio)**:

- The critical ratio is the estimate divided by its standard error (Estimate / S.E.). It is analogous to the t-value in regression analysis and indicates how many standard errors the estimate is away from zero.

d. **P (p-value)**:

- The p-value indicates the statistical significance of the regression weight. A p-value of less than 0.05 suggests that the relationship between the latent factor and the observed variable is statistically significant. In this table, "***" indicates a highly significant relationship ($p < 0.001$).

Interpretation of Rows:

Att9 <--- Attitude:

- **Estimate**: 1.000 (fixed parameter for scaling purposes)

Interpretation: This attribute serves as a reference point, with its estimate fixed at 1.000 to scale the latent factor (Attitude). This helps in comparing the other estimates.

- **Att8 <--- Attitude**:

Estimate: -1.901

- **S.E.**: 0.282
- **C.R.**: -6.743
- **P**: ***

Interpretation: There is a significant negative relationship between Att8 and Attitude. For each unit increase in Attitude, Att8 decreases by 1.901 units. The relationship is highly significant ($p < 0.001$).

Att7 <--- Attitude:

- **Estimate**: 1.054
- **S.E.**: 0.194
- **C.R.**: 5.430
- **P**: ***

Interpretation: There is a significant positive relationship between Att7 and Attitude. For each unit increase in Attitude, Att7 increases by 1.054 units. The relationship is highly significant ($p < 0.001$).

Att6 <--- Attitude:

- **Estimate**: -0.985
- **S.E.**: 0.171
- **C.R.**: -5.762
- **P**: ***

Interpretation: There is a significant negative relationship between Att6 and Attitude. For each unit increase in Attitude, Att6 decreases by 0.985 units. The relationship is highly significant ($p < 0.001$).

Att5 <--- Attitude:

- **Estimate**: 1.415
- **S.E.**: 0.233
- **C.R.**: 6.071
- **P**: ***

Interpretation: There is a significant positive relationship between Att5 and Attitude. For each unit increase in Attitude, Att5 increases by 1.415 units. The relationship is highly significant ($p < 0.001$).

Att4 <--- Attitude:

- **Estimate**: -1.897
- **S.E.**: 0.280
- **C.R.**: -6.768
- **P**: ***

Interpretation: There is a significant negative relationship between Att4 and Attitude. For each unit increase in Attitude, Att4 decreases by 1.897 units. The relationship is highly significant ($p < 0.001$).

Att3 <--- Attitude:

- **Estimate**: -0.873
- **S.E.**: 0.158
- **C.R.**: -5.522
- **P**: ***

Interpretation: There is a significant negative relationship between Att3 and Attitude. For each unit increase in Attitude, Att3 decreases by 0.873 units. The relationship is highly significant ($p < 0.001$).

- **Att2 <--- Attitude**:
- **Estimate**: -1.652
- **S.E.**: 0.249
- **C.R.**: -6.626
- **P**: ***

Interpretation: There is a significant negative relationship between Att2 and Attitude. For each unit increase in Attitude, Att2 decreases by 1.652 units. The relationship is highly significant ($p < 0.001$).

Att1 <--- Attitude:

- **Estimate**: -1.742
- **S.E.**: 0.261
- **C.R.**: -6.685
- **P**: ***

Interpretation: There is a significant negative relationship between Att1 and Attitude. For each unit increase in Attitude, Att1 decreases by 1.742 units. The relationship is highly significant ($p < 0.001$).

Att10 <--- Attitude:

- **Estimate**: -1.531
- **S.E.**: 0.236
- **C.R.**: -6.501
- **P**: ***

Interpretation: There is a significant negative relationship between Att10 and Attitude. For each unit increase in Attitude, Att10 decreases by 1.531 units. The relationship is highly significant ($p < 0.001$).

❖ **General Observations:**

- All attributes (Att1 through Att10) have significant relationships with the latent factor "Attitude" as indicated by the p-values (***), meaning $p < 0.001$.

The regression weights (estimates) show both positive and negative relationships:

- Positive estimates (e.g., Att5: 1.415) indicate that as the latent factor "Attitude" increases, the attribute also increases.
- Negative estimates (e.g., Att8: -1.901) indicate that as the latent factor "Attitude" increases, the attribute decreases.

The magnitude of the estimates reflects the strength of the relationship:

- Larger absolute values (e.g., Att8: -1.901) indicate stronger relationships.
- Smaller absolute values (e.g., Att3: -0.873) indicate weaker relationships.

- The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

Managerial Implications:

Enhancing Positive Indicators:

❖ **Att7 and Att5**:

- **Att7 (User Friendly)**: Since this indicator positively influences attitude, ensuring that the m-commerce platform is user-friendly and intuitive can significantly enhance user attitudes. Managers should focus on seamless navigation, easy-to-understand interfaces, and a smooth user experience.
- **Att5 (Convenience)**: Highlighting the convenience of using m-commerce, such as the ability to shop anytime and anywhere, quick transactions, and fast delivery options, can further boost positive attitudes. Marketing campaigns should emphasize these convenience factors.

Addressing Negative Indicators:

- **Att8, Att6, Att4, Att3, Att2, Att1, and Att10**:
- **Att8 (Safety Concerns)** and **Att4 (Privacy Issues)**: These indicators have the highest negative loadings. It is critical for managers to address safety and privacy concerns. Implementing robust security measures, communicating these measures effectively, and ensuring that user data is protected can help mitigate these negative perceptions.
- **Att6 (Bad Past Experience)** and **Att3 (Unreliable Review)**: These indicate that negative past experiences and unreliable reviews detract from positive attitudes. Companies should focus on improving customer service, addressing complaints promptly, and ensuring that product reviews are genuine and reliable. Encouraging satisfied customers to leave positive feedback can help counterbalance the impact of negative reviews.
- **Att2 (Lack of Knowledge)** and **Att1 (Difficult to Use)**: These reflect a lack of user knowledge and perceived difficulty in using the platform. Providing comprehensive guides, tutorials, and customer support can help users become more familiar and comfortable with m-commerce.
- **Att10 (Shopping Addiction)**: This indicates a negative perception linked to potential shopping addiction. Companies should promote responsible shopping habits and provide tools for users to monitor and control their spending.

The SEM analysis highlights the critical factors that influence user attitudes towards m-commerce. By focusing on enhancing positive aspects such as user-friendliness and convenience and addressing negative perceptions related to safety, privacy, past experiences, and ease of use, managers can significantly improve user attitudes. This, in turn, can lead to higher adoption rates and increased user satisfaction with m-commerce platforms.

Summary:

The table indicates that the latent factor "Attitude" has a significant impact on all observed variables (Att1 through Att10), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The

statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

- **Testing of Measurement Construct: Perceived Behaviour Control:**

H1b: All measurement variables are relevant and valid to the 'Perceived Behavioural Control' construct in the proposed structural model of the "Theory of Planned Behaviour".

This hypothesis asserts that each of the measurement variables included in your SEM model effectively captures and contributes to the Perceived Behaviour Control (PBC) construct. In SEM, PBC is a latent variable that represents an individual's perception of the ease or difficulty of performing a behaviour. Measurement variables (indicators) associated with PBC are observable variables that are expected to reflect or measure this underlying construct.

Testing this hypothesis involves examining the factor loadings (path coefficients) between the latent PBC construct and its corresponding measurement variables. Significant factor loadings indicate that the measurement variables are statistically associated with the PBC construct, supporting the validity of the measurement model.

In SEM analysis, confirming this hypothesis is crucial for establishing that the chosen indicators adequately measure the intended construct (PBC) and contribute meaningfully to the overall structural model. It helps ensure that the model accurately reflects the relationships and interactions between variables as hypothesized in the theoretical framework.

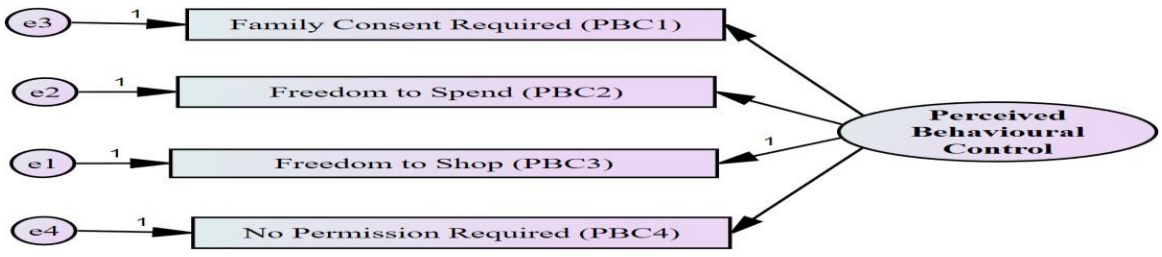


Figure 4.2: Measurement Model-Perceived Behavioural Control (Source: Researcher's compilation based on the TPB Model)

The following table presents the unstandardized regression weights, standard errors, critical ratios, and significance values for the construct "Perceived Behavioural Control".

Table 4.7: Regression Weights: (Group number 1- Default model)

			Estimate	S.E.	C.R.	P	Label
PBC 3	<--	Perceived_Behavioura Control	1.00				
PBC 2	<--	Perceived_Behavioural _Control	.77	.12	6.19	0.00	Significant
PBC 1	<--	Perceived_Behavioural _Control	1.36	.16	8.26	0.00	Significant
PBC 4	<--	Perceived_Behavioural Control	-1.21	.13	-8.81	0.00	Significant

(Source: Researcher's Computation)

PBC3 <--- Perceived_Behavioural_Control:

- **Estimate**: 1.000 (fixed parameter for scaling purposes)

Interpretation: This attribute serves as a reference point, with its estimate fixed at 1.000 to scale the latent factor (Perceived_Behavioural_Control). This helps in comparing the other estimates.

PBC2 <--- Perceived_Behavioural_Control:

- **Estimate**: 0.773
- **S.E.**: 0.125
- **C.R.**: 6.191
- **P**: ***

Interpretation: There is a significant positive relationship between PBC2 and Perceived_Behavioural_Control. For each unit increase in Perceived_Behavioural_Control, PBC2 increases by 0.773 units. The relationship is highly significant ($p < 0.001$).

PBC1 <--- Perceived_Behavioural_Control:

- **Estimate**: 1.361
- **S.E.**: 0.165
- **C.R.**: 8.263
- **P**: ***

Interpretation: There is a significant positive relationship between PBC1 and Perceived_Behavioural_Control. For each unit increase in Perceived_Behavioural_Control, PBC1 increases by 1.361 units. The relationship is highly significant ($p < 0.001$).

PBC4 <--- Perceived_Behavioural_Control:

- **Estimate**: -1.219
- **S.E.**: 0.138
- **C.R.**: -8.818
- **P**: ***

Interpretation: There is a significant negative relationship between PBC4 and Perceived_Behavioural_Control. For each unit increase in Perceived_Behavioural_Control, PBC4 decreases by 1.219 units. The relationship is highly significant ($p < 0.001$).

General Observations:

All attributes (PBC1 through PBC4) have significant relationships with the latent factor "Perceived_Behavioural_Control" as indicated by the p-values (***), meaning $p < 0.001$.
The regression weights (estimates) show both positive and negative relationships:

- Positive estimates (e.g., PBC1: 1.361) indicate that as the latent factor "Perceived_Behavioural_Control" increases, the attribute also increases.
- Negative estimates (e.g., PBC4: -1.219) indicate that as the latent factor "Perceived_Behavioural_Control" increases, the attribute decreases.

The magnitude of the estimates reflects the strength of the relationship:

- Larger absolute values (e.g., PBC4: -1.219) indicate stronger relationships.
- Smaller absolute values (e.g., PBC2: 0.773) indicate weaker relationships.

The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

Summary:

Significance: All the indicators are statistically significant at the 0.05 level, as indicated by the P-Value of 0.000 for each path. This suggests that each indicator significantly contributes to the construct of "Perceived Behavioral Control".

Direction and Magnitude:

Positive Loadings:

PBC2 (Ease of Use): This indicator shows a positive relationship with perceived behavioral control (Estimate = 0.773). It suggests that as users find m-commerce easier to use, their perceived control over the behavior increases.

PBC1 (Knowledge of Use): This indicator has a strong positive relationship (Estimate = 1.361). It indicates that greater knowledge about using m-commerce significantly enhances perceived behavioral control.

Negative Loadings:

PBC4 (Perceived Risks): This indicator shows a strong negative relationship with perceived behavioral control (Estimate = -1.219). This suggests that higher perceived risks associated with m-commerce reduce the users' perceived control over engaging in m-commerce activities.

- **Managerial Implications:**

Enhancing Positive Indicators

a. **Improve Ease of Use (PBC2)**:
   User-Friendly Interfaces: Ensure that the m-commerce platform is intuitive and easy to navigate. This can involve investing in UX/UI design to create a seamless user experience.
b. **Simplified Processes**: Streamline processes such as registration, checkout, and payment to make them as straightforward as possible. Providing clear instructions and reducing the number of steps required to complete transactions can enhance users' sense of control.
c. **Increase Knowledge of Use (PBC1)**:

- **Educational Campaigns**: Conduct educational campaigns to inform users about how to use the m-commerce platform effectively. This can include video tutorials, FAQs, webinars, and interactive guides.
- **Customer Support**: Offer robust customer support to help users overcome any difficulties they might face. Live chat, phone support, and email support can assist users in real-time, enhancing their confidence and perceived control.

Addressing Negative Indicators:

a. Mitigate Perceived Risks (PBC4):

- **Security Measures**: Enhance the security measures on the m-commerce platform to protect user data and financial information. Implementing features like two-factor authentication, encryption, and secure payment gateways can reduce perceived risks.
- **Transparent Policies**: Clearly communicate the platform's security policies and measures to users. Transparency about how user data is protected and how transactions are secured can alleviate concerns and reduce perceived risks.
- **Trust Signals**: Display trust signals such as security badges, customer testimonials, and third-party endorsements to reassure users about the safety of the platform.

The SEM analysis of perceived behavioural control highlights the critical factors influencing users' perceptions of control over using m-commerce. By focusing on improving ease of use and increasing user knowledge, while mitigating perceived risks, managers can enhance users perceived behavioural control. This, in turn, can lead to greater adoption and satisfaction with m-commerce platforms.

Summary:

The table indicates that the latent factor "Perceived Behavioural Control" has a significant impact on all observed variables (PBC1 through PBC4), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

- ❖ **Testing of Measurement Construct: Subjective Norms:**

H1c: All measurement variables are relevant and valid to the 'Subjective Norms' construct in the proposed structural model of the "Theory of Planned Behaviour".

This hypothesis posits that each of the measurement variables included in your SEM model effectively measures and contributes to the Subjective Norms construct as defined by the Theory of Planned Behaviour (TPB). In TPB, Subjective Norms represent an individual's perception of social pressure or influence from significant others to perform or not perform a particular behaviour.

Measurement variables (indicators) associated with Subjective Norms are observable variables that are expected to reflect this latent construct. Testing this hypothesis involves examining the factor loadings (path coefficients) between the latent Subjective Norms construct and its corresponding measurement variables.

Significant factor loadings indicate that the measurement variables are statistically related to the Subjective Norms construct, supporting the validity of the measurement model within the TPB framework. This validation is crucial for ensuring that the indicators adequately capture the intended construct and contribute meaningfully to the overall structural model.

In SEM analysis, hypotheses like this one are essential for establishing the measurement validity of constructs and understanding how different factors (such as subjective norms) influence behaviours as predicted by theoretical frameworks like the TPB. It forms a foundational step in testing and refining the structural relationships within the model, thereby contributing to a deeper understanding of behavioural intentions and decision-making processes.

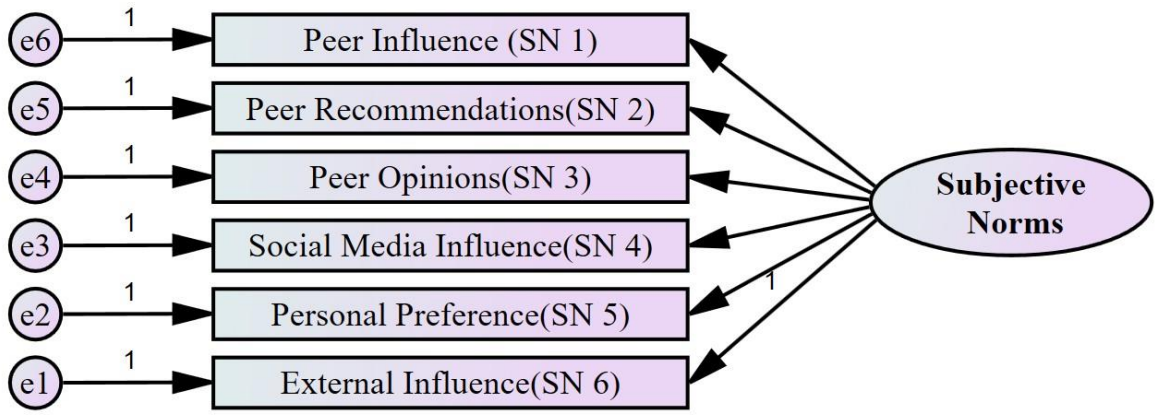


Figure 4.3: Measurement Model-Subjective Norms (Source: Researcher's compilation based on original model of TPB)

Table 4.8: Significance of attributes of Subjective Norms

			Estimate	S.E.	C.R.	P	Label
SN 6	<---	Subjective_Norms	1.000				
SN 5	<---	Subjective_Norms	-.879	.024	-35.995	***	Significant

			Estimate	S.E.	C.R.	P	Label
SN4	<---	Subjective_Norms	.971	.020	49.435	***	Significant
SN3	<---	Subjective_Norms	.956	.020	47.239	***	Significant
SN2	<---	Subjective_Norms	.969	.019	51.584	***	Significant
SN1	<---	Subjective_Norms	.960	.019	50.364	***	Significant

(Source: Researcher's Computation)

The table represents the regression weights for the relationship between the latent factor "Subjective Norms" and the observed variables (SN1 through SN6). Here is a detailed interpretation of the regression weights:

Column Descriptions:

a. **Estimate**:

- The regression weight indicates the strength and direction of the relationship between the latent factor (Subjective Norms) and each observed variable (SN1 to SN6).

b. **S.E. (Standard Error)**:

- This represents the standard error of the regression weight, reflecting the variability or precision of the estimate.

c. **C.R. (Critical Ratio)**:

- The critical ratio is the estimate divided by its standard error (Estimate / S.E.). It is analogous to the t-value in regression analysis and indicates how many standard errors the estimate is away from zero.

d. **P (p-value)**:

- The p-value indicates the statistical significance of the regression weight. A p-value of less than 0.05 suggests that the relationship between the latent factor and the observed variable is statistically significant. In this table, "***" indicates a highly significant relationship ($p < 0.001$).

Interpretation of Rows:

SN6 <--- Subjective_Norms:

- **Estimate**: 1.000 (fixed parameter for scaling purposes)

Interpretation: This attribute serves as a reference point, with its estimate fixed at 1.000 to scale the latent factor (Subjective_Norms). This helps in comparing the other estimates.

- **SN5 <--- Subjective_Norms**:
- **Estimate**: -0.879
- **S.E.**: 0.024
- **C.R.**: -35.995
- **P**: ***

Interpretation: There is a significant negative relationship between SN5 and Subjective_Norms. For each unit increase in Subjective_Norms, SN5 decreases by 0.879 units. The relationship is highly significant ($p < 0.001$).

SN4 <--- Subjective_Norms:

- **Estimate**: 0.971
- **S.E.**: 0.020
- **C.R.**: 49.435
- **P**: ***

Interpretation: There is a significant positive relationship between SN4 and Subjective_Norms. For each unit increase in Subjective_Norms, SN4 increases by 0.971 units. The relationship is highly significant ($p < 0.001$).

SN3 <--- Subjective_Norms:

- **Estimate**: 0.956
- **S.E.**: 0.020
- **C.R.**: 47.239
- **P**: ***

Interpretation: There is a significant positive relationship between SN3 and Subjective_Norms. For each unit increase in Subjective_Norms, SN3 increases by 0.956 units. The relationship is highly significant ($p < 0.001$).

- **SN2 <--- Subjective_Norms**:
- **Estimate**: 0.969

- **S.E.**: 0.019
- **C.R.**: 51.584
- **P**: ***

Interpretation: There is a significant positive relationship between SN2 and Subjective_Norms. For each unit increase in Subjective_Norms, SN2 increases by 0.969 units. The relationship is highly significant ($p < 0.001$).

- **SN1 <--- Subjective_Norms**:
- **Estimate**: 0.960
- **S.E.**: 0.019
- **C.R.**: 50.364
- **P**: ***

Interpretation: There is a significant positive relationship between SN1 and Subjective Norms. For each unit increase in Subjective Norms, SN1 increases by 0.960 units. The relationship is highly significant ($p < 0.001$).

General Observations:

All attributes (SN1 through SN6) have significant relationships with the latent factor "Subjective Norms" as indicated by the p-values (***), meaning $p < 0.001$.

The regression weights (estimates) show both positive and negative relationships:

- Positive estimates (e.g., SN4: 0.971) indicate that as the latent factor "Subjective Norms" increases, the attribute also increases.
- Negative estimates (e.g., SN5: -0.879) indicate that as the latent factor "Subjective Norms" increases, the attribute decreases.

The magnitude of the estimates reflects the strength of the relationship:

- Larger absolute values (e.g., SN5: -0.879) indicate stronger relationships.
- Smaller absolute values (e.g., SN1: 0.960) indicate weaker relationships.

The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

Interpretation and Managerial Implications:

a. **Strength and Direction of Relationships**: The estimates (coefficients) indicate the strength and direction of each SN variable's influence on the overall construct of Subjective Norms. Positive estimates (like 1.000, .971, .956, .969, .960) suggest that higher values of these SN variables positively contribute to the overall Subjective Norms. A negative estimate (-.879 for SN5) suggests an inverse relationship, where higher values of SN5 may actually decrease the overall Subjective Norms.
b. **Significance**: The Critical Ratio (C.R.) values are very high (e.g., 35.995 to 51.584), indicating that the relationships between each SN variable and the overall construct are statistically significant. The asterisks (***) in the "P" column confirm this high significance level (typically indicating $p < 0.001$), suggesting robust relationships that are unlikely to be due to chance.
c. **Managerial Implications**:

- **Enhancing Subjective Norms**: Managers should focus on factors represented by SN1 to SN6 to strengthen overall subjective norms within their teams or organizations. These factors are crucial as they significantly influence employees' perceptions of what is socially expected or normative in their work context.

- **Identifying Key Drivers**: SN4, SN2, and SN3 have particularly high regression weights, indicating they might be more influential in shaping subjective norms compared to others. Understanding these key drivers can help in targeted interventions and policy decisions aimed at fostering desired norms and behaviours.

- **Monitoring SN5**: Given its negative coefficient, SN5 might represent a factor that could potentially undermine subjective norms. Managers should investigate why this is the case and consider strategies to mitigate its negative impact or adjust perceptions associated with SN5.

d. **Further Analysis**: While the table provides valuable insights, further analysis such as examining interactions between SN variables or considering additional contextual factors could provide a more nuanced understanding. Managers should consider conducting deeper explorations or qualitative studies to complement these findings.

Summary:

The table indicates that the latent factor "Subjective Norms" has a significant impact on all observed variables (SN1 through SN6), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

- **Testing of Measurement Construct: Mobile Commerce Intention:**

H1d: All measurement variables are relevant and valid to the 'Mobile Commerce Intention' construct in the proposed structural model of the "Theory of Planned Behaviour".

This hypothesis asserts that each of the measurement variables included in your SEM model effectively captures and contributes to the Mobile Commerce Intention construct. In the context of SEM, Mobile Commerce Intention represents individuals' behavioural intentions to engage in mobile commerce activities, such as purchasing goods or services via mobile devices.

Measurement variables (indicators) associated with Mobile Commerce Intention are observable variables that are expected to reflect this latent construct. Testing this hypothesis involves examining the factor loadings (path coefficients) between the latent Mobile Commerce Intention construct and its corresponding measurement variables.

Significant factor loadings indicate that the measurement variables are statistically related to the Mobile Commerce Intention construct, supporting the validity of the measurement model within the SEM framework. This validation is crucial for ensuring that the indicators accurately measure the intended construct and contribute meaningfully to the overall structural model.

In SEM analysis, hypotheses like this one are fundamental for establishing the measurement validity of constructs and understanding the factors influencing behavioural intentions related to mobile commerce. It helps researchers assess the strength and direction of relationships between variables, refine theoretical models, and provide insights into how

various factors (e.g., attitudes, perceived ease of use) collectively influence mobile commerce intentions.

By testing and confirming this hypothesis, researchers can enhance the robustness of their SEM model and gain valuable insights into the predictors of mobile commerce intentions among the studied population. This, in turn, can inform strategies for promoting and enhancing mobile commerce adoption and usage.

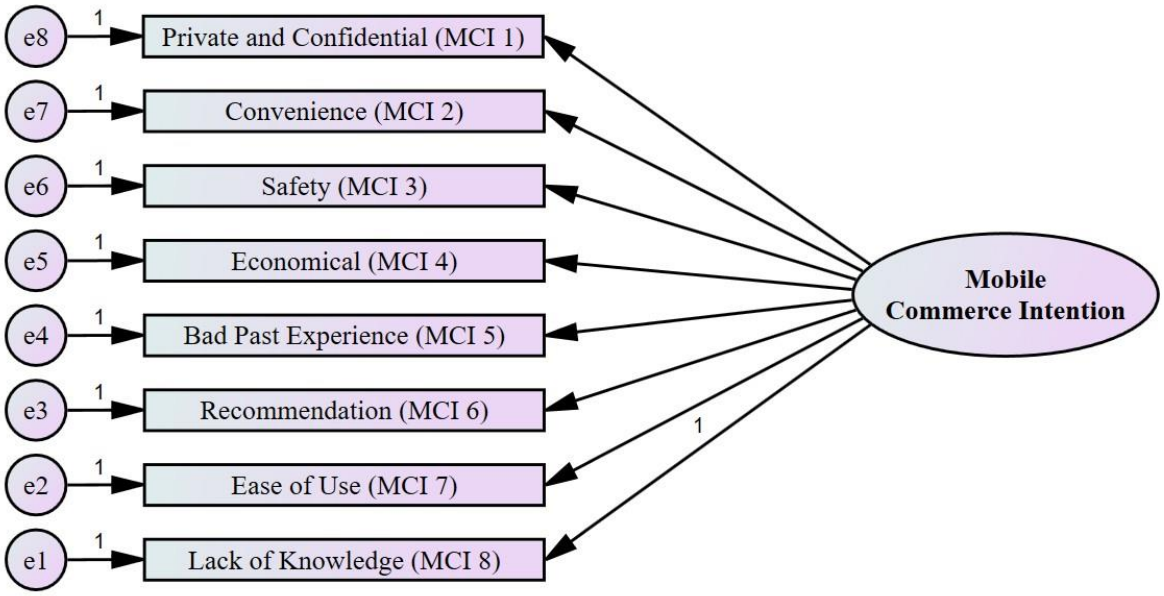


Figure 4.4: Measurement Model-Intention (Source: Researcher's compilation based on the original model of TPB)

Table 4.9: Significance of attributes of Mobile Commerce Intention

	Estimate	S.E.	C.R.	P	Label
MCI8 <--- Mobile_Commerce_Intention	1.000				
MCI7 <--- Mobile_Commerce_Intention	-1.366	.106	-12.939	***	Significant
MCI6 <--- Mobile_Commerce_Intention	-.523	.082	-6.389	***	Significant
MCI5 <--- Mobile_Commerce_Intention	**-.136**	**.072**	**-1.897**	**.058**	**Marginally Significant**
MCI4 <--- Mobile_Commerce_Intention	-1.380	.107	-12.884	***	Significant

	Estimate	S.E.	C.R.	P	Label
MCI3 <--- Mobile_Commerce_Intention	-1.277	.100	-12.832	***	Significant
MCI2 <--- Mobile_Commerce_Intention	-1.421	.107	-13.261	***	Significant
MCI1 <--- Mobile_Commerce_Intention	-1.069	.098	-10.870	***	Significant

(Source: Researcher's Computation)

The table represents the regression weights for the relationship between the latent factor "Mobile_Commerce_Intention" and the observed variables (MCI1 through MCI8). Here is a detailed interpretation of the regression weights:

Column Descriptions:

a. **Estimate**:
- The regression weight indicates the strength and direction of the relationship between the latent factor (Mobile_Commerce_Intention) and each observed variable (MCI1 to MCI8).

b. **S.E. (Standard Error)**:
- This represents the standard error of the regression weight, reflecting the variability or precision of the estimate.

c. **C.R. (Critical Ratio)**:
- The critical ratio is the estimate divided by its standard error (Estimate / S.E.). It is analogous to the t-value in regression analysis and indicates how many standard errors the estimate is away from zero.

d. **P (p-value)**:
    - The p-value indicates the statistical significance of the regression weight. A p-value of less than 0.05 suggests that the relationship between the latent factor and the observed variable is statistically significant. In this table, "***" indicates a highly significant relationship ($p < 0.001$).

Interpretation of Rows:

MCI8 <--- Mobile_Commerce_Intention:
- **Estimate**: 1.000 (fixed parameter for scaling purposes)

Interpretation: This attribute serves as a reference point, with its estimate fixed at 1.000 to scale the latent factor (Mobile_Commerce_Intention). This helps in comparing the other estimates.

MCI7 <--- Mobile_Commerce_Intention:

- Estimate: -1.366
- S.E.: 0.106
- C.R.: -12.939
- P: ***

Interpretation: There is a significant negative relationship between MCI7 and Mobile_Commerce_Intention. For each unit increase in Mobile_Commerce_Intention, MCI7 decreases by 1.366 units. The relationship is highly significant ($p < 0.001$).

MCI6 <--- Mobile_Commerce_Intention:

- Estimate: -0.523
- S.E.: 0.082
- C.R.: -6.389
- P: ***

Interpretation: There is a significant negative relationship between MCI6 and Mobile_Commerce_Intention. For each unit increase in Mobile_Commerce_Intention, MCI6 decreases by 0.523 units. The relationship is highly significant ($p < 0.001$).

MCI5 <--- Mobile_Commerce_Intention:

- Estimate: -0.136
- S.E.: 0.072
- C.R.: -1.897
- P: 0.058

Interpretation: There is a negative relationship between MCI5 and Mobile_Commerce_Intention, but it is not statistically significant at the conventional 0.05 level ($p = 0.058$).

MCI4 <--- Mobile_Commerce_Intention:

- Estimate: -1.380
- S.E.: 0.107
- C.R.: -12.884
- P: ***

Interpretation: There is a significant negative relationship between MCI4 and Mobile_Commerce_Intention. For each unit increase in Mobile_Commerce_Intention, MCI4 decreases by 1.380 units. The relationship is highly significant ($p < 0.001$).

MCI3 <--- Mobile_Commerce_Intention:

- Estimate: -1.277
- S.E.: 0.100
- C.R.: -12.832
- P: ***

Interpretation: There is a significant negative relationship between MCI3 and Mobile_Commerce_Intention. For each unit increase in Mobile_Commerce_Intention, MCI3 decreases by 1.277 units. The relationship is highly significant ($p < 0.001$).

MCI2 <--- Mobile_Commerce_Intention:

- Estimate: -1.421
- S.E.: 0.107
- C.R.: -13.261
- P: ***

Interpretation: There is a significant negative relationship between MCI2 and Mobile Commerce Intention. For each unit increase in Mobile Commerce Intention, MCI2 decreases by 1.421 units. The relationship is highly significant ($p < 0.001$).

MCI1 <--- Mobile_Commerce_Intention:

- **Estimate**: -1.069
- **S.E.**: 0.098
- **C.R.**: -10.870
- **P**: ***

Interpretation: There is a significant negative relationship between MCI1 and Mobile Commerce Intention. For each unit increase in Mobile Commerce Intention, MCI1 decreases by 1.069 units. The relationship is highly significant ($p < 0.001$).

General Observations:

All attributes (MCI1 through MCI8) except MCI5 have significant relationships with the latent factor "Mobile Commerce Intention" as indicated by the p-values (***), meaning $p < 0.001$. MCI5 has a p-value of 0.058, indicating a marginally significant relationship.

The regression weights (estimates) show negative relationships between Mobile Commerce Intention and the observed variables (MCI1 to MCI7):

- Negative estimates (e.g., MCI7: -1.366) indicate that as the latent factor "Mobile Commerce Intention" increases, the observed variables decrease.

The magnitude of the estimates reflects the strength of the relationship:

- Larger absolute values (e.g., MCI2: -1.421) indicate stronger relationships.
- Smaller absolute values (e.g., MCI5: -0.136) indicate weaker relationships.
- The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

Managerial Implications:

- **Identifying Inhibitors**: MCI1 to MCI8 represent factors that inhibit or negatively impact mobile commerce intention. Understanding these factors is crucial for managers to address barriers that prevent customers from adopting mobile commerce platforms or making purchases via mobile devices.
- **Prioritizing Improvement Efforts**: MCI2, MCI3, MCI4, MCI7, and MCI8 have particularly high negative regression weights, indicating they might be more influential in reducing mobile commerce intention compared to others. Managers should prioritize efforts to mitigate the impact of these factors through targeted strategies such as user experience improvements, trust-building initiatives, or marketing campaigns tailored to mobile users.
- **Addressing Marginally Significant Factors**: While MCI5 shows marginal significance, indicating it may have a weaker impact, managers should still monitor its effect closely as it could influence mobile commerce intention under specific conditions or in conjunction with other factors.

- **Strategy Formulation**: Based on these findings, managers can devise strategies to enhance mobile commerce intention by addressing identified inhibitors. This might involve improving website or app usability, addressing security concerns, offering incentives for mobile purchases, or enhancing the overall mobile shopping experience.
- **Further Investigation**: Beyond regression analysis, qualitative research or customer feedback surveys could provide deeper insights into why these factors (MCI1 to

MCI8) negatively influence mobile commerce intention. Such insights can guide more nuanced and effective managerial interventions.

In summary, The table indicates that the latent factor "Mobile Commerce Intention" has a significant negative impact on most observed variables (MCI1 through MCI8), with varying strengths. Positive estimates are not present in this context, suggesting inverse relationships throughout. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios, except for MCI5, which is marginally significant. Managers can use this information to prioritize improvement efforts, enhance mobile commerce platforms, and ultimately increase customer engagement and transactions via mobile devices.

- **Testing of Confirmatory Model of Theory of Planned Behaviour:**

H1e: Measurement model is having goodness-of-fit indices.

The measurement variables significantly contribute to their respective latent constructs (Attitude, Subjective Norms, Perceived Behavioural Control, and Behavioural Intention) in the proposed structural model of the Theory of Planned Behaviour.

Objective Components:

a. **Measurement Validation**: Assess the validity and reliability of measurement variables (indicators) in relation to their respective latent constructs within the TPB framework. This involves examining factor loadings, composite reliability, and discriminant validity.
b. **Model Fit**: Evaluate the overall fit of the measurement model to determine how well the chosen indicators represent the theoretical constructs of TPB. Good model fit indicates that the measurement variables effectively capture the intended constructs.
c. **Construct Relationships**: Explore the interrelationships between the latent constructs (Attitude, Subjective Norms, PBC, Behavioural Intention) based on the measurement model. This includes examining path coefficients and their significance to understand how attitudes, norms, and perceived control influence behavioural intentions.

d. **Model Refinement**: Based on empirical findings, refine the measurement model by potentially revising or removing indicators that do not contribute meaningfully to their respective constructs. This iterative process enhances the validity and utility of the TPB model in explaining and predicting behaviours.

By addressing this objective and hypothesis, researchers aim to strengthen the theoretical foundation of TPB, provide empirical support for its applicability in specific contexts, and contribute to the broader understanding of human decision-making and behavior change processes.

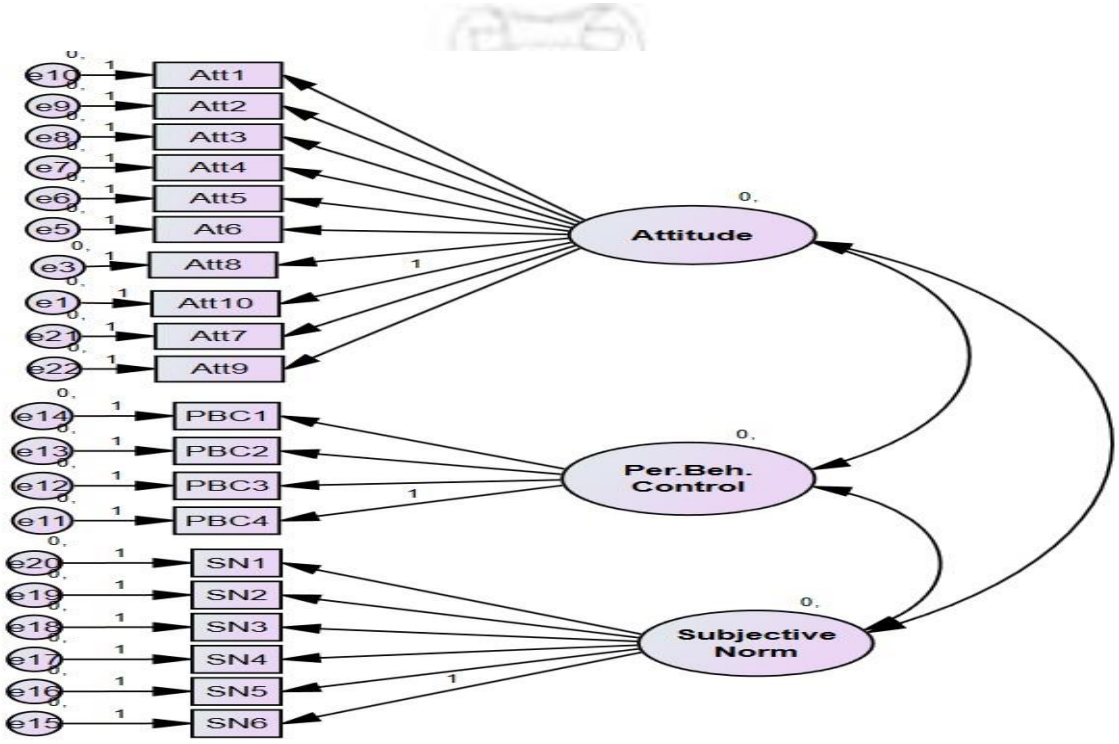


Figure 4.5: TPB Model (Source: Researcher's compilation based on the original model of TPB)

Table 4.10: Factor loading of attributes of TPB

	Estimate
Att10 <--- Attitude	.685
Att8 <--- Attitude	.844

			Estimate
Att6	<---	Attitude	.450
Att5	<---	Attitude	-.523
Att4	<---	Attitude	.868
Att3	<---	Attitude	.404
Att2	<---	Attitude	.758
PBC4	<---	Per.Beh._Control	.730
PBC3	<---	Per.Beh._Control	-.440
PBC2	<---	Per.Beh._Control	-.370
PBC1	<---	Per.Beh._Control	-.907
SN6	<---	Subjective_Norm	.945
SN5	<---	Subjective_Norm	-.898
SN4	<---	Subjective_Norm	.967
SN3	<---	Subjective_Norm	.958
SN2	<---	Subjective_Norm	.974
SN1	<---	Subjective_Norm	.970
Att1	<---	Attitude	.798
Att7	**<---**	**Attitude**	**-.389**
Att9	**<---**	**Attitude**	**-.314**

(Source: Researcher's Computation)

In evaluating the standardized regression weights for the constructs of Attitude, Perceived Behavioural Control (PBC), and Subjective Norm within a conceptual model based on the Theory of Planned Behaviour (TPB), it is essential to adhere to methodological guidelines

for factor loading. According to Anderson (2020), factor loading values less than 0.40 should be deleted from further analysis, as these indicate lower factor loading and insufficient representation of the underlying construct.

Deletion Recommendations:

Based on Anderson's guideline, Att7 (-.389) and Att9 (-.314) should be deleted from further analysis due to their lower factor loadings.

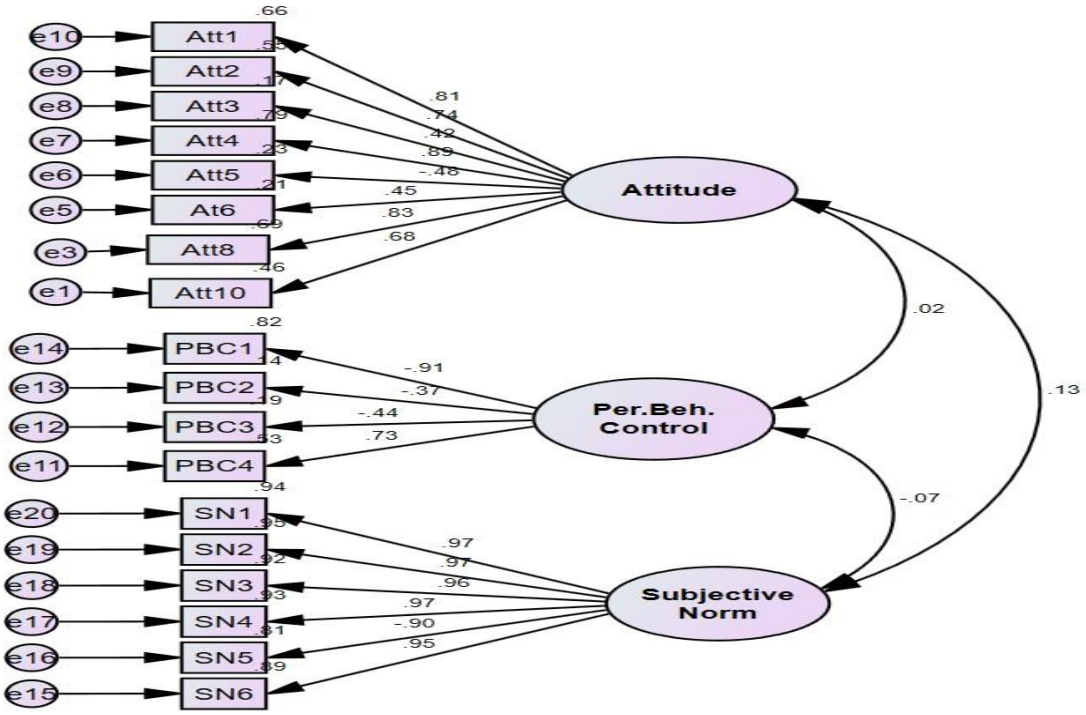


Figure 4.6: TPB Model after Deletion of Variables (Source: Researcher's compilation based on the original model)

Testing of Goodness-of fit:

H1e: Measurement model is having goodness-of-fit indices.

Table 4.11: Significance of attributes of TPB Model

	Estimate	S.E.	C.R.	P	Label
Att10 <--- Attitude	1.000				
Att8 <--- Attitude	1.237	.077	16.142	***	Significant
Att6 <--- Attitude	.655	.071	9.255	***	Significant

		Estimate	S.E.	C.R.	P	Label
Att5	<--- Attitude	-.857	.088	-9.784	***	Significant
Att4	<--- Attitude	1.278	.075	16.950	***	Significant
Att3	<--- Attitude	.592	.069	8.533	***	Significant
Att2	<--- Attitude	1.071	.073	14.622	***	Significant
Att1	<--- Attitude	1.174	.074	15.840	***	Significant
PBC4	<--- Per.Beh._Control	1.000				
PBC3	<--- Per.Beh._Control	-.822	.093	-8.828	***	Significant
PBC2	<--- Per.Beh._Control	-.636	.085	-7.443	***	Significant
PBC1	<--- Per.Beh._Control	-1.116	.099	-11.300	***	Significant
SN6	<--- Subjective_Norm	1.000				
SN5	<--- Subjective_Norm	-.878	.024	-36.004	***	Significant
SN4	<--- Subjective_Norm	.971	.020	49.451	***	Significant
SN3	<--- Subjective_Norm	.956	.020	47.264	***	Significant
SN2	<--- Subjective_Norm	.969	.019	51.610	***	Significant
SN1	<--- Subjective_Norm	.960	.019	50.360	***	Significant

(Source: Researcher's Computation)

Table 4.12: Standardized Regression Weights: (Group number 1 - Default model)/ Factor Loading of TPB Constructs

		Estimate
Att10	<--- Attitude	.678
Att8	<--- Attitude	.833
Att6	<--- Attitude	.455
Att5	<--- Attitude	-.482
Att4	<--- Attitude	.886
Att3	<--- Attitude	.418
Att2	<--- Attitude	.743
Att1	<--- Attitude	.815
PBC4	<--- Per.Beh._Control	.730
PBC3	<--- Per.Beh._Control	-.440
PBC2	<--- Per.Beh._Control	-.370
PBC1	<--- Per.Beh._Control	-.907

			Estimate
SN6	<---	Subjective_Norm	.945
SN5	<---	Subjective_Norm	-.898
SN4	<---	Subjective_Norm	.967
SN3	<---	Subjective_Norm	.958
SN2	<---	Subjective_Norm	.974
SN1	<---	Subjective_Norm	.970

(Source: Researcher's Computation)

Managerial Implications:

- **Enhancing Positive Attitudes:**

a. Leverage Strong Positive Indicators:

- **Att4 (Private and Confidential):** This item has the highest standardized loading (0.886), indicating that ensuring privacy and confidentiality in m-commerce is crucial. Managers should emphasize robust security measures in their communication and marketing strategies.
- **Att8, Att2, and Att1 (Convenience, Ease of Use, and Reasonably Priced Products):** These items are significant positive predictors of attitude. Companies should focus on highlighting these aspects in their advertising and user experiences. For example, emphasizing user-friendly interfaces, convenience, and competitive pricing can enhance positive attitudes toward m-commerce.

b. Address Negative Indicators:

- **Att5 (Bad Past Experience):** This negative relationship indicates that previous negative experiences significantly impact attitudes towards m-commerce. Companies must prioritize customer satisfaction and address any issues promptly to prevent bad experiences. Implementing strong customer service and feedback mechanisms can mitigate this effect.

- **Improving Perceived Behavioural Control:**

a. Address Negative Influences:

- **PBC1, PBC3, and PBC2 (Lack of Knowledge and Negative Past Experience):** These items have negative estimates, suggesting that lack of knowledge and negative experiences with m-commerce hinder users' perceived control. Educational

campaigns, tutorials, and user support can help improve users' comfort and confidence in using m-commerce platforms.

b. Strengthen Positive Influences:

- **PBC4 (Perceived Ease of Use):** This item positively influences perceived behavioural control. Ensuring the platform is intuitive and easy to navigate can enhance users' perceived control and, consequently, their likelihood of using m-commerce.

❖ **Reinforcing Subjective Norms:**

a. Leverage Social Influence:

- **SN2, SN1, SN4, and SN3:** These items show very strong positive relationships with subjective norms. Marketing strategies that leverage social proof, such as testimonials, endorsements from influencers, and peer reviews, can significantly boost positive subjective norms. Highlighting positive feedback from other users can also reinforce positive perceptions.

b. Mitigate Negative Influences:

- **SN5 (Negative Recommendations):** Negative social influences can severely impact subjective norms. Companies should actively manage their online reputation and address negative reviews or feedback. Encouraging satisfied customers to leave positive reviews can help counterbalance any negative recommendations.

Summary: By focusing on enhancing the factors that positively impact attitudes, perceived behavioural control, and subjective norms while addressing the negative factors, companies can foster a more favourable environment for m-commerce adoption. Ensuring a secure, user-friendly, and positively reviewed platform will be key in driving m-commerce growth.

Table 4.13: Goodness-of-fit Model

Name of Category	Goodness-of-fit model index	Recommended Value*	Planned Behavior Model Value	Interpretation
1.Absolute fit	***Root mean square error of approximation (RMSEA)***	***< .10***	***.079***	Excellent

	Goodness-of-fit index(GFI)	**≥ .80**	**.890**	Excellent
2.Incremental fit	**Adjusted goodness-of-fit index (AGFI)**	**≥ .80**	**.858**	Excellent
	Normalized fit index (NFI)	**≥ .80**	**.932**	Excellent
	Comparative fit index (CFI)	***≥ .90***	***.948***	Excellent
	Tucker Fit Index (TLI)	**≥ .90**	**.940**	Excellent
3.Parsimonious fit	***Chi-square/degree of freedom(CMIN/df)*****	***≤ 5.00***	***3.931***	Acceptable

(Source: Researcher's Computation)

The table provided outlines various goodness-of-fit indices used to assess the fit of a model, likely in the context of structural equation modelling (SEM) or a similar statistical analysis. Here's an interpretation of each index based on the values provided:

A. Absolute Fit:

- **Chi-Square**:

Value: .000

Recommended: P-value > 0.05 (indicating good fit)

Interpretation: A chi-square value of .000 suggests that the model fits the data perfectly in terms of absolute fit, as the p-value is greater than 0.05, indicating no significant difference between the observed and expected covariance matrices.

- **Root Mean Square Error of Approximation (RMSEA)**:

Value: .079

Recommended: < 0.10

Interpretation: RMSEA of .079 indicates a reasonable fit, as it is below the threshold of 0.10, suggesting that the model has a good fit to the data.

Goodness-of-Fit Index (GFI):

- Value: .890
- Recommended: ≥ 0.80

Interpretation: GFI of .890 meets the recommended threshold of 0.80, indicating a good fit of the model.

B. Incremental Fit:

Adjusted Goodness-of-Fit Index (AGFI):

- Value: .858
- Recommended: ≥ 0.80

Interpretation: AGFI of .858 meets the recommended threshold of 0.80, suggesting adequate incremental fit of the model.

Normalized Fit Index (NFI):

- Value: .932
- Recommended: ≥ 0.80

Interpretation: NFI of .932 exceeds the recommended threshold of 0.80, indicating good incremental fit.

Comparative Fit Index (CFI):

- Value: .948
- Recommended: ≥ 0.90

Interpretation: CFI of .948 meets the recommended threshold of 0.90, suggesting very good incremental fit of the model.

Tucker-Lewis Index (TLI):

- Value: .940
- Recommended: ≥ 0.90

Interpretation: TLI of .940 meets the recommended threshold of 0.90, indicating good incremental fit.

C. Parsimonious Fit:

Chi-Square/Degree of Freedom (CMIN/df):

- Value: 3.931

- Recommended: ≤ 5.00

Interpretation: CMIN/df of 3.931 is below the recommended threshold of 5.00, indicating good parsimonious fit of the model.

Summary: Based on the provided values and recommendations:

- The model shows excellent absolute fit (chi-square p-value > 0.05, RMSEA < 0.10, GFI ≥ 0.80).
- Incremental fit indices (AGFI, NFI, CFI, TLI) also indicate good to very good fit of the model.
- Parsimonious fit (CMIN/df) suggests the model is adequately parsimonious.

Overall, these indices collectively suggest that the model fits the data well across different aspects of fit (absolute, incremental, and parsimonious), providing confidence in its validity for explaining the relationships among variables in the theoretical framework of Theory of Planned Behaviour.

❖ **Discriminant Validity:**

The heterotrait-monotrait (HTMT) ratio is a statistical measure used in the context of assessing discriminant validity in research involving latent variables or constructs. It's primarily used in structural equation modeling (SEM) and confirmatory factor analysis (CFA) to evaluate the distinction between different constructs in a measurement model.

In the context of these analyses, discriminant validity refers to the idea that distinct constructs should be more dissimilar than similar to one another. In other words, the measures of different constructs should correlate less strongly with each other compared to their correlations with their own measures (monotrait correlations).

The HTMT ratio is a way to quantify this concept. It involves calculating the average correlation between indicators of different constructs (heterotrait correlations) and comparing it to the average correlation between indicators of the same construct (monotrait correlations). The formula is as follows:

HTMT = √ (average heterotrait correlations) / √ (average monotrait correlations)

In an ideal scenario, the HTMT ratio should be less than 1.0, indicating that the constructs have good discriminant validity. If the HTMT ratio is close to or greater than 1.0, it suggests that the constructs might not be distinct enough and might be overlapping or measuring similar underlying concepts.

Researchers use the HTMT ratio to assess the extent to which their measurement model demonstrates discriminant validity. This is important for ensuring that the constructs being studied are truly distinct and not simply measuring the same underlying concept.

Table 4.14 a: Correlation Metrics

	SN1	SN2	SN3	SN4	SN5	SN6	PBC1	PBC2	PBC3	PBC4	Att1	Att2	Att3	Att4	Att5
SN1	1.00														
SN2	0.94	1.00													
SN3	0.93	0.93	1.00												
SN4	0.94	0.94	0.93	1.00											
SN5	-0.87	-0.88	-0.86	-0.87	1.00										
SN6	0.92	0.92	0.91	0.91	-0.85	1.00									
PBC1	0.06	0.06	0.06	0.06	-0.06	0.06	1.00								
PBC2	0.03	0.03	0.03	0.03	-0.02	0.02	0.34	1.00							
PBC3	0.03	0.03	0.03	0.03	-0.03	0.03	0.40	0.16	1.00						
PBC4	-0.05	-0.05	-0.05	-0.05	0.05	-0.05	-0.66	-0.27	-0.32	1.00					

Att1	0.11	0.11	0.11	0.11	-0.10	0.10	-0.02	-0.01	-0.01	0.01	1.00				
Att2	0.10	0.10	0.10	0.10	-0.09	0.10	-0.01	-0.01	-0.01	0.01	0.61	1.00			
Att3	0.06	0.06	0.05	0.05	-0.05	0.05	-0.01	0.00	0.00	0.01	0.34	0.31	1.00		
Att4	0.12	0.12	0.11	0.12	-0.11	0.11	-0.02	-0.01	-0.01	0.01	0.72	0.66	0.37	1.00	
Att5	-0.06	-0.06	-0.06	-0.06	0.06	-0.06	0.01	0.00	0.00	-0.01	-0.39	-0.36	-0.20	-0.43	1.00
At6	0.06	0.06	0.06	0.06	-0.06	0.06	-0.01	0.00	0.00	0.01	0.37	0.34	0.19	0.40	-0.22
Att8	0.11	0.11	0.11	0.11	-0.10	0.11	-0.02	-0.01	-0.01	0.01	0.68	0.62	0.35	0.74	-0.40
Att10	0.09	0.09	0.09	0.09	-0.08	0.09	-0.01	-0.01	-0.01	0.01	0.55	0.50	0.28	0.60	-0.33

(Source: Researcher's Computation)

Table 4.14 b: HTMT Ratio

HTMT Ratio	Estimated Value	Threshold Value	Interpretation
LS-BE	**0.324**	**Below .90**	**Acceptable**
LS-AT	**0.078**	**Below .90**	**Acceptable**
BE-AT	**-0.020**	**Below .90**	**Acceptable**

(Source: Researcher's Computation)

❖ **No Discriminant Validity Issues**:

- All the HTMT ratios provided are below the threshold value of 0.90.
- This indicates that the constructs are distinct from each other and do not have discriminant validity issues.

❖ **Overall Interpretation**:

- The data demonstrates acceptable discriminant validity for the constructs involved.
- Therefore, it is appropriate to proceed with further analysis, as the constructs are not overly correlated and are sufficiently distinct from one another.

4.5.2 Objective 2: To evaluate the significance and extent to which the constructs of the 'Theory of Planned Behaviour' influence the intentions to use mobile commerce.

H2: Theory of Planned Behaviour constructs significantly influence the intentions to use m-commerce.

Sub Hypothesis:

H2a: Attitude towards mobile commerce significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that a positive attitude towards using mobile commerce (e.g., perception of convenience, trustworthiness of mobile platforms) leads to a higher intention to make purchases via mobile devices.

H2b: Subjective norms significantly influence the intentions to use m-commerce.

Explanation: This hypothesis posits that perceived social influences or norms regarding mobile commerce usage (e.g., recommendations from friends, social media influencers) affect consumers' intention to engage in mobile commerce transactions.

H2c: Perceived behavioural control significantly influences the intentions to use m-commerce.

Explanation: This hypothesis proposes that consumers' perception of their ability to control and execute mobile commerce transactions (e.g., ease of use, technical skills required) impacts their intention to purchase goods or services via mobile devices.

H2d: Attitude, subjective norms, and perceived behavioural control significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that when combined, attitude, subjective norms, and perceived behavioural control explain a significant proportion of variance in consumers' buying intention in the context of mobile commerce.

Additional Objectives and Considerations:

a. **Measurement Model Validation**: Validate the measurement model by examining the relationships between the indicators (measurement variables) and their respective latent constructs (Attitude, Subjective Norms, Perceived Behavioural Control).
b. **Mediating Effects**: Explore potential mediating effects of attitude, subjective norms, and perceived behavioural control on the relationship between other variables (e.g., demographic factors, past behaviour) and buying intention.
c. **Comparative Analysis**: Compare the strength of relationships between TPB constructs and buying intention across different demographic segments (e.g., age groups, income levels) to identify variations in consumer behaviour.
d. **Practical Implications**: Discuss practical implications of the findings for mobile commerce providers, marketers, and policymakers to enhance consumer engagement and adoption of mobile commerce platforms.

By addressing these objectives and hypotheses, the study aims to deepen understanding of the psychological determinants influencing buying intentions in mobile commerce and provide actionable insights for stakeholders in improving user experience, marketing strategies, and policy frameworks.

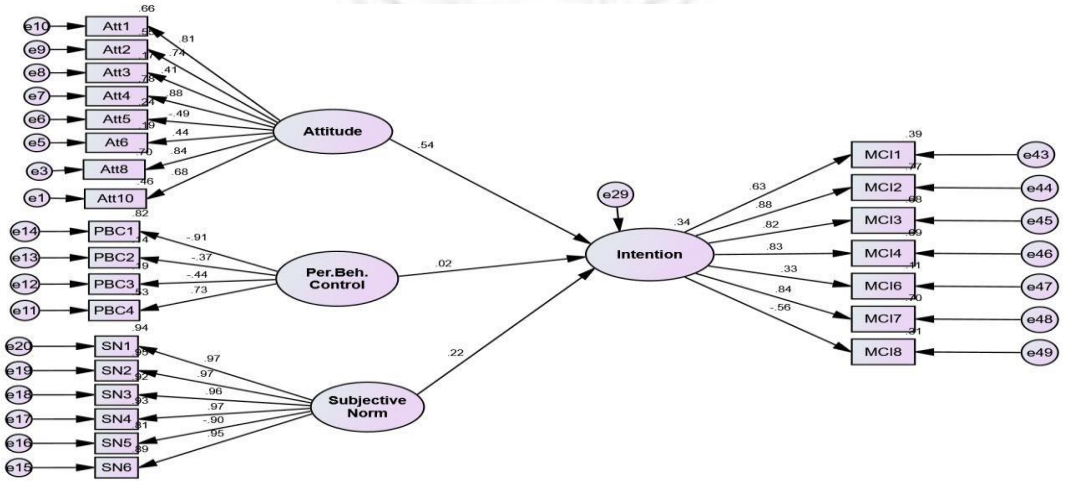


Figure 4.7: TPB and Behavioural Intention (Source: Researcher's Compilation based on the original model of TPB)

Table 4.15: Goodness-of-fit of Antecedents of TPB and Intention Model

Goodness-of-fit model index	Recommended Value	Estimated Model Value	Interpretation
Root mean square error of approximation (RMSEA)	***< .10***	***.071***	Excellent
Normalized fit index (NFI)	**≥ .80**	**.902**	Excellent
Comparative fit index (CFI)	***≥ .90***	***.928***	Excellent
Tucker Fit Index (TLI)	**≥ .90**	**.920**	Excellent
Chi-square/degree of freedom(CMIN/df)**	***≤ 5.00***	***3.39***	Acceptable
SRMR	***<0.08***	**0.089**	Acceptable

(Source: Researcher's Computation)

a. **Root Mean Square Error of Approximation (RMSEA < 0.10)**:

- Recommended Value: < 0.10
- Estimated Model Value: 0.071
- Interpretation: An RMSEA of 0.071 indicates a good fit, as it is below the threshold of 0.10. RMSEA values between 0.05 and 0.08 suggest a reasonable fit, and values below 0.05 indicate close fit.

b. **Normalized Fit Index (NFI ≥ 0.80)**:

- Recommended Value: ≥ 0.80
- Estimated Model Value: 0.902
- Interpretation: An NFI of 0.902 exceeds the recommended threshold of 0.80, indicating an excellent fit of the model. The NFI compares the fit of the model to a null model and values closer to 1 indicate better fit.

c. **Comparative Fit Index (CFI ≥ 0.90)**:

- **Recommended Value**: ≥ 0.90
- **Estimated Model Value**: 0.928

- **Interpretation**: A CFI of 0.928 is above the recommended threshold of 0.90, indicating an excellent fit. The CFI considers the model complexity and penalizes for adding parameters that do not improve the model fit significantly.

d. Tucker-Lewis Index (TLI ≥ 0.90):

- Recommended Value: ≥ 0.90
- Estimated Model Value: 0.920
- Interpretation: A TLI of 0.920 meets the recommended value of 0.90, suggesting an excellent fit. The TLI is similar to the CFI but includes a penalty for model complexity.

e. Chi-square/degree of freedom (CMIN/df ≤ 5.00):

- Recommended Value: ≤ 5.00
- Estimated Model Value: 3.39
- Interpretation: A CMIN/df of 3.39 is within the acceptable range, suggesting an acceptable fit. This index adjusts the chi-square value by the degrees of freedom to account for model complexity, with lower values indicating better fit.

f. Standardized Root Mean Square Residual (SRMR < 0.08):

- **Recommended Value**: < 0.08
- **Estimated Model Value**: 0.089
- **Interpretation**: An SRMR of 0.089 is slightly above the recommended threshold of 0.08, indicating an acceptable but not optimal fit. SRMR values below 0.08 are generally considered to indicate a good fit.

Summary: Overall, the model demonstrates a good fit to the data based on multiple indices:

- **RMSEA, NFI, CFI, and TLI**: These indices all indicate good to excellent fit.
- **CMIN/df**: This index suggests an acceptable fit.
- **SRMR**: This index is slightly above the optimal threshold but still within an acceptable range.

The combination of these indices suggests that the model is a good representation of the other indices strongly support the model's adequacy.

Table 4.16: Impact of Antecedents on buying Intention

Sr. No			Estimate	S.E.	C.R.	P	Remark
H2a	Intention	<--- Perceived Behaviour Control	.080	.053	1.498	.134	Non-Significant
H2 b	Intention	<--- Subjective Norms	.341	.034	10.049	***	Significant
H2c	Intention	<--- Attitude	.529	.067	7.836	***	Significant
H2 d	***RMSEA=.071, NFI=.902 ,CFI=.928, TLI=.920, CMIN/df=3.39***						Model is Fit

(Source: Researcher's Computation)

Intention <--- Perceived Behaviour Control

- Estimate: .080
- S.E.: .053
- C.R.: 1.498
- P: .134

Interpretation: The relationship between Perceived Behavioural Control (P.B.C.) and Intention is not statistically significant (p > .05).

Intention <--- Subjective Norm:

- **Estimate**: .341
- **S.E.**: .034
- **C.R.**: 10.049
- **P**: ***

Interpretation: Subjective Norms significantly influence Intention with a strong positive relationship.

Intention <--- Attitude:

- **Estimate**: .529
- **S.E.**: .067
- **C.R.**: 7.836
- **P**: ***

Interpretation: Attitude significantly influences Intention with a strong positive relationship.

Summary of Key Relationships:

- **Attitude** and **Subjective Norms** significantly influence **Intention**.
- **Perceived Behavioural Control** does not have a significant direct effect on **Intention**.

- This model demonstrates significant paths between the key constructs, with most indicators showing strong, significant loadings on their respective constructs. The primary takeaway is the importance of **Attitude** and **Subjective Norms** in predicting **Intention**, and subsequently, the significant impact of **Intention** on actual **Use**. And collectively all three Antecedents are impacting on intention to use mobile commerce.

4.5.3 Objective 3: To examine the impact of 'Demographic Variables' on consumers' 'Attitude', 'Perceived Behaviour Control', 'Subjective Norms' and 'Intention' to use m-commerce.

Hypothesis 3: Demographic variables significantly influence consumers' attitudes, Perceived Behaviour Control, Subjective Norms and intention towards m-commerce.

Attitudes towards Technology Adoption:

- Venkatesh et.al, (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.

This study discusses the influence of demographic variables, including gender, on technology acceptance, highlighting potential differences in attitudes between males and females.

Subjective Norms and Demographics:

- Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behaviour: An introduction to theory and research. Addison-Wesley.

This work explains how subjective norms, influenced by demographic factors such as gender, shape intentions and behaviours.

Perceived Behavioural Control and Demographics:

- Taylor, S., & Todd, P.A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144-176.

This study explores the impact of demographic factors, including gender, on perceived behavioural control over technology usage.

Intention to Use Technology:

- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

This research highlights how demographic variables, particularly gender, can influence the intention to use new technologies, providing a basis for understanding gender differences in m-commerce adoption.

These hypotheses aim to identify and measure the differences between male and female consumers regarding their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce. By testing these hypotheses, the research will contribute to a deeper understanding of gender-based differences in m-commerce adoption, which can inform targeted marketing and policy strategies.

H3a: There is no statistically significant difference between male and female consumers and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.17: Test of Significance-Gender and TPB Constructs

Gender				
	t	**df**	**Sig. (2-tailed)**	**Finding**
Subjective Norms	-0.266	412.076	0.791	Non Significant
Perceived Behaviour Control	0.792	399.908	0.429	Non Significant
Attitude	0.715	439.040	0.475	Non Significant
Intention	0.014	394.159	0.989	Non Significant

(Source: Researcher's Computation)

According to the results of t-test, all four constructs namely Subjective Norm, Perceived Behavioural Control, Attitude, and Intention show no significant differences between genders and their intention to use mobile commerce.

H3b: There is no statistically significant difference between Area of Location and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.18: Test of Significance- Area of Location and TPB Constructs

Area of Location				
	t	df	Sig. (2-tailed)	Finding
Subjective Norms	-0.465	468.306	0.642	Non-Significant
Perceived Behaviour Control	0.636	461.122	0.525	Non-Significant
Attitude	0.848	463.467	0.397	Non-Significant
Intention	1.923	427.314	0.055	Significant

(Source: Researcher's Computation)

All three variables (Subjective Norm, Perceived Behavioural Control, and Attitude) show no significant differences between areas of location. This means that area of location does not have a statistically significant effect on these variables according to the results of this t-test except in Intention.

Table 4.19: Test of Significance- Area of Location and Intention

Group Statistics					
	Area of location	N	Mean	Std. Deviation	Std. Error Mean
Intention	**Municipal Area (Urban)**	**246**	**3.2043**	.53922	.03438
	Panchayat Area (Rural)	227	3.0942	.68999	.04580

(Source: Researcher's Computation)

Urban respondents (Municipal Area) tend to have a slightly higher intention to purchase (Mean = 3.2043) compared to rural respondents (Panchayat Area) (Mean = 3.0942). The scores for urban respondents are less variable and provide a more precise estimate of the population mean than those for rural respondents. This suggests that location may influence

purchase intentions, with urban respondents showing a marginally higher propensity to purchase.

Table 4.20: Variables of Intention and Area of Location: Independent Samples Test

Intention	t	df	Sig. (2-tailed)	Mean Difference	Findings
Private and Confidential (MCI 1)	1.551	466.043	0.122	0.163	Non-Significant
Convenience (MCI 2)	**3.698**	**440.991**	**0.000**	0.367	Significant
Safety (MCI 3)	1.735	448.968	0.083	0.167	Non-significant
Economical (MCI 4)	**2.34**	**448.117**	**0.02**	0.24	Significant
Bad Past Experience (MCI 5)	-0.346	462.758	0.73	-0.032	Non-significant
Recommendation (MCI 6)	1.172	462.901	0.242	0.117	Non-significant
Ease of Use (MCI 7)	**2.149**	**429.629**	**0.032**	0.218	Significant
Lack of Knowledge (MCI 8)	**-3.257**	**427.737**	**0.001**	-0.358	Significant

(Source: Researcher's Computation)

Table 4.21: Group Statistics of Intention and Area of Location

Intention	Area of location	N	Mean	Std. Deviation	Std. Error Mean
Private and Confidential (MCI 1)	Municipal Area (Urban)	246	3.27	1.125	.072
	Panchayat Area (Rural)	227	3.11	1.151	.076
Convenience (MCI 2)	**Municipal Area (Urban)**	**246**	**3.93**	.971	.062
	Panchayat Area (Rural)	**227**	**3.57**	1.167	.077
Safety (MCI 3)	Municipal Area (Urban)	246	3.48	.963	.061
	Panchayat Area (Rural)	227	3.32	1.111	.074
Economical (MCI 4)	**Municipal Area (Urban)**	**246**	**3.76**	1.028	.066
	Panchayat Area (Rural)	**227**	**3.52**	1.191	.079

Bad Past Experience (MCI 5)	Municipal Area (Urban)	246	2.43	.978	.062
	Panchayat Area (Rural)	227	2.47	1.032	.068
Recommendation (MCI 6)	Municipal Area (Urban)	246	2.81	1.058	.067
	Panchayat Area (Rural)	227	2.69	1.114	.074
Ease of Use (MCI 7)	**Municipal Area (Urban)**	**246**	**3.77**	.960	.061
	Panchayat Area (Rural)	**227**	**3.55**	1.216	.081
Lack of Knowledge (MCI 8)	**Municipal Area (Urban)**	**246**	**2.17**	1.037	.066
	Panchayat Area (Rural)	**227**	**2.53**	1.325	.088

(Source: Researcher's Computation)

The research explored how demographic variables, specifically area of location (urban vs. rural), influence consumers' intentions regarding the use of mobile commerce. The analysis, based on an independent samples test, yielded several significant findings:

a. **Convenience (MCI 2):** There is a statistically significant difference between urban and rural consumers ($t = 3.698$, $p < 0.001$), with urban consumers perceiving mobile commerce as more convenient (mean = 3.93) compared to rural consumers (mean = 3.57). This suggests urban consumers might have better access to resources and infrastructure that enhance the convenience of using mobile commerce.
b. **Economical (MCI 4):** The difference between urban and rural consumers is significant ($t = 2.34$, $p = 0.02$), with urban consumers finding mobile commerce more economical (mean = 3.76) than rural consumers (mean = 3.52). This might be due to higher levels of awareness and accessibility to cost-effective mobile commerce solutions in urban areas.
c. **Ease of Use (MCI 7):** There is a significant difference ($t = 2.149$, $p = 0.032$), with urban consumers perceiving mobile commerce as easier to use (mean = 3.77) compared to rural consumers (mean = 3.55). This could be attributed to higher technological literacy in urban areas.
d. **Lack of Knowledge (MCI 8):** The significant negative difference ($t = -3.257$, $p = 0.001$) indicates that rural consumers report a greater lack of knowledge about

mobile commerce (mean = 2.53) than urban consumers (mean = 2.17). This reflects a potential barrier to adoption in rural areas due to insufficient information and awareness.

Other variables such as "Private and Confidential" (MCI 1), "Safety" (MCI 3), "Bad Past Experience" (MCI 5), and "Recommendation" (MCI 6) showed no statistically significant differences between urban and rural consumers.

Managerial Implications:

The findings offer several actionable insights for businesses and policymakers aiming to enhance mobile commerce adoption:

a. **Targeted Education and Awareness Campaigns:** Given the significant difference in knowledge levels, it is crucial to implement educational initiatives focused on rural areas to increase awareness and understanding of mobile commerce. These campaigns could include workshops, local seminars, and digital literacy programs.
b. **Improving Convenience and Accessibility:** For rural consumers to perceive mobile commerce as convenient, businesses should enhance the infrastructure and provide user-friendly platforms. This could involve simplifying the user interface and offering localized support to address specific needs and challenges faced by rural users.
c. **Cost-Effective Solutions:** To make mobile commerce more appealing to rural consumers, companies should emphasize the economic benefits and offer cost-effective solutions. Promotional campaigns highlighting savings, discounts, and financial incentives could encourage adoption in rural areas.
d. **Enhancing User Experience:** Since urban consumers find mobile commerce easier to use, businesses should leverage this by ensuring their platforms are intuitive and accessible. Continuous user experience improvements and responsive customer support can maintain high satisfaction levels among urban users.
e. **Safety and Security Measures:** Although there were no significant differences found in the perception of safety, maintaining and communicating robust security measures is essential. Building trust through transparent privacy policies and secure transaction processes can address potential concerns from both urban and rural consumers.

f. **Personalized Marketing Strategies:** Recognizing the different perceptions between urban and rural consumers, marketers should tailor their strategies accordingly. Urban areas may benefit from advanced features and convenience- focused messages, while rural areas might require more basic, informative, and trust- building approaches.

Citations of Previous Research:

a. **Attitudes towards Technology Adoption:**

- Venkatesh et.al (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.
- This study discusses how demographic variables, such as location, influence technology acceptance, supporting the finding that urban users are more inclined towards technology adoption.

b. **Subjective Norms and Demographics:**

- Fishbein et.al, (1975). Belief, attitude, intention, and behaviour: An introduction to theory and research. Addison-Wesley.
- The theory highlights the impact of social norms and demographic factors on behaviour, which is relevant to understanding differences in mobile commerce adoption between urban and rural consumers.

By leveraging these insights, businesses and policymakers can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of urban and rural consumers.

H3c: There is no statistically significant difference between 'Marital Status' of consumers and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.22: Test of Significance-Marital Status and TPB Constructs

Marital Status				
	t	df	Sig. (2-tailed)	Finding
Subjective Norms	-0.638	446.959	0.524	Non-Significant

Perceived Behaviour Control	-0.067	438.233	0.947	Non-Significant
Attitude	0.153	467.000	0.879	Non-Significant
Intention	-2.551	435.887	0.011	Significant

(Source: Researcher's Computation)

All three variables (Subjective Norm, Perceived Behavioural Control, and Attitude) show no significant differences between marital statuses. This means that marital status does not have a statistically significant effect on these variables according to the results of this t-test except in intention.

Table 4.23: Variables of Intention and Marital Status: Independent Samples Test

Group Statistics					
	Marital Status	N	Mean	Std. Deviation	Std. Error Mean
Intention	Married	210	3.0702	.63418	.04376
	Unmarried	**263**	**3.2163**	.59808	.03688

(Source: Researcher's Computation)

Unmarried respondents tend to have a higher intention to purchase (Mean = 3.2163) compared to married respondents (Mean = 3.0702). The scores for unmarried respondents are slightly less variable and provide a more precise estimate of the population mean than those for married respondents. This suggests that marital status may influence purchase intentions, with unmarried respondents showing a higher propensity to purchase.

Table 4.24: Test of Significance-Intention and Marital Status

Intention	t	df	Sig. (2-tailed)	Mean Difference	Findings
Private and Confidential (MCI 1)	**-2.611**	**471**	**0.009**	-0.274	Significant
Convenience (MCI 2)	-1.831	471	0.068	-0.183	Non Significant
Safety (MCI 3)	**-2.217**	**471**	**0.027**	**-0.212**	Significant
Economical (MCI 4)	**-2.709**	**471**	**0.007**	**-0.278**	Significant
Bad Past Experience (MCI 5)	**-2.089**	**471**	**0.037**	-0.193	Non Significant

Recommendation (MCI 6)	-0.857	471	0.392	-0.086	Non Significant
Ease of Use (MCI 7)	-1.729	471	0.084	-0.175	Non Significant
Lack of Knowledge (MCI 8)	**2.111**	**471**	**0.035**	0.233	Non Significant

(Source: Researcher's Computation)

Table 4.25: Group Statistics-Marital Status and Intention

Group Statistics					
Intention	Marital Status	N	Mean	Std. Deviation	Std. Error Mean
Private and Confidential (MCI 1)	**Married**	**210**	**3.04**	1.197	.083
	Unmarried	**263**	**3.31**	1.078	.066
Convenience (MCI 2)	Married	210	3.66	1.156	.080
	Unmarried	263	3.84	1.018	.063
Safety (MCI 3)	**Married**	**210**	**3.29**	1.130	.078
	Unmarried	**263**	**3.50**	.953	.059
Economical (MCI 4)	**Married**	**210**	**3.49**	1.207	.083
	Unmarried	**263**	**3.77**	1.020	.063
Bad Past Experience (MCI 5)	**Married**	**210**	**2.34**	.942	.065
	Unmarried	**263**	**2.54**	1.044	.064
Recommendation (MCI 6)	Married	210	2.70	1.106	.076
	Unmarried	263	2.79	1.069	.066
Ease of Use (MCI 7)	Married	210	3.57	1.161	.080
	Unmarried	263	3.74	1.035	.064
Lack of Knowledge (MCI 8)	**Married**	**210**	**2.48**	1.309	.090
	Unmarried	**263**	**2.24**	1.088	.067

(Source: Researcher's Computation)

The research investigated how marital status influences consumers' intentions regarding the use of mobile commerce among individuals. The analysis of the independent samples test provides several key findings:

Private and Confidential (MCI 1): There is a statistically significant difference between married and unmarried consumers ($t = -2.611$, $p = 0.009$), with unmarried consumers rating

the privacy and confidentiality of mobile commerce higher (mean = 3.31) than married consumers (mean = 3.04). This suggests that privacy concerns may be more prominent among married individuals.

a. **Safety (MCI 3):** The results indicate a significant difference (t = -2.217, p = 0.027), with unmarried consumers perceiving mobile commerce as safer (mean = 3.50) compared to married consumers (mean = 3.29). This might be due to higher confidence in technology security among the younger, unmarried demographic.
b. **Economical (MCI 4):** The difference is significant (t = -2.709, p = 0.007), with unmarried consumers finding mobile commerce more economical (mean = 3.77) than married consumers (mean = 3.49). Unmarried individuals may have greater price sensitivity and awareness of cost-saving benefits.
c. **Bad Past Experience (MCI 5):** There is a significant difference (t = -2.089, p = 0.037), with unmarried consumers reporting fewer bad past experiences (mean = 2.54) compared to married consumers (mean = 2.34). This could indicate that married consumers have encountered more issues with mobile commerce, possibly due to higher usage rates.
d. **Lack of Knowledge (MCI 8):** A significant difference exists (t = 2.111, p = 0.035), with married consumers reporting a greater lack of knowledge about mobile commerce (mean = 2.48) compared to unmarried consumers (mean = 2.24). This suggests that unmarried individuals might be more technologically savvy or better informed about mobile commerce.

Other variables such as "Convenience" (MCI 2), "Recommendation" (MCI 6), and "Ease of Use" (MCI 7) showed no statistically significant differences between married and unmarried consumers.

❖ **Managerial Implications:**

The findings provide several important implications for businesses and policymakers aiming to enhance mobile commerce adoption among different demographic segments:

a. **Enhanced Privacy Measures:** Given the significant concern for privacy among married consumers, businesses should focus on enhancing and communicating robust privacy and confidentiality measures. Transparent data handling policies and secure transaction processes can help address these concerns.

b. **Safety Assurance Campaigns:** Unmarried consumers perceive mobile commerce as safer than married consumers. To bridge this perception gap, businesses should implement safety assurance campaigns that highlight security features and educate married consumers on how their data is protected.
c. **Cost-Saving Promotions:** Since unmarried consumers find mobile commerce more economical, targeted marketing campaigns highlighting discounts, offers, and cost-saving opportunities can appeal to this demographic. For married consumers, emphasizing value for money and long-term savings could be more effective.
d. **Addressing Past Experience:** To mitigate the impact of bad past experiences reported more frequently by married consumers, businesses should focus on improving customer service, providing easy resolution processes, and ensuring reliable and consistent performance of their mobile commerce platforms.
e. **Educational Initiatives:** The lack of knowledge reported by married consumers suggests a need for educational initiatives. These could include tutorials, workshops, and informational campaigns that simplify the use of mobile commerce and increase digital literacy among this group.
f. **Tailored User Experience:** While ease of use is not significantly different between the groups, businesses should continuously refine the user experience to cater to both married and unmarried consumers. Simplified navigation, intuitive design, and personalized support can enhance user satisfaction across the board.

❖ **Attitudes towards Technology Adoption:**

- Venkatesh et.al, (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.
- This study discusses the influence of demographic variables, including gender, on technology acceptance, highlighting potential differences in attitudes between males and females.

❖ **Subjective Norms and Demographics:**

- Fishbein et.al (1975). Belief, attitude, intention, and behaviour: An introduction to theory and research. Addison-Wesley.
- This work explains how subjective norms, influenced by demographic factors such as gender, shape intentions and behaviours.

❖ **Perceived Behavioural Control and Demographics:**

- Taylor, S., & Todd, P.A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144-176.
- This study explores the impact of demographic factors, including gender, on perceived behavioural control over technology usage.

❖ **Intention to Use Technology:**

- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.
- This research highlights how demographic variables, particularly gender, can influence the intention to use new technologies, providing a basis for understanding gender differences in m-commerce adoption.

These hypotheses aim to identify and measure the differences between male and female consumers regarding their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce. By testing these hypotheses, the research will contribute to a deeper understanding of gender-based differences in m-commerce adoption, which can inform targeted marketing and policy strategies.

H3d: There is no statistically significant difference between consumers 'Age' and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.26: ANOVA-Age

Age							
ANOVA							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Subjective Norm	Between Groups	8.195	3	2.732	2.035	0.108	
	Within Groups	629.433	469	1.342			
	Total	637.628	472				Non Significant
Perceived Behaviour Control	Between Groups	2.435	3	0.812	2.254	0.081	
	Within Groups	168.882	469	0.360			
	Total	171.318	472				Non Significant

Attitude	**Between Groups**	**4.310**	**3**	**1.437**	**4.289**	**0.005**	
	Within Groups	**157.108**	**469**	**0.335**			
	Total	**161.418**	**472**				**Significant**
Intention	**Between Groups**	**22.562**	**3**	**7.521**	**22.366**	**0.000**	
	Within Groups	157.701	469	0.336			
	Total	180.263	472				**Significant**

(Source: Researcher's Computation)

The p-value for Subjective Norm is 0.108, which is greater than the common significance level of 0.05. This suggests that there is no statistically significant difference in the means of Subjective Norm across the different age groups.

The p-value for Perceived Behaviour Control is 0.081, which is also greater than 0.05. Therefore, there is no statistically significant difference in the means of Perceived Behaviour Control across the different age groups.

The p-value for Attitude is 0.005, which is less than 0.05. This indicates that there is a statistically significant difference in the means of Attitude across the different age groups.

The p-value for Intention is 0.000, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Intention across the different age groups.

Summary:

- **Subjective Norm** and **Perceived Behaviour Control** do not show significant differences across age groups.
- **Attitude** and **Intention** show significant differences across age groups, indicating that these factors are affected by age.

Table 4.27: Age and Attitude-Intention

		Mean	Std. Deviation
Less than 20 years	Intention	3.1503	.57003
	Attitude	3.0876	.60327

21 to 40 years	Intention	3.2694	.57934
	Attitude	3.1181	.61179
41 to 60 years	Intention	3.1892	.59308
	Attitude	3.1803	.54236
61 years and above	Intention	2.5027	.57160
	Attitude	2.8232	.42368

(Source: Researcher's Computation)

The table provides the mean and standard deviation of two key variables, intention and attitude, across four different age groups.

❖ **Interpretation:**

a. Less than 20 years:

- **Intention:** Mean = 3.1503, Std. Deviation = 0.57003
- **Attitude:** Mean = 3.0876, Std. Deviation = 0.60327

This age group shows moderate intention and attitude towards mobile commerce (m-commerce), with both means slightly above 3 on a 5-point scale. The standard deviations indicate moderate variability in responses.

b. 21 to 40 years:

- **Intention:** Mean = 3.2694, Std. Deviation = 0.57934
- **Attitude:** Mean = 3.1181, Std. Deviation = 0.61179

The 21 to 40 years age group has the highest mean intention among all groups, suggesting a relatively strong inclination towards m-commerce. The mean attitude is also slightly higher than in the younger group, indicating generally positive attitudes towards m-commerce.

c. 41 to 60 years:

- **Intention:** Mean = 3.1892, Std. Deviation = 0.59308
- **Attitude:** Mean = 3.1803, Std. Deviation = 0.54236

For the 41 to 60 years age group, the means for both intention and attitude are slightly lower than the 21 to 40 years group but still indicate moderate levels of

both variables. This group has the lowest variability in attitude, suggesting more consistent attitudes within this age group.

d. 61 years and above:

- **Intention:** Mean = 2.5027, Std. Deviation = 0.57160
- **Attitude:** Mean = 2.8232, Std. Deviation = 0.42368

The oldest age group shows the lowest mean intention to use m-commerce, indicating relatively low interest or inclination. The mean attitude is also lower than the younger groups, though not as low as the mean intention. This group has the lowest variability in attitude, suggesting consistent attitudes towards m-commerce.

❖ **Targeted Marketing Strategies:**

- **Young Adults (21 to 40 years):** This group shows the highest intention and positive attitude towards m-commerce. Marketing strategies should focus on enhancing user experience, offering personalized promotions, and leveraging social media and digital marketing channels to engage this demographic effectively (Chaffey & Ellis-Chadwick, 2019).
- **Teenagers (Less than 20 years):** Although this group has a moderate intention and attitude, they represent a potential future market. Businesses should focus on building brand loyalty through interactive and engaging content, gamification, and social media presence (Smith, 2019).

❖ **Older Adults (41 to 60 years):**

- This group has a moderate intention and attitude towards m-commerce. Strategies should include highlighting the convenience and security of m-commerce, possibly through educational campaigns and testimonials from satisfied customers. Simplifying the user interface can also help increase adoption among this age group (Mclean et al., 2020).

❖ **Senior Citizens (61 years and above):**

- With the lowest intention and attitude scores, this group may require more convincing about the benefits of m-commerce. Businesses should consider offering detailed guides, customer support, and simplified purchasing processes to help this demographic feel more comfortable with m-commerce platforms (Venkatesh,

Thong, & Xu, 2012). Addressing security concerns and providing guarantees could also help improve their attitude and intention to use m-commerce.

- **Consistency in Attitude:**
  - The relatively consistent attitudes within the 41 to 60 and 61+ age groups suggest that once convinced, these groups could become loyal users. Businesses should focus on building trust and reliability in their m-commerce services to retain these customers (Gefen, Karahanna, & Straub, 2003).

- **Product and Service Customization:**
  - Understanding the distinct preferences and behaviors of each age group can help businesses tailor their product offerings and services. For instance, tech-savvy products and trendy items may appeal more to younger users, while essential services and easy-to-use interfaces might be more attractive to older consumers (Rogers, 2003).

In summary analysis indicates that younger age groups, particularly those between 21 and 40 years, show higher intention and positive attitudes towards m-commerce, suggesting a greater readiness to adopt and engage with mobile shopping. In contrast, older age groups exhibit lower intention and more negative attitudes, highlighting the need for targeted interventions to improve their perception and usage of m-commerce. Businesses should develop age-specific strategies to address these differences, ensuring broader adoption and satisfaction across all age demographics.

Table 4.28: ANOVA between Age Group and Attitude and Intention.

ANOVA between Age Group							
Attitude							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Reasonably Priced Products (Att 1)	**Between Groups**	**8.900**	**3**	**2.967**	**3.898**	**.009**	Significant
	Within Groups	**356.973**	**469**	**.761**			
	Total	**365.873**	**472**				

Prompt Customer Service (Att 2)	**Between Groups**	**9.633**	**3**	**3.211**	**4.230**	**.006**	Significant
	Within Groups	**356.058**	**469**	**.759**			
	Total	**365.691**	**472**				
Physical Shopping Experience (Att 3)	Between Groups	3.315	3	1.105	1.476	.220	Non Significant
	Within Groups	351.074	469	.749			
	Total	354.389	472				
Shopping Convenience (Att 4)	**Between Groups**	**6.276**	**3**	**2.092**	**2.720**	**.044**	Significant
	Within Groups	**360.675**	**469**	**.769**			
	Total	**366.951**	**472**				
Safe & Secure (Att 5)	**Between Groups**	**36.146**	**3**	**12.049**	**10.845**	**.000**	Significant
	Within Groups	**521.034**	**469**	**1.111**			
	Total	**557.180**	**472**				
Unsafe without Technological Knowledge (Att 6)	Between Groups	5.501	3	1.834	2.387	.068	Non Significant
	Within Groups	360.283	469	.768			
	Total	365.784	472				
Unreliable Review (Att 7)	**Between Groups**	**22.748**	**3**	**7.583**	**6.642**	**.000**	Significant
	Within Groups	**535.438**	**469**	**1.142**			
	Total	**558.186**	**472**				
User Friendly (Att 8)	**Between Groups**	**22.843**	**3**	**7.614**	**9.754**	**.000**	Significant
	Within Groups	**366.104**	**469**	**.781**			
	Total	**388.947**	**472**				

Shopping Addiction (Att 9)	**Between Groups**	**41.870**	**3**	**13.957**	**8.998**	**.000**	Significant
	Within Groups	**727.449**	**469**	**1.551**			
	Total	**769.319**	**472**				
Privacy (Att 10)	**Between Groups**	**7.055**	**3**	**2.352**	**2.932**	**.033**	Significant
	Within Groups	**376.100**	**469**	**.802**			
	Total	**383.154**	**472**				
Intention							
Private and Confidential (MCI 1)	**Between Groups**	**61.951**	**3**	**20.650**	**17.580**	**.000**	Significant
	Within Groups	**550.924**	**469**	**1.175**			
	Total	**612.875**	**472**				
Convenience (MCI 2)	**Between Groups**	**94.826**	**3**	**31.609**	**32.248**	**.000**	Significant
	Within Groups	**459.699**	**469**	**.980**			
	Total	**554.524**	**472**				
Safety (MCI 3)	**Between Groups**	**63.602**	**3**	**21.201**	**22.281**	**.000**	Significant
	Within Groups	**446.271**	**469**	**.952**			
	Total	**509.873**	**472**				
Economical (MCI 4)	**Between Groups**	**93.176**	**3**	**31.059**	**29.537**	**.000**	Significant
	Within Groups	**493.154**	**469**	**1.052**			
	Total	**586.330**	**472**				
Bad Past Experience (MCI 5)	Between Groups	7.258	3	2.419	2.425	.065	Non Significant
	Within Groups	467.825	469	.997			

	Total	475.082	472				
Recommendation (MCI 6)	**Between Groups**	**13.826**	**3**	**4.609**	**3.986**	**.008**	Significant
	Within Groups	**542.234**	**469**	**1.156**			
	Total	**556.059**	**472**				
Ease of Use (MCI 7)	**Between Groups**	**83.555**	**3**	**27.852**	**27.101**	**.000**	Significant
	Within Groups	**481.997**	**469**	**1.028**			
	Total	**565.552**	**472**				
Lack of Knowledge (MCI 8)	**Between Groups**	**133.514**	**3**	**44.505**	**38.537**	**.000**	Significant
	Within Groups	**541.623**	**469**	**1.155**			
	Total	**675.137**	**472**				

(Source: Researcher's Computation)

- **Interpretation by Attribute:**

The research examined how age groups influence consumers' attitudes and intentions regarding the use of mobile commerce in Goa. The analysis was conducted using ANOVA, and the results highlight significant differences across various constructs:

a. **Reasonably Priced Products (Att 1):** Significant differences were found between age groups ($F = 3.898$, $p = 0.009$). This indicates that perceptions of product pricing in mobile commerce vary significantly with age.
b. **Prompt Customer Service (Att 2):** Age groups show significant differences ($F = 4.230$, $p = 0.006$), suggesting that the expectation of customer service speed differs across age groups.
c. **Shopping Convenience (Att 4):** Significant differences were observed ($F = 2.720$, $p = 0.044$), indicating that convenience in mobile commerce is perceived differently across age groups.
d. **Safe & Secure (Att 5):** There is a highly significant difference ($F = 10.845$, $p < 0.001$), showing that age groups vary greatly in their perceptions of safety and security in mobile commerce.

e. **Unreliable Review (Att 7):** Significant differences were found ($F = 6.642$, $p < 0.001$), suggesting age-related variations in trust in online reviews.
f. **User Friendly (Att 8):** The results show significant differences ($F = 9.754$, $p < 0.001$), indicating that user-friendliness of mobile commerce platforms is perceived differently by various age groups.
g. **Shopping Addiction (Att 9):** Significant differences were found ($F = 8.998$, $p < 0.001$), suggesting that the tendency for shopping addiction varies with age.
h. **Privacy (Att 10):** There are significant differences between age groups ($F = 2.932$, $p = 0.033$), indicating that privacy concerns vary with age.
i. **Private and Confidential (MCI 1):** Highly significant differences were observed ($F = 17.580$, $p < 0.001$), showing that age impacts perceptions of privacy and confidentiality in mobile commerce.
j. **Convenience (MCI 2):** Significant differences were found ($F = 32.248$, $p < 0.001$), indicating that convenience in mobile commerce is perceived differently by different age groups.
k. **Safety (MCI 3):** Significant differences were observed ($F = 22.281$, $p < 0.001$), suggesting age-related variations in perceptions of safety.
l. **Economical (MCI 4):** There are significant differences ($F = 29.537$, $p < 0.001$), indicating that the perceived economic benefits of mobile commerce vary across age groups.
m. **Recommendation (MCI 6):** Significant differences were found ($F = 3.986$, $p = 0.008$), suggesting age-related variations in the impact of recommendations on mobile commerce usage.
n. **Ease of Use (MCI 7):** Significant differences were observed ($F = 27.101$, $p < 0.001$), indicating that perceptions of ease of use vary with age.
o. **Lack of Knowledge (MCI 8):** Highly significant differences were found ($F = 38.537$, $p < 0.001$), suggesting that the perceived lack of knowledge about mobile commerce varies significantly across age groups.

❖ **Managerial Implications:**

The findings offer actionable insights for businesses and policymakers aiming to enhance mobile commerce adoption among different age groups in Goa:

a. **Tailored Pricing Strategies:** Since perceptions of reasonably priced products vary by age, businesses should consider age-specific pricing strategies and promotions to cater to the unique needs of each age group.
b. **Customized Customer Service:** Given the differing expectations of prompt customer service, businesses should tailor their customer support approaches to meet the specific demands of various age groups.
c. **Enhancing Convenience:** To address varying perceptions of shopping convenience, companies should optimize their mobile commerce platforms to be user-friendly for all age groups, perhaps offering features that cater to both tech-savvy younger users and older, less technologically adept users.
d. **Safety and Security Communication:** With significant age-related differences in perceptions of safety, businesses should emphasize security features and ensure clear communication about safety protocols to inculcate confidence in users of all ages.
e. **Building Trust in Reviews:** Since trust in online reviews varies with age, businesses should focus on generating authentic and reliable reviews and perhaps implement age-specific review verification methods.
f. **Improving User Experience:** The perception of user-friendliness differs across age groups, so businesses should continuously improve the user experience to cater to the diverse technological proficiencies of different age segments.
g. **Addressing Shopping Addiction:** With variations in shopping addiction tendencies, businesses should promote responsible shopping habits and offer tools for users to manage their shopping behaviour.
h. **Privacy Measures:** Since privacy concerns differ with age, businesses should ensure robust privacy measures and communicate them effectively to build trust among users of all ages.

i. **Personalized Marketing:** The significant differences in perceptions of mobile commerce convenience, economic benefits, and ease of use suggest that personalized marketing strategies targeting specific age groups could be more effective.
j. **Educational Initiatives:** Given the significant differences in the perceived lack of knowledge, especially among older age groups, businesses should implement educational initiatives to improve digital literacy and awareness about mobile commerce.

❖ **Citation of Previous Research:**

a. Attitudes towards Technology Adoption:

- Venkatesh et.al, (2003) study discusses how demographic variables, such as age, influence technology acceptance, supporting the finding that different age groups perceive mobile commerce differently.

b. Subjective Norms and Demographics:

- Fishbein, M., & Ajzen, I. (1975) work highlighted how demographic factors shape subjective norms and behaviour, relevant to understanding differences in mobile commerce adoption across age groups.

By leveraging these insights, businesses and policymakers can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of various age groups in Goa.

Summary: There are significant differences between age groups for most attributes and intention concerns, indicating that age influences shopping attitudes and intention. The attributes with the highest F-values, such as Safety (MCI 3) and Lack of Knowledge (MCI 8), show particularly strong differences across age groups. Conversely, some factors like Physical Shopping Experience (Att 3) and Unsafe without Technological Knowledge (Att 6) show no significant differences, suggesting that these concerns are relatively consistent across different age groups.

H3e: There is no statistically significant difference between 'Educational level' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.29: ANOVA-Education

Education							
ANOVA							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Attitude	**Between Groups**	**18.204**	**4**	**4.551**	**3.438**	**0.009**	**Significant**

	Within Groups	619.424	468	1.324			
	Total	637.628	472				
Perceived Behaviour Control	Between Groups	0.660	4	0.165	0.452	0.771	
	Within Groups	170.658	468	0.365			Non Significant
	Total	171.318	472				
Subjective Norms	Between Groups	2.853	4	0.713	2.105	0.079	
	Within Groups	158.565	468	0.339			Non Significant
	Total	161.418	472				
Intention	**Between Groups**	**7.864**	**4**	**1.966**	**5.337**	**0.000**	
	Within Groups	172.399	468	0.368			
	Total	180.263	472				**Significant**

(Source: Researcher's Computation)

The p-value for Subjective Norm is 0.009, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Subjective Norm across the different education levels.

The p-value for Perceived Behavioural Control is 0.771, which is greater than 0.05. This indicates that there is no statistically significant difference in the means of Perceived Behavioural Control across the different education levels.

The p-value for Attitude is 0.079, which is greater than 0.05. Therefore, there is no statistically significant difference in the means of Attitude across the different education levels.

The p-value for Intention is 0.000, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Intention across the different education levels.

Summary:

- **Subjective Norm** and **Intention** show significant differences across education levels.
- **Perceived Behavioural Control** and **Attitude** do not show significant differences across education levels.

Table 4.30: ANOVA and Educational level

ANOVA and Education level							
Intention							
		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**	**Findings**
Peer Influence (SN 1)	Between Groups	18.659	4	4.665	3.549	.007	Significant
	Within Groups	615.108	468	1.314			
	Total	633.767	472				
Peer Recommendations(SN 2)	Between Groups	17.295	4	4.324	3.250	.012	Significant
	Within Groups	622.671	468	1.330			
	Total	639.966	472				
Peer Opinions(SN 3)	Between Groups	19.027	4	4.757	3.569	.007	Significant
	Within Groups	623.768	468	1.333			
	Total	642.795	472				
Social Media Influence (SN 4)	Between Groups	17.752	4	4.438	3.274	.012	Significant
	Within Groups	634.455	468	1.356			
	Total	652.207	472				
Personal Preference (SN 5)	Between Groups	19.986	4	4.997	3.908	.004	Significant
	Within Groups	598.293	468	1.278			
	Total	618.279	472				
External Influence (SN 6)	Between Groups	14.682	4	3.670	2.424	.047	Significant
	Within Groups	708.638	468	1.514			
	Total	723.319	472				
Attitude							
Reasonably Priced Products (Att 1)	Between Groups	6.894	4	1.724	2.247	.063	Non Significant
	Within Groups	358.979	468	.767			
	Total	365.873	472				
Prompt Customer Service (Att 2)	Between Groups	7.032	4	1.758	2.294	.058	Non Significant
	Within Groups	358.659	468	.766			
	Total	365.691	472				
Physical Shopping Experience (Att 3)	Between Groups	9.537	4	2.384	3.236	.012	Significant
	Within Groups	344.852	468	.737			
	Total	354.389	472				

Shopping Convenience (Att 4)	Between Groups	6.969	4	1.742	2.265	.061	Non Significant
	Within Groups	359.982	468	.769			
	Total	366.951	472				
Safe & Secure (Att 5)	Between Groups	5.648	4	1.412	1.198	.311	Non Significant
	Within Groups	551.532	468	1.178			
	Total	557.180	472				
Unsafe without Technological Knowledge (Att 6)	Between Groups	1.696	4	.424	.545	.703	Non Significant
	Within Groups	364.088	468	.778			
	Total	365.784	472				
Unreliable Review (Att 7)	Between Groups	16.653	4	4.163	3.598	.007	Significant
	Within Groups	541.533	468	1.157			
	Total	558.186	472				
User Friendly (Att 8)	Between Groups	6.654	4	1.664	2.036	.088	Non Significant
	Within Groups	382.293	468	.817			
	Total	388.947	472				
Shopping Addiction (Att 9)	Between Groups	29.249	4	7.312	4.624	.001	Significant
	Within Groups	740.071	468	1.581			
	Total	769.319	472				
Privacy (Att 10)	Between Groups	2.532	4	.633	.778	.540	Non Significant
	Within Groups	380.622	468	.813			
	Total	383.154	472				

(Source: Researcher's Computation)

- **Impact of educational level on consumer's attitudes and subjective norms towards mobile commerce using ANOVA:** The results indicate significant differences across various constructs, demonstrating how education influences these factors.
- **Peer Influence (SN 1):** Significant differences were observed ($F = 3.549$, $p = 0.007$), indicating that the influence of peers on mobile commerce adoption varies significantly with education level.

- **Peer Recommendations (SN 2):** Significant differences were found (F = 3.250, p = 0.012), suggesting that the impact of peer recommendations differs across educational groups.

- **Peer Opinions (SN 3):** There are significant differences (F = 3.569, p = 0.007), showing that educational levels influence how peer opinions affect mobile commerce behavior.

- **Social Media Influence (SN 4):** Significant differences were observed (F = 3.274, p = 0.012), indicating that the influence of social media on mobile commerce adoption varies with education level.

- **Personal Preference (SN 5):** The results show significant differences (F = 3.908, p = 0.004), suggesting that personal preferences in mobile commerce are influenced by education level.

- **External Influence (SN 6):** Significant differences were found (F = 2.424, p = 0.047), indicating that external influences on mobile commerce usage vary across educational levels.

- **Physical Shopping Experience (Att 3):** Significant differences were observed (F = 3.236, p = 0.012), showing that the perceived importance of physical shopping experiences varies with education level.

- **Unreliable Review (Att 7):** Significant differences were found (F = 3.598, p = 0.007), suggesting that educational levels influence trust in online reviews.

- **Shopping Addiction (Att 9):** The results show significant differences (F = 4.624, p = 0.001), indicating that the tendency for shopping addiction varies with education level.

❖ **Managerial Implications:**

The findings provide crucial insights for businesses and policymakers aiming to enhance mobile commerce adoption by targeting different educational groups in Goa:

a. **Peer Influence Strategies:** Since peer influence varies with education, businesses should tailor their marketing strategies to leverage peer recommendations and opinions effectively. For instance, educational campaigns and testimonials can be designed to resonate more with specific educational groups.
b. **Social Media Marketing:** With significant differences in social media influence, businesses should develop targeted social media campaigns that cater to the preferences and behaviours of different educational groups.
c. **Educational Content:** Businesses should create educational content that addresses the specific concerns and preferences of various educational levels, thereby enhancing the perceived value and trustworthiness of mobile commerce platforms.

d. **Personalized User Experience:** Given the differences in personal preferences and physical shopping experiences, businesses should focus on providing personalized user experiences that cater to the unique needs of different educational groups.

e. **Trust Building Initiatives:** With varying trust in online reviews, companies should implement trust-building initiatives such as verified reviews and transparent customer feedback mechanisms to cater to the different levels of scepticism among educational groups.

f. **Addressing Shopping Addiction:** The significant differences in shopping addiction tendencies suggest that businesses should promote responsible shopping habits and provide tools for users to manage their shopping behaviour, especially targeting educational groups that show higher tendencies towards shopping addiction.

g. **Targeted External Influence:** Understanding that external influences vary with education, businesses should tailor their external influence strategies, such as endorsements and collaborations, to appeal to different educational segments.

❖ **Citations of Previous Research:**

a. Impact of Education on Technology Adoption:

- Rogers, E.M. (2003) discussed how educational levels influence the adoption of innovations, supporting the finding that education significantly affects mobile commerce adoption.

b. Subjective Norms and Educational Influence:

- Ajzen, I. (1991) highlighted the role of subjective norms in shaping behaviour, relevant to understanding how educational levels influence subjective norms in mobile commerce adoption.

By leveraging these insights, businesses and policymakers can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of different educational groups in Goa.

Summary: The ANOVA analysis shows significant differences in social norms and attitude towards mobile commerce based on education levels. Attributes like Peer Influence (SN 1), Peer Opinions (SN 3), and Personal Preference (SN 5) show notable differences between groups, suggesting that education level significantly affects these perceptions. On the other hand, attributes like Safe & Secure (Att 5), Unsafe without Technological Knowledge (Att 6), and Privacy (Att 10) do not show significant differences, indicating these concerns are consistent across different education levels.

Table 4.31: Education and Subjective Norms-Intention

Education		Mean	Std. Deviation
Up to HSSC	Subjective Norms	2.3021	1.04260
	Intention	2.9549	.65793
Graduation	Subjective Norms	2.4240	1.13780
	Intention	3.1551	.59302
Post-Graduation and above	Subjective Norms	2.3502	1.24559
	Intention	3.2953	.55140
Professional	Subjective Norms	2.1076	1.28300
	Intention	3.2554	.69339
Others	Subjective Norms	3.1230	1.06627
	Intention	3.1920	.64324

(Source: Researcher's Computation)

The table presents descriptive statistics for subjective norms and intention to use mobile commerce (m-commerce) across different education levels. The variables include the mean and standard deviation for subjective norms and intention for each education category.

Interpretation:

a. **Up to HSSC (Higher Secondary School Certificate):**

- **Subjective Norms:** Mean = 2.3021, Std. Deviation = 1.04260
- **Intention:** Mean = 2.9549, Std. Deviation = 0.65793

Explanation: Individuals with education up to HSSC have relatively low subjective norms (mean = 2.3021) and a moderate intention to use m-commerce (mean = 2.9549).

b. **Graduation:**

- **Subjective Norms:** Mean = 2.4240, Std. Deviation = 1.13780
- **Intention:** Mean = 3.1551, Std. Deviation = 0.59302

Explanation: Graduates exhibit slightly higher subjective norms (mean = 2.4240) and intention (mean = 3.1551) compared to those with up to HSSC education.

c. **Post-Graduation and Above:**

- **Subjective Norms:** Mean = 2.3502, Std. Deviation = 1.24559
- **Intention:** Mean = 3.2953, Std. Deviation = 0.55140

Explanation: Individuals with post-graduation or higher education have a mean subjective norm of 2.3502 and the highest intention to use m-commerce (mean = 3.2953) among all groups.

d. **Professional:**

- **Subjective Norms:** Mean = 2.1076, Std. Deviation = 1.28300
- **Intention:** Mean = 3.2554, Std. Deviation = 0.69339

Explanation: Professionals show the lowest subjective norms (mean = 2.1076) but a high intention to use m-commerce (mean = 3.2554).

e. **Others:**

- **Subjective Norms:** Mean = 3.1230, Std. Deviation = 1.06627
- **Intention:** Mean = 3.1920, Std. Deviation = 0.64324

Explanation: This group has the highest subjective norms (mean = 3.1230) and a relatively high intention to use m-commerce (mean = 3.1920).

Managerial Implications:

a. **Tailoring Marketing Strategies:**

- **For Less Educated Segments (Up to HSSC):** The relatively low subjective norms and moderate intention indicate a need for marketing campaigns that build social influence and emphasize the benefits of m-commerce. Testimonials and endorsements from trusted sources could be effective (Ajzen, 1991).
- **For Graduates and Post-Graduates:** These groups exhibit higher intentions to use m-commerce. Marketing efforts should focus on advanced features, convenience, and security to appeal to their higher educational background and potentially higher technological proficiency (Davis, 1989).

b. **Enhancing Professional Engagement:**

- **Professionals:** Despite having the lowest subjective norms, professionals show high intention to use m-commerce. Targeting this segment with professional-oriented benefits such as time-saving features, exclusive offers, and productivity-enhancing tools can further increase their engagement (Venkatesh et. al,2003).

c. **Leveraging Social Influence:**

- **Other Educational Categories:** The group labelled 'Others' has the highest subjective norms, suggesting that social influence plays a significant role in their intention to use m-commerce. Leveraging social proof, community-driven content, and peer reviews can enhance m-commerce adoption within this group (Bandura, 1986).

d. **Education-Specific Campaigns:**

- Developing education-specific marketing campaigns can help in addressing the unique needs and perceptions of each educational group. For instance, less educated segments may benefit from more educational content about the benefits and safety of m-commerce, while more educated groups might appreciate detailed information

on privacy policies and advanced functionalities (Gefen, Karahanna, & Straub, 2003).

e. **Focus on Ease of Use and Reliability:**

- Across all educational levels, ensuring that m-commerce platforms are easy to use and reliable can help in enhancing both subjective norms and intention to use m-commerce. Simplifying the user interface and providing robust customer support can address potential barriers to adoption (Rogers, 2003).

In summary analysis highlights significant differences in subjective norms and intention to use m-commerce across various educational levels. Understanding these differences can help businesses develop targeted strategies that address the specific needs and preferences of each group. By focusing on social influence, tailored marketing campaigns, and improving ease of use and reliability, businesses can enhance m-commerce adoption and usage across all educational segments.

H3f: There is no statistically significant difference between 'Occupation' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.32: ANOVA-Occupation

Occupation							
ANOVA							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Subjective Norm	Between Groups	7.289	4	1.822	1.353	0.249	
	Within Groups	630.339	468	1.347			
	Total	637.628	472				Non Significant
Perceived Behaviour Control	Between Groups	1.618	4	0.404	1.115	0.349	
	Within Groups	169.700	468	0.363			
	Total	171.318	472				Non Significant
Attitude	Between Groups	2.981	4	0.745	2.201	0.068	
	Within Groups	158.437	468	0.339			
	Total	161.418	472				Non Significant
Intention	**Between Groups**	**6.959**	**4**	**1.740**	**4.698**	**0.001**	**Significant**

	Within Groups	**173.305**	**468**	**0.370**			
	Total	**180.263**	**472**				

(Source: Researcher's Computation)

The p-value for Subjective Norm is 0.249, which is greater than 0.05. This suggests that there is no statistically significant difference in the means of Subjective Norm across the different occupation groups.

The p-value for Perceived Behavioural Control is 0.349, which is greater than 0.05. This indicates that there is no statistically significant difference in the means of Perceived Behavioural Control across the different occupation groups.

The p-value for Attitude is 0.068, which is slightly greater than 0.05. This suggests that there is no statistically significant difference in the means of Attitude across the different occupation groups, although it is close to the threshold.

The p-value for Intention is 0.001, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Intention across the different occupation groups.

Summary:

- **Subjective Norm** and **Perceived Behavioural Control** do not show significant differences across occupation groups.
- **Attitude** is not significantly different across occupation groups, but it is close to the significance threshold.
- **Intention** shows significant differences across occupation groups.

Table 4.33: Occupation And Intention Statistics

Occupation		Mean	Std. Deviation
Unemployed	Intention	3.2141	.57742
Service	Intention	3.1791	.62127
Business	Intention	3.1818	.52475
Home Maker	Intention	2.9306	.74728
Retired	Intention	2.6964	.67265

(Source: Researcher's Computation)

The table presents descriptive statistics for the intention to use mobile commerce (m-commerce) across different occupational groups. The variables include the mean and standard deviation for intention for each occupation category.

❖ **Interpretation:**

a. Unemployed:

- **Intention:** Mean = 3.2141, Std. Deviation = 0.57742

- The unemployed group shows a relatively high intention to use m-commerce with a mean of 3.2141, indicating a favourable disposition towards m-commerce. The standard deviation of 0.57742 suggests moderate variability in responses.

b. Service:

- **Intention:** Mean = 3.1791, Std. Deviation = 0.62127
- Individuals in service occupations also show a high intention to use m-commerce, with a mean of 3.1791. The standard deviation of 0.62127 indicates moderate variability in their responses.

c. Business:

- **Intention:** Mean = 3.1818, Std. Deviation = 0.52475
- Business professionals have a high intention to use m-commerce, with a mean intention of 3.1818. The standard deviation of 0.52475 suggests relatively consistent responses within this group.

d. Home Maker:

- **Intention:** Mean = 2.9306, Std. Deviation = 0.74728
- Homemakers have a lower intention to use m-commerce compared to unemployed, service, and business groups, with a mean of 2.9306. The standard deviation of 0.74728 indicates higher variability in responses.

e. Retired:

- **Intention:** Mean = 2.6964, Std. Deviation = 0.67265
- Retired individuals show the lowest intention to use m-commerce with a mean of 2.6964. The standard deviation of 0.67265 suggests moderate variability in their responses.

❖ **Managerial Implications:**

a. Targeted Marketing Strategies:

- **High Intention Groups (Unemployed, Service, and Business):** These groups exhibit the highest intention to use m-commerce. Marketing strategies should focus on highlighting the convenience, efficiency, and variety of products available through m-commerce. Offering personalized promotions, loyalty programs, and easy-to-navigate interfaces can further increase engagement among these groups (Chaffey & Ellis-Chadwick, 2019).

b. Engagement Strategies for Homemakers:

- The lower intention among homemakers suggests a need for tailored marketing approaches. Emphasizing the convenience of shopping from home, providing special offers for household products, and creating content that resonates with their daily needs can help boost their intention to use m-commerce (Smith, 2019).

c. Addressing Concerns of Retired Individuals:

- The retired group shows the lowest intention to use m-commerce. To increase adoption, businesses should focus on addressing their specific concerns such as security, ease of use, and trust. Providing educational resources, simplified interfaces, and customer support specifically designed for older adults can help alleviate apprehensions and encourage usage (Venkatesh, Thong, & Xu, 2012).

d. Consistency in Business and Service Occupations:

- The relatively consistent intention scores within the business and service occupations suggest that once convinced, these groups can become reliable and frequent users of m-commerce. Efforts to maintain high levels of satisfaction through consistent quality, reliability, and customer service will be crucial (Gefen, Karahanna, & Straub, 2003).

e. Personalized User Experience:

- Understanding the distinct preferences and behaviours of each occupational group can help businesses tailor their product offerings and services. For instance, business professionals might value efficiency and productivity-enhancing tools, while service professionals might appreciate flexible delivery options and time-saving features (Rogers, 2003).

f. Utilizing Social Influence:

- Leveraging social proof and testimonials from peers within each occupational category can enhance trust and perceived value of m-commerce. Peer recommendations and user-generated content can be particularly effective in influencing intention among undecided users (Bandura, 1986).

In summary analysis indicates that different occupational groups exhibit varying levels of intention to use m-commerce. Understanding these differences allows businesses to develop targeted strategies that address the specific needs and preferences of each group. By focusing on convenience, security, and personalized user experiences, businesses can enhance m-commerce adoption and satisfaction across all occupational categories.

Table 4.34: ANOVA-Occupation

ANOVA and Different Occupation							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Private and Confidential (MCI 1)	**Between Groups**	**25.173**	**4**	**6.293**	**5.012**	**.001**	Significant
	Within Groups	**587.702**	**468**	**1.256**			
	Total	**612.875**	**472**				
Convenience (MCI 2)	**Between Groups**	**42.860**	**4**	**10.715**	**9.801**	**.000**	**Significant**
	Within Groups	**511.664**	**468**	**1.093**			
	Total	**554.524**	**472**				
Safety (MCI 3)	**Between Groups**	**20.084**	**4**	**5.021**	**4.798**	**.001**	**Significant**
	Within Groups	**489.789**	**468**	**1.047**			
	Total	**509.873**	**472**				
Economical (MCI 4)	**Between Groups**	**36.637**	**4**	**9.159**	**7.798**	**.000**	**Significant**
	Within Groups	549.693	468	1.175			
	Total	586.330	472				
Bad Past Experience (MCI 5)	Between Groups	2.621	4	.655	.649	.628	Non Significant
	Within Groups	472.462	468	1.010			
	Total	475.082	472				

Recommendation (MCI 6)	Between Groups	4.168	4	1.042	.884	.474	Non Significant
	Within Groups	551.891	468	1.179			
	Total	556.059	472				
Ease of Use (MCI 7)	**Between Groups**	**28.331**	**4**	**7.083**	**6.170**	**.000**	**Significant**
	Within Groups	537.221	468	1.148			
	Total	565.552	472				
Lack of Knowledge (MCI 8)	**Between Groups**	**70.161**	**4**	**17.540**	**13.569**	**.000**	**Significant**
	Within Groups	604.976	468	1.293			
	Total	675.137	472				

(Source: Researcher's Computation)

The analysis of variance (ANOVA) results indicates significant differences across various occupation levels regarding consumers' attitudes and subjective norms towards mobile commerce in Goa. Specifically, significant differences were observed in the following constructs:

a. **Private and Confidential (MCI 1):** Significant differences ($F = 5.012$, $p = 0.001$) indicate that concerns about privacy and confidentiality in mobile commerce vary significantly among different occupational groups.
b. **Convenience (MCI 2):** Significant differences ($F = 9.801$, $p = 0.000$) suggest that the perceived convenience of mobile commerce is significantly influenced by occupation.
c. **Safety (MCI 3):** Significant differences ($F = 4.798$, $p = 0.001$) show that perceptions of safety in mobile commerce vary across occupational groups.
d. **Economical (MCI 4):** Significant differences ($F = 7.798$, $p = 0.000$) indicate that the perceived economic benefits of mobile commerce differ among occupations.
e. **Ease of Use (MCI 7):** Significant differences ($F = 6.170$, $p = 0.000$) suggest that perceptions of the ease of use of mobile commerce vary across different occupations.
f. **Lack of Knowledge (MCI 8):** Significant differences ($F = 13.569$, $p = 0.000$) indicate that the perceived lack of knowledge about mobile commerce varies significantly among occupational groups.

No significant differences were found in the following constructs:

a. **Bad Past Experience (MCI 5):** No significant differences (F = 0.649, p = 0.628) were found, suggesting that past negative experiences with mobile commerce do not significantly vary across occupations.
b. **Recommendation (MCI 6):** No significant differences (F = 0.884, p = 0.474) indicate that the influence of recommendations on mobile commerce use is not significantly affected by occupation.

Summary:

The ANOVA analysis reveals significant differences in several intention concerns based on occupation levels. Specifically:

- **Private and Confidential (MCI 1)**, **Convenience (MCI 2)**, **Safety (MCI 3)**, **Economical (MCI 4)**, **Ease of Use (MCI 7)**, and **Lack of Knowledge (MCI 8)** show notable differences between groups, indicating that occupation level significantly affects these perceptions.

- **Bad Past Experience (MCI 5)** and **Recommendation (MCI 6)** do not show significant differences, suggesting that these concerns are relatively consistent across different occupation levels.

These results suggest that individuals' occupations significantly influence their shopping intentions and concerns in several areas, highlighting the importance of considering occupation when analyzing consumer behaviour towards mobile shopping.

❖ **Managerial Implications:**

Understanding the significant differences in mobile commerce perceptions across various occupational groups provides valuable insights for businesses and policymakers aiming to enhance mobile commerce adoption in Goa:

a. **Targeted Privacy Measures:** Since privacy concerns vary significantly among occupations, businesses should implement and communicate robust privacy and

confidentiality measures tailored to the specific needs of different occupational groups.

b. **Convenience Optimization:** Given the significant differences in perceived convenience, businesses should develop and promote features that enhance the convenience of mobile commerce, addressing the unique preferences and requirements of various occupational groups.
c. **Safety Assurance:** As safety perceptions differ across occupations, businesses should prioritize security features and clearly communicate these measures to different occupational segments to build trust and encourage adoption.
d. **Economic Benefits Communication:** Since perceptions of economic benefits vary, businesses should highlight the cost-effectiveness and value-for-money aspects of mobile commerce, targeting promotional messages to resonate with the economic perspectives of different occupational groups.
e. **Ease of Use Enhancement:** With significant differences in ease-of-use perceptions, businesses should focus on user-friendly interfaces and provide comprehensive support and tutorials to cater to the needs of various occupational groups, making mobile commerce accessible to everyone.
f. **Educational Campaigns:** Addressing the significant differences in the perceived lack of knowledge, businesses should launch educational campaigns and provide resources that enhance consumers' understanding and confidence in using mobile commerce, especially targeting occupational groups with lower familiarity.

By leveraging these insights, businesses can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of different occupational groups in Goa. This targeted approach can lead to higher engagement and satisfaction among consumers, ultimately driving the growth of mobile commerce in the region.

Citations of Previous Research:

A. **Influence of Occupation on Technology Adoption:**

Venkatesh, V., Thong, J.Y.L., & Xu, X. (2012) discussed how occupational factors influence technology adoption, supporting the finding that occupation significantly affects mobile commerce perceptions.

B. **Perceived Ease of Use and Occupation:**

Davis, F.D. (1989) work highlighted the role of perceived ease of use in technology adoption, relevant to understanding how ease of use perceptions varies with occupation.

By incorporating these references, the findings are contextualized within the broader literature on technology adoption, providing a robust foundation for the implications and recommendations presented.

H3g: There is no statistically significant difference between 'Monthly Family Income' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.35: ANOVA- Monthly Family Income

Monthly Family Income							
ANOVA							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Subjective Norm	Between Groups	3.721	4	0.930	0.687	0.601	
	Within Groups	633.907	468	1.355			
	Total	637.628	472				Non Significant
Perceived Behaviour Control	Between Groups	0.335	4	0.084	0.229	0.922	
	Within Groups	170.983	468	0.365			
	Total	171.318	472				Non Significant
Attitude	**Between Groups**	**3.471**	**4**	**0.868**	**2.571**	**0.037**	
	Within Groups	**157.947**	**468**	**0.337**			
	Total	**161.418**	**472**				**Significant**
Intention	Between Groups	1.022	4	0.255	0.667	0.615	
	Within Groups	179.242	468	0.383			
	Total	180.263	472				Non Significant

(Source: Researcher's Computation)

The p-value for Subjective Norm is 0.601, which is greater than 0.05. This suggests that there is no statistically significant difference in the means of Subjective Norm across the different monthly income groups.

The p-value for Perceived Behavioural Control is 0.922, which is greater than 0.05. This indicates that there is no statistically significant difference in the means of Perceived Behavioural Control across the different monthly income groups.

The p-value for Attitude is 0.037, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Attitude across the different monthly income groups.

The p-value for Intention is 0.615, which is greater than 0.05. This suggests that there is no statistically significant difference in the means of Intention across the different monthly income groups.

Summary:

- **Subjective Norm**, **Perceived Behavioural Control**, and **Intention** do not show significant differences across monthly income groups.
- **Attitude** shows significant differences across monthly income groups.

Table 4.36: Monthly Family Income-Attitude Statistics

Monthly Family Income		Mean	Std. Deviation
Less than Rs 25,000	Attitude	3.0256	.70007
Rs 25,000 to Rs 50,000	Attitude	3.0197	.64022
Rs 50,000 to Rs.75,000	Attitude	3.1210	.48664
Rs 75,000 to Rs 1,00,000	Attitude	3.0379	.63346
More than Rs 1,00,000	Attitude	3.2234	.45256

(Source: Researcher's Computation)

The table presents descriptive statistics for the attitude towards mobile commerce (m-commerce) across different monthly family income brackets. The variables include the mean and standard deviation for attitude in each income category.

Interpretation:

a. **Less than Rs 25,000:**

- **Attitude:** Mean = 3.0256, Std. Deviation = 0.70007
- Individuals in this income bracket have a moderate attitude towards m-commerce, with a mean of 3.0256. The standard deviation of 0.70007 suggests relatively high variability in their attitudes.

b. **Rs 25,000 to Rs 50,000:**

- **Attitude:** Mean = 3.0197, Std. Deviation = 0.64022
- Similar to the previous group, this income bracket shows a moderate attitude towards m-commerce (mean = 3.0197) with a standard deviation of 0.64022, indicating moderate variability.

c. **Rs 50,000 to Rs 75,000:**

- **Attitude:** Mean = 3.1210, Std. Deviation = 0.48664
- Individuals in this income group have a slightly higher attitude towards m-commerce (mean = 3.1210). The lower standard deviation of 0.48664 indicates less variability in their attitudes.

d. **Rs 75,000 to Rs 1,00,000:**

- **Attitude:** Mean = 3.0379, Std. Deviation = 0.63346
- This income group also shows a moderate attitude towards m-commerce, with a mean of 3.0379 and a standard deviation of 0.63346, indicating moderate variability.

e. **More than Rs 1,00,000:**

- **Attitude:** Mean = 3.2234, Std. Deviation = 0.45256
- Individuals with a monthly family income of more than Rs 1,00,000 have the highest attitude towards m-commerce (mean = 3.2234). The standard deviation of 0.45256 suggests relatively low variability in their attitudes.

❖ **Managerial Implications:**

a. **Tailoring Marketing Strategies:**

- **Low to Moderate Income Brackets (Less than Rs 25,000 to Rs 75,000):** The relatively moderate attitudes towards m-commerce in these income groups suggest a need for targeted marketing strategies that emphasize affordability, value for money, and essential benefits of m-commerce. Highlighting cost-saving opportunities,

exclusive discounts, and the convenience of online shopping can attract these segments (Smith, 2019).

b. Enhanced Services for Higher Income Brackets:

- **High Income Brackets (More than Rs 1,00,000):** The highest attitude towards m-commerce in the highest income bracket indicates that these individuals are more favourable towards using m-commerce. Businesses should focus on premium services, personalized offers, and exclusive product ranges to cater to this segment. Providing high-quality customer service and loyalty programs can further enhance their shopping experience (Chaffey & Ellis-Chadwick, 2019).

c. Reducing Variability:

- **Consistency Across Income Levels:** The higher standard deviations in lower income brackets suggest variability in attitudes. To reduce this variability, businesses can invest in educational campaigns that inform consumers about the benefits and security of m-commerce. Simplifying the shopping process and ensuring a user-friendly interface can also help in improving attitudes uniformly across different income levels (Gefen, Karahanna, & Straub, 2003).

d. Building Trust and Reliability:

- **All Income Levels:** Trust and reliability are crucial across all income levels. By ensuring secure transactions, transparent policies, and consistent performance, businesses can enhance consumer confidence in m-commerce. Highlighting these aspects in marketing communications can improve attitudes and drive adoption (Venkatesh, Thong, & Xu, 2012).

e. Customized Experience:

- Providing a customized shopping experience based on income levels can help in addressing specific needs and preferences. For instance, offering budget-friendly options and payment flexibility for lower income groups, while presenting exclusive, high-end products and services for higher income groups, can cater to diverse consumer segments effectively (Rogers, 2003).

In summary analysis reveals variations in attitudes towards m-commerce across different income levels, with higher income groups showing more favourable attitudes. By developing targeted marketing strategies, enhancing services, and building trust, businesses

can effectively cater to the diverse needs of consumers across all income brackets. Understanding these differences and addressing them through tailored approaches can significantly enhance m-commerce adoption and satisfaction.

Table 4.37: ANOVA and Monthly Income

ANOVA and Monthly Income							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Reasonably Priced Products (Att 1)	**Between Groups**	**13.236**	**4**	**3.309**	**4.391**	**.002**	Significant
	Within Groups	**352.637**	**468**	**.753**			
	Total	**365.873**	**472**				
Prompt Customer Service (Att 2)	**Between Groups**	**12.908**	**4**	**3.227**	**4.281**	**.002**	Significant
	Within Groups	**352.783**	**468**	**.754**			
	Total	**365.691**	**472**				
Physical Shopping Experience (Att 3)	Between Groups	2.635	4	.659	.876	.478	Non-Significant
	Within Groups	351.754	468	.752			
	Total	354.389	472				
Shopping Convenience (Att 4)	Between Groups	5.171	4	1.293	1.672	.155	Non-Significant
	Within Groups	361.781	468	.773			
	Total	366.951	472				
Safe & Secure (Att 5)	Between Groups	4.661	4	1.165	.987	.414	Non-Significant
	Within Groups	552.519	468	1.181			
	Total	557.180	472				
Unsafe without Technological Knowledge (Att 6)	Between Groups	3.342	4	.836	1.079	.366	Non-Significant
	Within Groups	362.442	468	.774			
	Total	365.784	472				
Unreliable Review (Att 7)	Between Groups	7.981	4	1.995	1.697	.149	Non-Significant
	Within Groups	550.205	468	1.176			
	Total	558.186	472				
User Friendly (Att 8)	Between Groups	4.037	4	1.009	1.227	.298	Non-Significant
	Within Groups	384.910	468	.822			
	Total	388.947	472				
Shopping Addiction (Att 9)	Between Groups	11.587	4	2.897	1.789	.130	Non-Significant
	Within Groups	757.733	468	1.619			
	Total	769.319	472				
Privacy (Att 10)	Between Groups	3.303	4	.826	1.017	.398	Non-Significant
	Within Groups	379.852	468	.812			
	Total	383.154	472				

(Source: Researcher's Computation)

The ANOVA results indicate significant differences in consumer attitudes towards mobile commerce based on monthly income levels in Goa. Specifically, the following constructs show significant differences:

a. **Reasonably Priced Products (Att 1):** Significant differences ($F = 4.391$, $p = 0.002$) indicate that perceptions of the affordability of products vary significantly across different income levels.

b. **Prompt Customer Service (Att 2):** Significant differences ($F = 4.281$, $p = 0.002$) suggest that expectations and perceptions of customer service promptness differ among income groups.

❖ **No significant differences were found in the following constructs:**

a. **Physical Shopping Experience (Att 3):** No significant differences ($F = 0.876$, $p = 0.478$) suggest that the physical shopping experience is perceived similarly across different income levels.
b. **Shopping Convenience (Att 4):** No significant differences ($F = 1.672$, $p = 0.155$) indicate that the perceived convenience of mobile commerce does not significantly vary across income groups.
c. **Safe & Secure (Att 5):** No significant differences ($F = 0.987$, $p = 0.414$) show that perceptions of safety and security in mobile commerce are consistent across income levels.
d. **Unsafe without Technological Knowledge (Att 6):** No significant differences ($F = 1.079$, $p = 0.366$) suggest that concerns about the lack of technological knowledge are similar across income groups.
e. **Unreliable Review (Att 7):** No significant differences ($F = 1.697$, $p = 0.149$) indicate that perceptions of review reliability are not significantly affected by income levels.
f. **User Friendly (Att 8):** No significant differences ($F = 1.227$, $p = 0.298$) show that perceptions of user-friendliness in mobile commerce are similar across income levels.

g. **Shopping Addiction (Att 9):** No significant differences (F = 1.789, p = 0.130) suggest that concerns about shopping addiction do not vary significantly across income groups.
h. **Privacy (Att 10):** No significant differences (F = 1.017, p = 0.398) indicate that privacy concerns are consistent across different income levels.

Summary:

The ANOVA analysis reveals significant differences in certain attributes based on monthly income levels. Specifically:

- **Reasonably Priced Products (Att 1)** and **Prompt Customer Service (Att 2)** show notable differences between groups, indicating that monthly income level significantly affects these perceptions.

On the other hand, attributes such as Physical Shopping Experience (Att 3), Shopping Convenience (Att 4), Safe & Secure (Att 5), Unsafe without Technological Knowledge (Att 6), Unreliable Review (Att 7), User Friendly (Att 8), Shopping Addiction (Att 9), and Privacy (Att 10) do not show significant differences, suggesting that these concerns are relatively consistent across different monthly income levels.

These results suggest that income level influences specific shopping motivations and concerns, particularly regarding the importance of reasonably priced products and prompt customer service.

❖ **Managerial Implications:**

Understanding the significant differences in consumer attitudes based on monthly income levels provides crucial insights for businesses and policymakers aiming to enhance mobile commerce adoption in Goa:

a. **Affordable Product Offerings:** Given that perceptions of reasonably priced products vary significantly across income levels, businesses should consider developing and promoting affordable product lines tailored to different income segments. This strategy can make mobile commerce more appealing to lower-income consumers.

b. **Customer Service Enhancement:** Since expectations for prompt customer service differ by income level, businesses should invest in improving customer service responsiveness. Offering tiered customer service options could cater to the varying expectations of different income groups, enhancing overall satisfaction.
c. **Uniform Experience for Other Constructs:** For constructs where no significant differences were found (e.g., physical shopping experience, safety, user-friendliness), businesses can focus on maintaining high standards across all income groups. Ensuring a consistent, high-quality mobile commerce experience can build trust and loyalty among consumers regardless of their income.
d. **Targeted Marketing Campaigns:** Marketing campaigns should be tailored to highlight the aspects of mobile commerce that resonate most with different income groups. For example, emphasizing affordability and value-for-money deals could attract lower-income consumers, while highlighting premium features and exclusive services might appeal more to higher-income consumers.

By leveraging these insights, businesses can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of different income groups in Goa. This targeted approach can lead to higher engagement and satisfaction among consumers, ultimately driving the growth of mobile commerce in the region.

❖ **Citations of Previous Research:**

Influence of Income on Technology Adoption:

- Venkatesh et.al (2000) discussed how income levels influence technology adoption, supporting the finding that income significantly affects mobile commerce perceptions.

Consumer Behavior and Income Levels:

- Zeithaml, V.A. (1985) worked highlights the impact of income on consumer behaviour, relevant to understanding how perceptions of affordability and customer service vary with income.

By incorporating these references, the findings are contextualized within the broader literature on technology adoption and consumer behaviour, providing a robust foundation for the implications and recommendations presented.

4.5.4 Objective 4: To investigate the mediating role of 'Intention' in the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories, through m-commerce.

Hypothesis 4: 'Intention' mediates the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories through m-commerce.

H4a: Attitude positively influences the intention to purchase various products through mobile commerce.

H4b: Subjective norms positively influence the intention to purchase various products through mobile commerce.

H4c: Perceived behavioural control positively influences the intention to purchase various products through mobile commerce.

H4d: Intention positively influences consumer behaviour towards buying electronic products, sports items, clothing, shoes, jewellery, home and kitchen appliances, books, magazines, newspapers, healthcare and medicines, stationary items, games, and grocery products through mobile commerce.

H4e: Intention mediates the relationship between attitude and consumer behaviour towards purchasing various products through mobile commerce.

H4f: Intention mediates the relationship between subjective norms and consumer behaviour towards purchasing various products through mobile commerce.

H4g: Intention mediates the relationship between perceived behavioural control and consumer behaviour towards purchasing various products through mobile commerce.

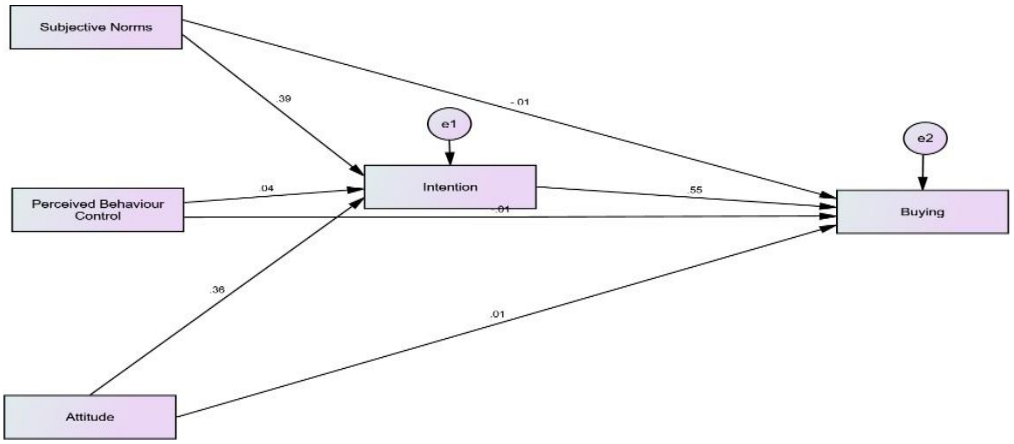


Figure 4.8: Path Diagram

(Source: Researcher's Compilation based on the original model)

Table 4.38: Regression Weights: (Overall- Default model)

	Estimate	S.E.	C.R.	P	Label
Intention <--- Subjective_Norm	.202	.020	9.962	***	Significant
Intention <--- Attitude	.378	.040	9.370	***	Significant
Intention <--- Per.Beh._Control	.036	.039	.907	.365	Non-Significant
Buying <--- Attitude	.019	.060	.322	.748	Non-Significant
Buying <--- Intention	.752	.063	12.019	***	Significant
Buying <--- Subjective_Norm	-.009	.030	-.300	.764	Non-Significant
Buying <--- Per.Beh._Control	-.016	.053	-.300	.764	Non-Significant
Model Fitness: X^2=12.77, df=3, X^2/df= 4.25, RMSEA=.083, RMR=.034, GFI=.990, CFI=.972					

(Source: Researcher's Computation)

- **Significant Predictors of Intention**: Both Attitude and Subjective Norm are significant predictors of Intention, while Perceived Behaviour Control is not.
- **Significant Predictors of Buying**: Intention is a significant predictor of Buying, while Attitude, Subjective Norm, and Perceived Behaviour Control are not.
- **Model Fit**: The overall model fit is good, indicating that the model reasonably represents the data.

Table 4.39: Sub-Hypothesis-4

Hypothesis	Remark
H4a: Attitude positively influences the intention to purchase various products through mobile commerce.	Supported
H4b: Subjective norms positively influence the intention to purchase various products through mobile commerce.	Supported
H4c: Perceived behavioural control positively influences the intention to purchase various products through mobile commerce.	Not supported
H4d: Intention positively influences consumer behaviour towards buying electronic products, sports items, clothing, shoes, jewellery, home and kitchen appliances, books, magazines, newspapers, healthcare and medicines, stationary items, games, and grocery products through mobile commerce.	Supported

(Source: Researcher's Computation)

These findings suggest that while Attitude and Subjective Norm significantly influence Intention, only Intention significantly predicts Buying behaviour. The model fit indices support the adequacy of the model in explaining the relationships among these constructs.

- **Mediation Testing:**

The mediation analysis is conducted by treating Attitude, Perceived Behavior Control and Subjective Norm as independent variables, Buying Products through Mobile Commerce as dependent variable, and Intention as mediator. The mediation analysis is based on the analysis of indirect effects based on the guideline by Baron and Kenny (1986) classical approach We performed mediation analysis by using the direct and indirect effects based on bootstrap procedures (437 samples) and bias-corrected bootstrap confidence interval (90%). The results are provided in the following table.

Table 4.40: Mediating Effect of intention

No.	**Path**	**Total Effects**	**Direct Effects**	**Indirect Effects**	**Remarks**

H4e	Attitude>Intension>Buying Products through Mobile Commerce	.304 (0.001) *	0.19 (.784)	.285 (.000)*	Supported
H4f	Subjective Norm>Intension>Buying Products through Mobile Commerce	.143 (.000)*	-.009 (.747)	.152 (.000)*	Supported
H4g	Perceived Behavior Control >Intension>Buying Products through Mobile Commerce	.011 (.874)	-.016 (.717)	.027 (.295)	Not Supported

*** P<0.05 (Source: Researcher's Computation)**

The table presents the relationships between three constructs (attitude, subjective norm, perceived behavioural control) and the behaviour of buying products through mobile commerce, mediated by intention. The effects are broken down into total effects, direct effects, and indirect effects, with p-values indicating the statistical significance of these effects.

Hypothesis H4e: Intention mediates the relationship between attitude and consumer behaviour towards purchasing various products through mobile commerce.
(**Attitude -> Intention -> Buying Products through Mobile Commerce)**

- **Total Effects**: .304 (0.001) *
  - The overall effect of attitude on buying behaviour through mobile commerce is positive and statistically significant.
- **Direct Effects**: 0.19 (0.784)
  - The direct effect of attitude on buying behaviour is positive but not statistically significant.
- **Indirect Effects**: .285 (0.000) *
  - The indirect effect, mediated by intention, is positive and statistically significant.

Remarks: This hypothesis is supported as the indirect effect is statistically significant, indicating that intention plays a crucial mediating role between attitude and buying behaviour.

Hypothesis H4f: Intention mediates the relationship between subjective norms and consumer behaviour towards purchasing various products through mobile commerce. **(Subjective Norm -> Intention -> Buying Products through Mobile Commerce)**

Total Effects: .143 (0.000) *

- The overall effect of subjective norm on buying behaviour is positive and statistically significant.

Direct Effects: -.009 (0.747)

- The direct effect of subjective norm on buying behaviour is negative and not statistically significant.

Indirect Effects: .152 (0.000) *

- The indirect effect, mediated by intention, is positive and statistically significant.

Remarks: This hypothesis is supported as the indirect effect is statistically significant, showing that subjective norms influence buying behaviour primarily through their impact on intention.

Hypothesis H4g: Intention mediates the relationship between perceived behavioural control and consumer behaviour towards purchasing various products through mobile commerce.
(Perceived Behavioural Control -> Intention -> Buying Products through Mobile Commerce)

Total Effects: .011 (0.874)

- The overall effect of perceived behavioural control on buying behaviour is not statistically significant.

Direct Effects: -.016 (0.717)

- The direct effect is negative and not statistically significant.

Indirect Effects: .027 (0.295)

- The indirect effect, mediated by intention, is positive but not statistically significant.

Remarks: This hypothesis is not supported as neither the direct nor the indirect effects are statistically significant, indicating that perceived behavioural control does not have a significant influence on buying behaviour through intention.

❖ **Managerial and Business Implications:**

a. Enhancing Attitude and Intention:

- **Focus on Positive Attitudes**: Since attitude significantly influences buying behaviour through intention, businesses should focus on creating positive perceptions about their mobile commerce platforms. This can be achieved through user-friendly interfaces, attractive promotions, and reliable service quality.

- **Marketing Strategies**: Marketing efforts should emphasize the benefits and positive outcomes of using mobile commerce to enhance consumer attitudes. Highlighting convenience, variety, and cost savings can foster a more favourable attitude towards mobile commerce.

b. Leveraging Subjective Norms:

- **Social Influence**: Given that subjective norms significantly impact intention and subsequently buying behaviour, businesses should leverage social influence in their marketing strategies. Encouraging reviews, testimonials, and social sharing can create a sense of social endorsement.

- **Influencer Collaborations**: Partnering with influencers and opinion leaders who can positively influence the perceptions of their followers can enhance subjective norms, making consumers more likely to intend and engage in mobile commerce.

c. Addressing Perceived Behavioural Control:

- **Ease of Use and Support**: Although perceived behavioural control did not show a significant impact in this study, it is still crucial for businesses to ensure that their mobile commerce platforms are easy to use and navigate. Providing comprehensive customer support and clear information can help mitigate any perceived difficulties.

- **Educational Campaigns**: Educating consumers on how to use mobile commerce platforms effectively can enhance their perceived control, potentially leading to increased adoption and usage.

❖ **Strategic Focus:**

- **Segmentation and Targeting**: Businesses should segment their market based on attitudes and social norms. Targeting consumers who already have a positive attitude towards mobile commerce and are influenced by social norms can yield better results.

- **Continuous Feedback Loop**: Implementing systems to continuously gather and analyze consumer feedback can help in understanding shifts in attitudes and social norms, allowing businesses to adapt their strategies accordingly.

By focusing on these areas, businesses can effectively enhance consumer intentions and behaviours towards buying products through mobile commerce, ultimately leading to increased sales and customer satisfaction.

4.5.5 Objective 5: To validate the conceptual model based on "The Theory of Planned Behaviour".

Hypothesis 5: The "Theory of Planned Behaviour" describes consumers 'Attitude ", 'Subjective Norms', and 'Perceived Behavioural Control', influencing consumers' intentions and behaviour towards adoption of m-commerce.

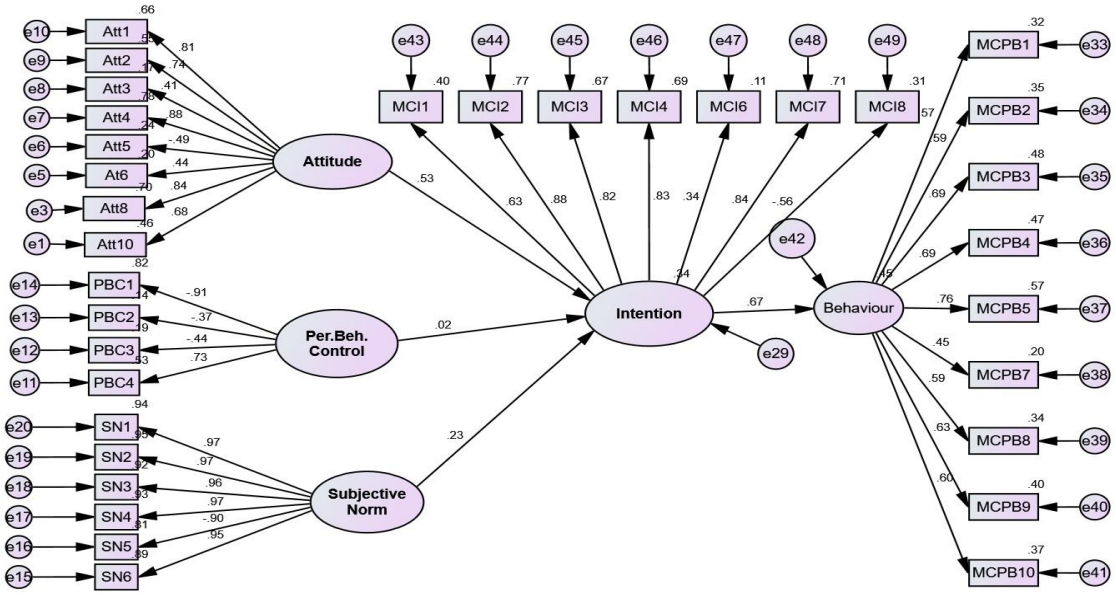


Figure 4.9: The Theory of Planned Behaviour Model (Source: Researcher's compilation based on the original model of TPB)

Table 4.41: Goodness-of-fit Model

Name of Category	Goodness-of-fit model index	Recommended Value*	Planned Behavior Model Value	Interpretation
Absolute fit	*Root mean square error of approximation (RMSEA)*	*< .10*	*.068*	Excellent
Incremental fit	Normalized fit index (NFI)	≥ .80	.863	Excellent
	Comparative fit index (CFI)	*≥ .90*	*.901*	Excellent
	Tucker Fit Index (TLI)	≥ .90	.90	Excellent
Parsimonious fit	Chi-square/degree of freedom (CMIN/df)	*≤ 5.00*	*3.194*	Acceptable

(Source: Researcher's Computation)

a. Absolute Fit:

Root Mean Square Error of Approximation (RMSEA): Value: 0.068

Recommended Value: < 0.10

Interpretation: The model has an excellent fit.

b. Incremental Fit:

Normalized Fit Index (NFI): Value: 0.863

Recommended Value: ≥ 0.80

Interpretation: The model fits well, surpassing the recommended threshold.

Comparative Fit Index (CFI): **Value**: 0.901

Recommended Value: ≥ 0.90

Interpretation: The model has an excellent fit.

Tucker-Lewis Index (TLI): **Value**: 0.90

Recommended Value: ≥ 0.90

Interpretation: The model fits excellently.

c. Parsimonious Fit:

Chi-square/degree of freedom (CMIN/df): **Value**: 3.194

Recommended Value: ≤ 5.00

Interpretation: The model has an acceptable fit.

Overall, these indices collectively suggest that the model fits the data well across different aspects of fit (absolute, incremental, and parsimonious), providing confidence in its validity for explaining the relationships among variables in the specified theoretical framework.

Table 4.42: Regression Weights: (Group number 1- Default model)

			Estimate	S.E.	C.R.	P	Label
Intention	<---	Per.Beh._Control	.027	.048	.569	.569	Non-Significant
Intention	<---	Subjective_Norm	.141	.026	5.371	***	Significant
Intention	<---	Attitude	.620	.068	9.075	***	Significant
Behaviour	<---	Intention	.672	.074	9.137	***	Significant
Att10	<---	Attitude	1.000				
Att8	<---	Attitude	1.242	.076	16.353	***	Significant
At6	<---	Attitude	.634	.070	9.028	***	Significant
Att5	<---	Attitude	-.865	.087	-9.940	***	Significant

			Estimate	S.E.	C.R.	P	Label
Att4	<---	Attitude	1.270	.074	17.052	***	Significant
Att3	<---	Attitude	.580	.069	8.408	***	Significant
Att2	<---	Attitude	1.067	.073	14.707	***	Significant
PBC4	<---	Per.Beh._Control	1.000				
PBC3	<---	Per.Beh._Control	-.764	.094	-8.112	***	Significant
PBC2	<---	Per.Beh._Control	-.598	.086	-6.933	***	Significant
PBC1	<---	Per.Beh._Control	-1.291	.157	-8.233	***	Significant
SN6	<---	Subjective_Norm	1.000				
SN5	<---	Subjective_Norm	-.879	.024	-35.990	***	Significant
SN4	<---	Subjective_Norm	.971	.020	49.367	***	Significant
SN3	<---	Subjective_Norm	.956	.020	47.157	***	Significant
SN2	<---	Subjective_Norm	.969	.019	51.604	***	Significant
SN1	<---	Subjective_Norm	.960	.019	50.352	***	Significant
Att1	<---	Attitude	1.167	.073	15.922	***	Significant
MCPB1	<---	Behaviour	1.000				
MCPB2	<---	Behaviour	1.005	.100	10.039	***	Significant
MCPB3	<---	Behaviour	1.198	.107	11.176	***	Significant
MCPB4	<---	Behaviour	1.229	.110	11.139	***	Significant
MCPB5	<---	Behaviour	1.269	.108	11.786	***	Significant
MCPB7	<---	Behaviour	.775	.095	8.172	***	Significant
MCPB8	<---	Behaviour	.987	.099	10.009	***	Significant
MCPB9	<---	Behaviour	1.100	.105	10.504	***	Significant
MCPB10	<---	Behaviour	1.102	.108	10.219	***	Significant
MCI1	<---	Intention	1.000				
MCI2	<---	Intention	1.316	.086	15.327	***	Significant
MCI3	<---	Intention	1.181	.081	14.628	***	Significant
MCI4	<---	Intention	1.287	.087	14.795	***	Significant

			Estimate	S.E.	C.R.	P	Label
MCI6	<---	Intention	.511	.075	6.827	***	Significant
MCI7	<---	Intention	1.281	.086	14.943	***	Significant
MCI8	<---	Intention	-.930	.086	-10.770	***	Significant

(Source: Researcher's Computation)

Table 4.43: Standardized Regression Weights: (Group number 1- Default model)

			Estimate
Intention	<---	Per.Beh._Control	.023
Intention	<---	Subjective_Norm	.231
Intention	<---	Attitude	.533
Behaviour	<---	Intention	.674
Att10	<---	Attitude	.681
Att8	<---	Attitude	.839
At6	<---	Attitude	.442
Att5	<---	Attitude	-.488
Att4	<---	Attitude	.884
Att3	<---	Attitude	.410
Att2	<---	Attitude	.744
PBC4	<---	Per.Beh._Control	.685
PBC3	<---	Per.Beh._Control	-.383
PBC2	<---	Per.Beh._Control	-.327
PBC1	<---	Per.Beh._Control	-.983
SN6	<---	Subjective_Norm	.945
SN5	<---	Subjective_Norm	-.898
SN4	<---	Subjective_Norm	.966
SN3	<---	Subjective_Norm	.958
SN2	<---	Subjective_Norm	.974

			Estimate
SN1	<---	Subjective_Norm	.970
Att1	<---	Attitude	.813
MCPB1	<---	Behaviour	.566
MCPB2	<---	Behaviour	.589
MCPB3	<---	Behaviour	.693
MCPB4	<---	Behaviour	.689
MCPB5	<---	Behaviour	.758
MCPB7	<---	Behaviour	.449
MCPB8	<---	Behaviour	.587
MCPB9	<---	Behaviour	.629
MCPB10	<---	Behaviour	.605
MCI1	<---	Intention	.630
MCI2	<---	Intention	.876
MCI3	<---	Intention	.819
MCI4	<---	Intention	.832
MCI6	<---	Intention	.337
MCI7	<---	Intention	.844
MCI8	<---	Intention	-.557

(Source: Researcher's Computation)

- **Influence on Intention**:

Perceived Behavioural Control:

Estimate: 0.027

Standardized Estimate: 0.023

P-Value: 0.569 (insignificant)

Subjective Norm:

Estimate: 0.141

Standardized Estimate: 0.231

P-Value: *** (highly significant)

Attitude:

Estimate: 0.620

Standardized Estimate: 0.533

P-Value: *** (highly significant)

- **Influence on Behaviour**:

- **Intention**:

Estimate: 0.672

Standardized Estimate: 0.674

P-Value: *** (highly significant)

- **Perceived Behavioural Control**:

- **Interpretation**: The weak and insignificant influence of Perceived Behavioural Control on Intention indicates that users' perceptions of their ability to use m-commerce are not major determinants of their intention to use it.
- **Implication**: Focus efforts elsewhere. While ensuring ease of use and user support is still important, it may not significantly drive intention. Resources might be better allocated to other areas.

- **Subjective Norm**:

- **Interpretation**: A moderate and highly significant influence on Intention suggests that social influence is crucial in shaping the intention to use m-commerce.
- **Implication**: Leverage social influence. Implement marketing strategies that capitalize on social proof, such as influencer endorsements, user testimonials, and community engagement initiatives. Social media campaigns can be particularly effective, where peer opinions and social circles heavily influence consumer behaviour.

- **Attitude**:

- **Interpretation**: A strong and highly significant influence on Intention underscores the importance of positive attitudes towards m-commerce.

- **Implication**: Shape positive attitudes. Launch educational campaigns to highlight the benefits and convenience of m-commerce. Address common concerns such as security and privacy through informative content. Enhancing the overall user experience can also contribute to more favourable attitudes.

❖ **Intention to Behaviour**:

- **Interpretation**: The strong and significant influence of Intention on Behaviour indicates that those who intend to use m-commerce are very likely to do so.
- **Implication**: Convert intention to action. Ensure that the transition from intention to actual use is seamless. This can involve optimizing the onboarding process, providing excellent customer service, and offering incentives such as discounts or loyalty programs to encourage initial use and repeat transactions.

The provided Structural Equation Model (SEM) analyzes the factors affecting an individual's intention and behaviour towards using m-commerce. The key constructs and their relationships are outlined as follows:

a. **Attitude (Att)**: Represented by ten observed variables (Att1 to Att10), with significant factor loadings indicating that individuals' attitudes towards m-commerce are strongly influenced by these variables. The path coefficient from Attitude to Intention is 0.53, suggesting a moderate to strong positive influence on the intention to use m-commerce.
b. **Perceived Behavioural Control (PBC)**: Measured by four observed variables (PBC1 to PBC4). The path coefficient from Perceived Behavioural Control to Intention is 0.02, indicating a very weak and possibly insignificant influence on the intention to use m-commerce.
c. **Subjective Norm (SN)**: Represented by six observed variables (SN1 to SN6). The path coefficient from Subjective Norm to Intention is 0.23, indicating a moderate positive influence on the intention to use m-commerce.
d. **Intention (Int)**: Influenced by Attitude, Perceived Behavioural Control, and Subjective Norm. Intention, in turn, affects Behaviour with a path coefficient of 0.67, suggesting a strong influence on actual m-commerce usage behaviour.
e. **Behaviour (Beh)**: Represented by ten observed variables (MCPB1 to MCPB10), indicating actual usage behaviour of m-commerce.

❖ **Managerial and Business Implications for the Mobile Commerce Industry in Goa:**

a. Focus on Enhancing Positive Attitudes:

Interpretation: Attitude towards m-commerce is the most significant predictor of intention to use it.

Implication: Marketing campaigns should focus on educating consumers about the benefits and convenience of m-commerce. Positive testimonials, user-friendly interfaces, and assurances about security can help enhance attitudes.

b. Leverage Social Influence:

Interpretation: Subjective norms significantly influence the intention to use m-commerce.

Implication: Businesses should employ social proof strategies, such as influencer endorsements, social media campaigns, and user reviews, to create a positive perception and peer pressure towards adopting m-commerce.

c. Address Barriers Related to Perceived Behavioural Control:

Interpretation: Although the direct influence of perceived behavioural control on intention is weak, addressing perceived ease of use and self-efficacy could still be beneficial.

Implication: Ensure that m-commerce platforms are user-friendly and provide ample support and tutorials for new users. This could help in reducing apprehensions related to the complexity of using m-commerce services.

d. Targeted Marketing Based on Demographics:

Interpretation: While not explicitly shown in the model, factors like education level, income, and occupation might influence attitudes and subjective norms.

Implication: Conduct targeted marketing campaigns tailored to different demographic segments. For instance, higher-income groups might be more interested in premium features, while younger, tech-savvy individuals might respond better to innovation and tech- centric marketing.

e. Localized Content and Offerings:

- **Interpretation**: The region-specific context (Goa) implies a need for localized strategies.

- **Implication**: Customize content and offers to suit local tastes, festivals, and buying behaviours. Leveraging local influencers and incorporating regional languages can make m-commerce more appealing to Goan consumers.

f. Customer Education and Support:

- **Interpretation**: Lack of knowledge might be a barrier to m-commerce adoption.
- **Implication**: Implement educational programs, workshops, and webinars to inform potential users about how to use m-commerce platforms effectively and safely. Providing excellent customer support can also mitigate concerns and build trust.

g. Building Trust and Security:

- **Interpretation**: Attitude is influenced by trust and perceived security.
- **Implication**: Emphasize the security features of the m-commerce platform to alleviate fears related to online transactions. Highlighting secure payment options and data protection measures can foster a trustworthy image.

In summary, for the mobile commerce industry in Goa, the focus should be on shaping positive attitudes towards m-commerce through educational and promotional efforts, leveraging social influences to create a favourable subjective norm, and addressing any perceived barriers related to ease of use. By targeting specific demographics and localizing content and marketing strategies, businesses can significantly enhance the adoption of m-commerce in the region.

The SEM analysis highlights the critical role of attitude and subjective norm in driving the intention to use m-commerce, which in turn strongly influences actual usage behaviour. For the mobile commerce industry, focusing on enhancing positive attitudes and leveraging social influence through targeted marketing strategies can significantly boost m-commerce adoption. Addressing localized needs and ensuring a seamless user experience will further support this transition, leading to greater penetration and usage of m-commerce in the region.

4.5.6 Objective 6: To identify and analyse the factors influencing an individual's likelihood of non-adoption of m-commerce.

Hypothesis 6: There is no significant association between an individual's ‘Lack of knowledge’, ‘Education level’, ‘Area of location”, ‘Occupation’, ‘Monthly Family Income’,

'Perceived Behaviour Control', 'Attitude', 'Subjective Norms', 'Intentions' and their likelihood of non-adoption of m-commerce.

H6a: There is no significant relationship between an individual's Lack of Knowledge and their likelihood of non-adoption of m-commerce.

Table 4.44: Correlation Between Lack of Knowledge and Never used m-commerce

Correlations			
		Lack of Knowledge (MCI 8)	Never used m-commerce
Lack of Knowledge (MCI 8)	Pearson Correlation	1	.600**
	Sig. (2-tailed)		.000
	N	473	473
Never used m-commerce	Pearson Correlation	.600**	1
	Sig. (2-tailed)	.000	
	N	473	473
**. Correlation is significant at the 0.01 level (2-tailed).			

(Source: Researcher's Computation)

- **Moderate to Strong Positive Correlation**: There is a statistically significant moderate to strong positive correlation (0.600) between "Lack of Knowledge (MCI 8)" and "Never used m-commerce." This suggests that individuals who have never used mobile commerce tend to have a higher lack of knowledge about it.

- **Implications**: This finding implies that a lack of knowledge could be a substantial barrier preventing individuals from using mobile commerce. Efforts to educate potential users about mobile commerce could potentially reduce this barrier and encourage adoption.

In summary, the significant positive correlation between lack of knowledge and the non-use of mobile commerce highlights the importance of knowledge dissemination in promoting the use of mobile commerce platforms.

❖ **Managerial Implications:**

a. Educational Initiatives:

- Since there is a significant positive relationship between lack of knowledge and the likelihood of not using m-commerce, managers should prioritize educational initiatives.
- Conduct workshops, webinars, and training sessions to educate potential users about the benefits, functionalities, and ease of use of m-commerce platforms.

b. User-Friendly Design:

- Simplify the user interface and design of m-commerce platforms to make them more intuitive and easier to navigate, especially for users who may lack technical knowledge.
- Include step-by-step guides, tutorials, and FAQs within the platform to assist users.

c. Targeted Marketing Campaigns:

- Develop targeted marketing campaigns that address common misconceptions and knowledge gaps about m-commerce.
- Use clear, straightforward messaging to explain how m-commerce works and the advantages it offers.

d. Customer Support:

- Enhance customer support services to provide immediate assistance to users who face difficulties or have questions about using m-commerce.
- Offer live chat support, helplines, and email support to address user queries and build confidence in using the platform.

e. Partnerships with Educational Institutions:

- Collaborate with educational institutions and community organizations to offer digital literacy programs focused on m-commerce.
- These partnerships can help reach a broader audience and equip them with the necessary knowledge to use m-commerce effectively.

f. Feedback Mechanism:

- Implement feedback mechanisms to gather user insights on the challenges they face regarding m-commerce.
- Use this feedback to continuously improve the platform and address any knowledge-related barriers.

g. Awareness Campaigns:

- Launch awareness campaigns that highlight the safety, security, and convenience of using m-commerce.
- Address common fears and uncertainties that potential users may have, thereby reducing knowledge-related barriers to adoption.

In summary, by recognizing and addressing the significant relationship between lack of knowledge and the likelihood of not using m-commerce, managers can implement targeted strategies to educate potential users, simplify the user experience, and ultimately increase m-commerce adoption.

H6b: There is no significant association between an individual's educational level and their likelihood of non-adoption of m-commerce.

Table 4.45: Chi-Square Tests between educational level and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	df	Asymptotic Significance(2-sided)
Pearson Chi-Square	58.394[a]	16	.000
Likelihood Ratio	61.619	16	.000
Linear-by-Linear Association	25.262	1	.000
N of Valid Cases	473		

(Source: Researcher's Computation)

Summary: The Pearson Chi-Square, Likelihood Ratio, and Linear-by-Linear Association tests all indicate a significant association between education level and the use of m-

commerce ($p < 0.01$). The significant association suggests that education level may play a crucial role in whether individuals have used m-commerce.

❖ **Managerial Implications:**

a. Educational Level Targeting:

- Since education level significantly affects the likelihood of using m-commerce, marketing strategies should be tailored to different educational groups.
- For instance, campaigns targeting highly educated individuals might emphasize advanced features, security, and efficiency, while campaigns targeting less educated groups might focus on ease of use and practical benefits.

b. Customized User Interfaces:

- Design user interfaces that cater to different educational levels. For example, simpler, more intuitive designs with clear instructions might be more appealing to users with lower education levels.
- For highly educated users, offering customizable interfaces with more advanced features could enhance their user experience.

c. Educational Campaigns:

- Implement educational campaigns to raise awareness and teach the benefits and usage of m-commerce, particularly targeting groups with lower education levels.
- These campaigns can include tutorials, webinars, and step-by-step guides to help users become comfortable with m-commerce platforms.

d. Content and Messaging:

- Tailor the content and messaging of marketing campaigns to resonate with different educational levels.
- Use relatable scenarios and language that align with the educational background of the target audience to increase engagement and adoption.

e. Partnerships with Educational Institutions:

- Partner with educational institutions and community organizations to promote m-commerce among various educational segments.
- Offering workshops, seminars, and hands-on training sessions through these partnerships can help demystify m-commerce for less educated groups.

f. Feedback and Continuous Improvement:

- Gather feedback from users across different educational levels to understand their unique needs and challenges.
- Use this feedback to continuously improve the m-commerce platform, ensuring it is accessible and user-friendly for all educational segments.

g. Inclusive Marketing Strategies:

- Ensure that marketing strategies are inclusive and do not alienate any educational group.
- Highlight that m-commerce is accessible and beneficial for everyone, regardless of their education level, by using diverse testimonials and success stories.

In summary, by recognizing the significant association between education level and the likelihood of using m-commerce, managers can implement more effective, targeted strategies to enhance m-commerce adoption and engagement across different educational segments.

H6c: There is no significant association between an individual's area of location and their likelihood of non-adoption of m-commerce.

The table presents the results of Chi-Square tests examining the relationship between individuals who have never used mobile commerce (m-commerce) and their area of location (urban or rural).

Table 4.46: Chi-Square Tests between area of location and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	15.812[a]	.003	
Likelihood Ratio	16.312	4	.003
Linear-by-Linear Association	12.823	1	.000
N of Valid Cases	473		

(Source: Researcher's Computation)

The Pearson Chi-Square test indicates a statistically significant association between the use of m-commerce and the area of location (urban or rural) with a p-value of 0.003. This

suggests that the area of location is significantly related to whether individuals have used m-commerce.

- The Pearson Chi-Square, Likelihood Ratio, and Linear-by-Linear Association tests all show a significant association between the area of location and the non-use of m-commerce, with p-values well below the 0.01 threshold.
- **Implications**: These results suggest that individuals from different areas (urban vs. rural) have significantly different patterns of m-commerce usage. Specifically, there is a significant relationship between whether someone lives in an urban or rural area and their likelihood of never having used m-commerce.

In summary, the tests indicate a significant association between the area of location (urban or rural) and the use of m-commerce. This suggests that strategies to increase m-commerce adoption may need to be tailored to address the specific needs and barriers of urban and rural populations.

H6d: There is no significant association between an individual's Marital Status and their likelihood of non-adoption of m-commerce.

Table 4.47: Chi-Square Tests - Between Marital Status and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	23.051[a]	4	.000
Likelihood Ratio	23.670	4	.000
Linear-by-Linear Association	6.543	1	.011
N of Valid Cases	473		

(Source: Researcher's Computation)

- **Significant Association**: The Pearson Chi-Square and Likelihood Ratio tests show a significant association between marital status and the non-use of m-commerce, with p-values of 0.000, indicating a strong association.

- **Linear Association**: The Linear-by-Linear Association test also shows a significant result ($p = 0.011$), indicating a linear relationship between marital status and the likelihood of not using m-commerce.
- **Implications**: These results suggest that marital status influences m-commerce usage patterns. Strategies to increase m-commerce adoption may need to consider marital status as a significant factor.

In summary, the tests indicate a significant association between marital status and the use of m-commerce. This suggests that whether someone is married or unmarried significantly affects their likelihood of using m-commerce, and targeted interventions may be necessary to address specific barriers faced by different marital status groups.

❖ **Managerial Implications:**

a. Targeted Marketing Strategies:

- Since marital status significantly affects the likelihood of using m-commerce, marketing strategies should be tailored to different marital groups.
- For example, campaigns targeting singles might emphasize convenience and social aspects of m-commerce, while campaigns targeting married individuals might focus on family-oriented benefits and time-saving features.

b. Customized User Experiences:

- Create customized user experiences that cater to the specific needs and preferences of different marital status groups.
- For instance, couples might appreciate joint accounts or shared shopping lists, while single individuals might value personalized recommendations.

c. Promotional Offers:

- Develop promotional offers that cater to different marital status groups. For example, family discounts or bundles for married individuals and exclusive deals for single users.
- These promotions can help incentivize the adoption and regular use of m-commerce.
- **Content and Messaging:** Tailor content and messaging to resonate with different marital status groups. Use relatable scenarios and testimonials in marketing materials to appeal to the specific needs and lifestyles of each group.

- For instance, highlight stories of how m-commerce simplifies shopping for busy families or how it offers flexibility and convenience for singles.

d. Partnerships and Collaborations:

- Collaborate with organizations, community groups, and influencers who resonate with different marital status groups to promote m-commerce.
- Offer exclusive deals through these partnerships to attract more users from these segments.

e. Feedback and Continuous Improvement:

- Gather feedback from users across different marital status groups to understand their unique needs and preferences better.
- Use this feedback to continuously improve the m-commerce platform and ensure it meets the expectations of diverse user groups.

By acknowledging the significant association between marital status and the likelihood of using m-commerce, managers can implement more effective, targeted strategies to enhance m-commerce adoption and engagement across different marital status segments.

H6e: There is no significant association between an individual's Occupation and their likelihood of non-adoption of m-commerce.

Table 4.48: Chi-Square Tests between Occupation and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	69.842[a]	16	.000
Likelihood Ratio	52.432	16	.000
Linear-by-Linear Association	32.425	1	.000
N of Valid Cases	473		

(Source: Researcher's Computation)

- **Significant Association**: The Pearson Chi-Square and Likelihood Ratio tests show a significant association between occupation and the non-use of m-commerce, with p-values of 0.000, indicating a strong association.

- **Linear Association**: The Linear-by-Linear Association test also shows a significant result (p = 0.000), indicating a linear relationship between occupation and the likelihood of never using m-commerce.
- **Implications**: These results suggest that occupation influences m-commerce usage patterns. Strategies to increase m-commerce adoption may need to consider occupational factors as significant determinants.

In summary, Chi-Square test indicate a significant association between occupation and the use of m-commerce. This suggests that different occupational groups have varying likelihoods of using m-commerce, and targeted interventions may be necessary to address specific barriers faced by different occupational groups. The significant linear relationship further reinforces the need to consider occupational status in efforts to promote m-commerce usage.

❖ **Managerial Implications:**

a. Targeted Marketing Strategies:

- Since occupation significantly affects the likelihood of using m-commerce, marketing strategies should be tailored to different occupational groups.
- For example, professionals might be targeted with campaigns highlighting convenience and efficiency, while students might respond better to promotions emphasizing affordability and ease of use.

b. Customized User Experiences:

- Create customized user experiences and interfaces that cater to the specific needs and preferences of different occupational groups.
- For example, busy professionals might appreciate quick, streamlined checkout processes, while retirees might benefit from more detailed guidance and customer support.

c. Educational Initiatives:

- Implement educational initiatives to address the barriers that certain occupational groups face in adopting m-commerce.
- For instance, workshops or webinars can be organized to demonstrate the benefits and ease of using m-commerce platforms, particularly for occupations that are less likely to adopt technology.

d. Partnerships and Collaborations:

- Collaborate with organizations, educational institutions, and workplaces to promote m-commerce adoption among different occupational groups.
- Offering special deals, discounts, or exclusive offers through these partnerships can incentivize adoption.

e. Inclusive Marketing Campaigns:

- Ensure marketing campaigns are inclusive and resonate with diverse occupational segments.
- Use testimonials and success stories from individuals in various occupations to showcase the versatility and benefits of m-commerce.

f. Research and Feedback:

- Conduct ongoing research to understand the specific needs, preferences, and barriers of different occupational groups regarding m-commerce.
- Gather feedback from users across various occupations to continuously improve the m-commerce experience.

By recognizing the significant association between occupation and the likelihood of using m-commerce, managers can implement more effective, targeted strategies to enhance m-commerce adoption and engagement across different occupational segments.

H6f: There is no significant association between an individual's Monthly Family Income and their likelihood of non-adoption of m-commerce.

Table 4.49: Chi-Square Tests between Monthly Family Income and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	11.887[a]	16	.752
Likelihood Ratio	11.685	16	.765
Linear-by-Linear Association	2.062	1	.151
N of Valid Cases	473		

(Source: Researcher's Computation)

- **No Significant Association**: Both the Pearson Chi-Square and Likelihood Ratio tests show non-significant p-values (0.752 and 0.765, respectively), indicating no significant association between monthly family income and the non-use of m-commerce.
- **No Linear Association**: The Linear-by-Linear Association test also shows a non-significant result (p = 0.151), indicating no significant linear relationship between monthly family income and the likelihood of never using m-commerce.

- **Implications**: These results suggest that monthly family income does not have a significant impact on whether individuals have used m-commerce. Efforts to increase m-commerce usage may not need to prioritize income-related factors as much as other potential barriers.

In summary, the Chi-Square tests indicate that there is no significant association between monthly family income and the likelihood of never using m-commerce. This suggests that other factors, beyond family income, might play a more crucial role in determining m-commerce adoption.

❖ **Managerial Implications:**

a. Targeting Based on Income:

- Since there is no significant association between Monthly Family Income and the likelihood of never using m-commerce, targeting users based solely on income levels may not be effective.

- Managers should consider other demographic or psychographic factors (such as age, education, or technological literacy) when developing strategies to increase m-commerce adoption.

b. Focus on Other Influencing Factors:

- The results suggest that factors other than income may be more critical in influencing the adoption of m-commerce. Managers should focus on improving perceived benefits, ease of use, and addressing specific barriers to adoption.
- Marketing efforts can highlight convenience, security, and unique benefits of m-commerce to attract a broader audience.

c. Segmenting the Market:

- While income is not a significant factor, segmenting the market based on other relevant criteria could help tailor marketing strategies more effectively.

- Conducting further research to identify key segments based on behaviour, attitudes, or specific needs may yield better insights for increasing m-commerce usage.

d. Educational and Awareness Campaigns:

- Since income does not play a significant role, educational and awareness campaigns that target a wider audience can be implemented to increase overall m-commerce usage.

- Providing tutorials, testimonials, and easy-to-understand information about the benefits and security of m-commerce can help convert non-users.

e. Inclusivity in Marketing:

- Ensure that marketing campaigns are inclusive and not biased towards any particular income group. Emphasize that m-commerce is accessible and beneficial for everyone, regardless of income level.

By understanding that Monthly Family Income does not significantly impact the likelihood of using m-commerce, managers can focus on more relevant factors to drive adoption and improve user engagement across different demographic segments.

H6g: There is no significant relationship between individuals, who have never used m-commerce, Perceived Behaviour Control, Attitude and Subjective norms.

Table 4.50: Correlations between individuals, who have never used m-commerce, Perceived Behaviour Control, Attitude and Subjective norms

Correlations						
		Never used m-commerce	Subjective Norms	Perceived Behaviour Control	Attitude	Intention
Never used m-commerce	Pearson Correlation	1.00				
	Sig. (2-tailed)					
	N	473.00				
Subjective Norms	Pearson Correlation	-.159**	1.00			
	Sig. (2-tailed)	0.00				
	N	473.00	473.00			
Perceived Behaviour Control	Pearson Correlation	-0.01	-0.08	1.00		
	Sig. (2-tailed)	0.90	0.10			
	N	473.00	473.00	473.00		
Attitude	Pearson Correlation	-.422**	.142**	0.02	1.00	
	Sig. (2-tailed)	0.00	0.00	0.62		
	N	473.00	473.00	473.00	473.00	
Intention	Pearson Correlation	-.565**	.429**	0.01	.413**	1.00
	Sig. (2-tailed)	0.00	0.00	0.76	0.00	
	N	473.00	473.00	473.00	473.00	473.00
**. Correlation is significant at the 0.01 level (2-tailed).						

(Source: Researcher's Computation)

- **Subjective Norms:** There is a weak negative correlation (r = -0.159, p = 0.001) indicating that individuals who never used m-commerce are slightly less likely to be influenced by subjective norms.
- **Perceived Behaviour Control:** There is no significant correlation (r = -0.006, p = 0.904).

- **Attitude:** There is a moderate negative correlation ($r = -0.422$, $p < 0.001$), suggesting that individuals who never used m-commerce tend to have a less positive attitude towards it.
- **Intention:** There is a strong negative correlation ($r = -0.565$, $p < 0.001$), indicating that those who never used m-commerce are much less likely to have the intention to use it.

Summary: The results highlight the importance of subjective norms and attitudes in influencing individuals' intentions to use m-commerce. While perceived behavioural control does not show a significant relationship with other variables in this context, addressing subjective norms and attitudes could be key strategies in promoting m-commerce usage.

❖ **Managerial Implications:**

a. Targeting Users with High Subjective Norms:

- Since subjective norms positively correlate with both attitude and intention, marketing strategies should leverage social influence and peer recommendations to enhance users' perception and intention towards m-commerce. Highlighting testimonials, social proof, and influencer endorsements can be effective.

b. Improving Attitudes:

- Given the significant negative correlation between "never used m-commerce" and attitude, efforts should focus on improving attitudes towards m-commerce among non-users. This could involve educational campaigns to address misconceptions, demonstrating benefits, and providing easy onboarding experiences.

c. Enhancing Intention:

- The strong negative correlation between "never used m-commerce" and intention suggests that increasing users' intention to engage in m-commerce can reduce the number of non-users. Promotions, incentives, and seamless user experiences can foster stronger intentions.

d. Addressing Perceived Behaviour Control:

- Although perceived behaviour control does not show significant correlations with other variables, ensuring that users feel capable and in control while using m-

commerce platforms is still important. Simplifying the user interface, providing clear instructions, and offering customer support can help.

e. **Leveraging Attitude-Intention Link:**

- The positive correlation between attitude and intention indicates that efforts to improve users' attitudes towards m-commerce will likely boost their intention to use it. Marketing campaigns should emphasize positive experiences, success stories, and satisfaction guarantees.

f. **Reducing Barriers for Non-Users:**

- Since "never used m-commerce" is negatively correlated with subjective norms, attitude, and intention, reducing barriers for non-users is crucial. Providing trial periods, offering low-risk opportunities to try m-commerce, and addressing security concerns can help convert non-users.

4.6 CONCLUSIONS:

The results highlight the importance of subjective norms and attitudes in influencing individuals' intentions to use m-commerce. While perceived behavioural control does not show a significant relationship with other variables in this context, addressing subjective norms and attitudes could be key strategies in promoting m-commerce usage. By understanding these correlations and their implications, managers can design targeted strategies to enhance m-commerce adoption and usage, leading to better customer engagement and increased sales.



CHAPTER 5

FINDINGS AND CONCLUSIONS

5.1 INTRODUCTION:

This chapter presents the key findings derived from the data analysis, based on the proposed structural model of the Theory of Planned Behaviour (TPB) with constructs including Attitude, Subjective Norms, Perceived Behavioural Control, and Mobile Commerce Intention. The results are organized according to the primary research objectives and hypotheses, highlighting statistically significant relationships and managerial insights.

5.2 FINDINGS OF THE STUDY:

5.2.1 Findings of Objective 1:

a. The latent factor **"Attitude"** has a significant impact on all observed variables (Att1 through Att10), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

All attributes (Att1 through Att10) have significant relationships with the latent factor "Attitude" as indicated by the p-values (***), meaning $p < 0.001$.The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

b: The latent factor **"Perceived Behavioural Control"** has a significant impact on all observed variables (PBC1 through PBC4), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

All the measurement variables are statistically significant at the 0.05 level, as indicated by the P-Value of 0.000 for each path. This suggests that each variable significantly contributes to the construct of "Perceived Behavioral Control".
The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

c: The latent factor **"Subjective Norms"** has a significant impact on all observed variables (SN1 through SN6), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

All attributes (SN1 through SN6) have significant relationships with the latent factor "Subjective Norms" as indicated by the p-values (***), meaning $p < 0.001$.
The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

d. The latent factor **"Mobile Commerce Intention"** has a significant negative impact on most observed variables (MCI1 through MCI8), with varying strengths.

Positive estimates are not present in this context, suggesting inverse relationships throughout. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios, except for MCI5, which is marginally significant.

Managers can use this information to prioritize improvement efforts, enhance mobile commerce platforms, and ultimately increase customer engagement and transactions via mobile devices.

e. Goodness of fit indices collectively suggest that the model fits the data well across different aspects of fit (absolute, incremental, and parsimonious), providing confidence in its validity and relevance for explaining the relationships among variables in the specified theoretical framework.
The model shows excellent absolute fit (chi-square p-value > 0.05, RMSEA < 0.10, GFI ≥ 0.80). Incremental fit indices (AGFI, NFI, CFI, TLI) also indicate good to very good fit of the model. Parsimonious fit (CMIN/df) suggests the model is adequately parsimonious.

HTMT ratio is used to assess the extent to which the measurement model demonstrates discriminant validity. HTMT ratio should be less than 0.90 (Hair & Alamer,2022), indicating that the constructs have good discriminant validity. All the HTMT ratios provided are below the threshold value of 0.90. Indicating that the constructs are distinct from each other and do not have discriminant validity issues**.**

In summary, the model overall demonstrates high construct validity, supporting its applicability in understanding behavioural intention toward mobile commerce.

5.2.2 Findings of Objective 2:

a. Among the three antecedents, **Attitude** ($\beta = 0.529$, $p < 0.001$) has the most substantial and statistically significant impact on the intention to use m-commerce. This suggests that individuals with positive evaluations of mobile commerce (e.g., convenience, trust, and usefulness) are more likely to intend to engage in m-commerce purchase behaviour.

b. **Subjective Norms** ($\beta = 0.341$, $p < 0.001$) also show a significant positive effect on the intention to use m-commerce, highlighting the role of social influence, such as peer recommendations or societal trends in shaping behavioural intentions.

c. **Perceived Behavioural Control** ($\beta = 0.080$, $p = 0.134$) does not significantly influence intention, implying that users' self-perception of control or technical ability may not directly determine their intention to adopt m-commerce.

d. Structural Equation Modeling (SEM) results demonstrate that the overall model has a good fit (RMSEA = 0.071, CFI = 0.928, TLI = 0.920), indicating strong model validity. Model demonstrates significant paths between the key constructs Attitude, Subjective Norms and Perceived Behavioural Control, with most indicators showing strong, significant loadings on their respective constructs. The primary takeaway is the importance of Attitude and Subjective Norms in predicting Intentions to use m-commerce. Collectively all three antecedents are impacting on intention to use mobile commerce

In summary, attitude and subjective norms are key predictors of m-commerce intention, offering valuable insights for marketers to focus on user perception and social influence strategies to drive adoption.

5.2.3 Findings of Objective 3:

a. According to the results of t-test, all four constructs namely Subjective Norm, Perceived Behavioural Control, Attitude, and Intention show no significant differences between **genders** and their intention to use mobile commerce.

b. **Area of Location** (urban vs. rural) shows no significant effect on Attitude, Perceived Behavioural Control or Subjective Norms, but impacts, intention to use m-commerce. This means that area of location does not have a statistically significant effect on these constructs according to the results of t-test except in Intention. Urban users report higher intention to use m-commerce compared to rural users.

c. **Marital status** shows no significant effect on Attitude, Subjective Norm and Perceived Behavioural Control, but influences intention to use m-commerce. This means that marital status has a statistically significant effect only on intention. Marital status influences intention, with unmarried respondents showing greater adoption tendency.

d. **Age** significantly affects both attitude and intention, with younger users (21-40 years) having the most favourable attitudes and strongest intention. As per the findings younger age groups, particularly those between 21 and 40 years, show higher intention and positive attitudes towards m-commerce, suggesting a greater readiness to adopt and engage with mobile shopping. In contrast, older age groups exhibit lower intention and more negative attitudes, highlighting the need for targeted interventions to improve their perception and usage of m-commerce. Subjective Norm and Perceived Behaviour Control do not show significant differences across age groups.

e. **Educational level** significantly impacts subjective norms and intention but not attitude and perceived behavioural control. Notably, higher education correlates with stronger intention to adopt m-commerce. There are significant differences in subjective norms and intention to use m-commerce across various educational levels. Understanding these differences can help businesses develop targeted strategies that address the specific needs and preferences of each group. By focusing on social influence, tailored marketing campaigns, and improving ease of use and reliability, businesses can enhance m-commerce adoption and usage across all educational segments.

f. Different **occupational groups** exhibit varying levels of intention to use m-commerce. Subjective Norm and Perceived Behavioural Control do not show significant differences across occupation groups. Attitude is not significantly different across occupation groups, but it is close to the significance threshold. Intention is the only construct which shows significant differences across occupational groups. Understanding these differences allows businesses to develop targeted strategies that address the specific needs and preferences of each group. By focusing on convenience, security, and personalized user experiences, businesses can enhance m-commerce adoption and satisfaction across all occupational categories.

g. **Monthly income** influences attitude (higher earners show more positive attitudes) but not Subjective Norm, Perceived Behavioural Control and intention. The most consistent predictors of intention appear to be attitude and social norms, moderated by demographics such as age and education. The findings reveal variations in attitudes towards m-commerce across different income levels, with higher income groups showing more favourable attitudes. By developing targeted marketing strategies, enhancing services, and building trust, businesses can effectively cater to the diverse needs of consumers across all income brackets.

In summary, m-commerce strategies must be demographically framed. Age- and education-specific campaigns, rural outreach, and simplified user experiences are critical for increasing m-commerce adoption across varied population segments.

Understanding these differences and addressing them through tailored approaches can significantly enhance m-commerce adoption among consumers.

5.2.4 Findings of Objective 4:

a. Mediation analysis confirmed that intention fully mediates the effect of Attitude (indirect effect = 0.285, $p < 0.001$) on purchase behaviour for the specified product categories, using m-commerce.
b. Intention fully mediates the effect of Subjective Norms (indirect effect = 0.152, $p < 0.001$) on purchase behaviour for the specified product categories, using m-commerce.

c. Intention does not mediate the relationship between Perceived Behavioural Control and actual purchase behaviour for the specified product categories, using m-commerce.

d. **Intention** is a strong and statistically significant predictor of actual purchase behaviour for the specified product categories, using m-commerce ($\beta = 0.752$, $p < 0.001$), whereas direct effects from attitude, subjective norms, and perceived control on purchase behaviour were found to be non-significant.

e. The overall effect of attitude on buying behaviour through mobile commerce is positive and statistically significant. The direct effect of attitude on buying behaviour is positive but not statistically significant. The indirect effect, mediated by intention, is positive and statistically significant, indicating that intention plays a crucial mediating role between attitude and buying behaviour.

f. The overall effect of subjective norm on buying behaviour is positive and statistically significant. The direct effect of subjective norm on buying behaviour is negative and not statistically significant. The indirect effect, mediated by intention, is positive and statistically significant, indicating that subjective norms influence buying behaviour primarily through their impact on intention.

g. The overall effect of perceived behavioural control on buying behaviour is not statistically significant. The direct effect is negative and not statistically significant. The indirect effect, mediated by intention, is positive but not statistically significant, indicating that perceived behavioural control does not have a significant influence on buying behaviour through intention.

In summary, findings suggest that while Attitude and Subjective Norm significantly influence Intention, only Intention significantly predicts Buying behaviour. The model fit indices support the adequacy of the model in explaining the relationships among these constructs. The model fit was acceptable (CFI = 0.972, RMSEA = 0.083), validating the structure. These findings highlight that intention acts as a critical factor between consumers' psychological factors and their actual purchase behaviour for the specified product categories, using m-commerce.

5.2.5 Findings of Objective 5:

Overall, goodness of fit indices collectively suggest that the model fits the data well across different aspects of fit (absolute, incremental, and parsimonious), providing confidence in its validity for explaining the relationships among variables in the specified theoretical framework. The model fit indices indicate a strong model: RMSEA = 0.068, CFI = 0.901, TLI = 0.90, and CMIN/df = 3.194-all within acceptable or excellent thresholds, confirming robust model validity.

The results confirm that attitude (β = 0.533) and subjective norms (β = 0.231) significantly and positively influence intention, whereas perceived behavioural control has a negligible and non-significant impact (β = 0.023). The SEM analysis highlight the critical role of 'Attitude' and 'Subjective Norms' in driving the intention to use m-commerce, which in turn strongly influences actual usage behaviour.

The strength of '**Attitude'** suggests that consumers' perception of benefits of using m-commerce strongly drive usage, while social influences also play a key role. A strong and highly significant influence on Intention highlights the importance of positive attitudes towards m-commerce. This indicates that, by launching educational campaigns to highlight the benefits and convenience of m-commerce and addressing common concerns such as

security and privacy through informative contents, overall user experience can be enhanced, which can also contribute to more favourable attitudes.

The weak and insignificant influence of '**Perceived Behavioural Control'** on Intention indicates that users' perceptions of their ability to use m-commerce are not major determinants of their intention to use it. This indicate that, ease of use and user support is still important, it may not significantly drive intention. Resources might be better allocated to other areas.

A moderate and highly significant influence of **'Subjective Norms'** on 'Intention', suggests that social influence is crucial in shaping the intention to use m-commerce. This suggests that, by implementing marketing strategies that capitalize on social proof, such as influencer endorsements, user testimonials, and community engagement initiatives, can drive intentions to use m-commerce.

Intention significantly predicts actual buying behaviour ($\beta = 0.674$), reinforcing its central role in consumer decision-making. The strong and significant influence of 'Intention' on 'Behaviour' indicates that those who intend to use m-commerce are very likely to do so. This suggests converting intention to action. This can involve optimizing the onboarding process, providing excellent customer service, and offering incentives such as discounts or loyalty programs to encourage initial use and repeat transactions.

In summary, findings confirm that TPB is effective in explaining m-commerce behaviour, with intention serving as the primary mediator between psychological constructs and consumer action. For practitioners, this emphasizes the need to build positive consumer attitudes and leverage peer influence, while simplifying usage to support behavioural control. This validated model offers a strategic foundation for enhancing m-commerce adoption.

5.2.6 Findings of Objective 6:

a. A moderate to strong positive correlation ($r = 0.600$) was found between individuals' **lack of knowledge** and their non-adoption of m-commerce. The significant positive correlation between lack of knowledge and the non-adoption of mobile commerce highlights the importance of knowledge dissemination in promoting the use of mobile commerce applications.

b. **Educational level** emerged as a crucial determinant, with higher educational attainment significantly associated with greater m-commerce usage. The Pearson Chi-Square, Likelihood Ratio, and Linear-by-Linear Association tests all indicate a significant association between education level and the use of m-commerce ($p < 0.01$). The significant association suggests that education level may play a crucial role in deciding whether individuals are using m-commerce or not.

c. **Geographical location** also plays a pivotal role. The study found a significant association between **urban or rural residency** and the likelihood of using m-commerce, indicating the need for area-specific strategies. The tests indicate a significant association between the area of location (urban or rural) and the use of m-commerce. This suggests that strategies to increase m-commerce adoption may need to be tailored to address the specific needs and barriers of urban and rural populations.

d. Chi-Square test indicates a significant association between **marital status** and the use of m-commerce. This suggests that marital status of an Individual significantly affects his/her likelihood of using m-commerce.

e. Chi-Square test indicates a significant association between **occupation** and the use of m-commerce. This suggests that different occupational groups have varying likelihoods of using m-commerce, and targeted interventions may be necessary to address specific barriers faced by different occupational groups. The significant linear relationship further reinforces the need to consider occupational status in efforts to promote m-commerce usage.

f. Interestingly, **monthly family income** showed no significant association with m-commerce usage, indicating that financial status may not be a primary barrier to m-commerce adoption. This suggests that other factors, beyond family income, might play a more crucial role in determining m-commerce adoption.

g. Psychological and behavioural variables such as **attitude (r = -0.422)** and **intention (r = -0.565)** demonstrated strong negative correlations with non-adoption. This suggests that users who had never engaged in m-commerce were less inclined or motivated to adopt the technology.

Subjective norms also showed a weak but significant negative correlation, implying a weak but significant negative correlation ($r = -0.159$, $p = 0.001$) indicating that social influence modestly affects adoption behaviour.

Perceived behavioural control, however, had no significant relationship, suggesting that users' confidence in their ability to use m-commerce may not be a deciding factor. There is no significant correlation between perceived behavioural control and non-adoption of m-commerce ($r = -0.006$, $p = 0.904$), indicating that perceived behavioural control does not have any significant impact on whether individuals will use or not use m-commerce for shopping.

There is a strong negative correlation ($r = -0.565$, $p < 0.001$) between intention and non-adoption of m-commerce., indicating that those who have no intention to use m-commerce are much less likely to have the intention to use it in future.

In summary, the results highlight the importance of subjective norms and attitudes in influencing individuals' intentions to use m-commerce. While perceived behavioural control does not show a significant relationship with other variables in this context, addressing subjective norms and attitudes could be key strategies in promoting m-commerce usage. The study emphasizes the need for targeted educational campaigns, simplified user experiences, and community-specific outreach strategies. Efforts to enhance users' attitudes and intentions through awareness and incentives are crucial for expanding m-commerce adoption across diverse demographic groups in Goa.

5.3 FINDINGS ON DEMOGRAPHIC INSIGHTS:

a. Gender Distribution

The analysis reveals that the proportion of female respondents is higher compared to male respondents. This indicates that women are increasingly engaging with mobile commerce platforms and playing a significant role in shaping digital consumer behaviour. Such

participation highlights the importance of considering gender-based preferences in m-commerce strategies.

b. Age Distribution

The sample predominantly consists of young adults between the ages of 21 and 40 years. This age group is generally more familiar with technology, adaptable to digital platforms, and actively participates in online shopping. Their strong presence suggests that young consumers are key drivers of m-commerce adoption.

c. Education Level

Most of the respondents possess at least a graduation degree. This reflects a consumer base that is relatively well-informed, digitally literate, and capable of making rational purchase decisions through mobile platforms. Education, therefore, appears to be an important antecedent influencing m-commerce behaviour.

d. Urban–Rural Split

The distribution of respondents between urban and rural areas is found to be nearly equal. This suggests that mobile commerce has penetrated not only in urban regions but also in rural areas, supported by greater internet accessibility and smartphone usage. It demonstrates the expanding geographical reach of m-commerce in Goa.

e. Marital Status

The study shows a higher proportion of unmarried respondents compared to married ones. Unmarried individuals, often characterized by greater discretionary spending and openness to digital innovations, seem to be more active in using mobile commerce platforms. This finding emphasizes the role of youth in shaping m-commerce trends.

f. Occupation

A significant share of respondents are employed in service sectors, while a notable portion are unemployed, which may include students or homemakers. Service professionals tend to prefer m-commerce for convenience, while unemployed respondents may engage due to time availability and attractive offers. Occupational status, therefore, influences the manner in which consumers interact with m-commerce.

g. Income Levels

A considerable proportion of respondents belong to families with a monthly income exceeding ₹1,00,000. This indicates the participation of financially strong households in mobile commerce, reflecting their ability to engage in frequent and high-value purchases. Higher income levels are thus an important determinant of consumer behaviour in this domain.

In summary, the applicability of the Theory of Planned Behaviour (TPB) to m-commerce adoption in Goa is evident through these findings. Attitude towards m-commerce is shaped by young, educated, and financially strong consumers who perceive it as convenient and reliable. Subjective norms emerge from the growing acceptance among women, youth, and urban as well as rural populations, reflecting social influence on adoption. Perceived behavioural control is evident as educated, tech-savvy, and higher-income groups feel confident in using digital platforms, while accessibility across regions enhances ease of use. Together, these factors explain consumers' intention and behaviour towards adopting m-commerce.

5.4 IMPLICATIONS FOR THEORY AND PRACTICE:

The application of the Theory of Planned Behaviour (TPB) in this study reaffirms its relevance in the domain of mobile commerce. The constructs of attitude, subjective norms, and perceived behavioural control together offer a comprehensive framework for understanding consumer intentions. The findings confirm that attitude and subjective norms are robust predictors of behavioural intention, emphasizing the psychological and social dimensions of technology adoption.

Practically, the insights derived from the analysis serve as a strategic roadmap for stakeholders in the mobile commerce ecosystem. Marketers, and policy makers must focus on reducing barriers to mobile commerce adoption, such as lack of knowledge and perceived risks, while amplifying enablers like convenience, ease of use, and social endorsement. These efforts can catalyse broader adoption, especially in understated rural demographics.

5.5 RECOMMENDATIONS:

Based on the findings, several recommendations can be made to improve mobile commerce adoption and user experience:

I. **User Education:** Launch targeted awareness and education campaigns to bridge knowledge gaps, especially in rural areas. These should include multimedia content, local language support, and practical demonstrations.

II. **Enhanced User Interface:** Ensure platforms are intuitive, with simplified navigation, real-time assistance, and accessible features that cater to a wide range of users, including the elderly and those with limited tech exposure.

III. **Security and Privacy:** Strengthen and visibly promote platform security features such as encryption, multi-factor authentication, and transparent privacy policies to build trust among users.

IV. **Social Proof Integration:** Integrate reviews, ratings, and testimonials into the commerce journey. Highlighting peer experiences, influencer endorsements, and family/friend recommendations can boost subjective norms positively.

V. **Localized Strategies:** Develop region-specific strategies that consider socio-economic and infrastructural differences between urban and rural users. This includes offering low-bandwidth versions of apps, offline support, and vernacular content.

VI. **Feedback Systems:** Implement robust feedback and grievance redressal mechanisms to swiftly address negative experiences and perceptions, thereby improving attitude and retention.

5.6 LIMITATIONS OF THE STUDY:

I. As an empirical study, the data collection occurred at a single point in time. This cross-sectional approach does not account for changes in consumer attitudes, technological advancements, or market trends over time, which can influence consumer behaviour towards m-commerce.

II. The data was gathered using surveys, which depend on participants' self-reporting. Such methods are prone to recall errors, and respondents' inability to accurately predict their future behaviour.

III. The study is based on the Theory of Planned Behaviour (TPB), which, has limitations. For instance, TPB may not fully capture other important factors influencing consumer behaviour, such as emotional, habitual, or contextual factors, particularly in rapidly evolving technological environments.

IV. The size of the sample could be a limitation. A small sample limits the ability to draw broader conclusions or generalize findings to a larger population.

V. Given the dynamic nature of m-commerce, the findings may become outdated quickly as new technologies, features, and platforms emerge, altering consumer preferences and behaviours.

VI. Construct measurement may pose challenges. For example, attitude, subjective norms and perceived behavioural control might be difficult to measure accurately, leading to potential measurement errors that impact the reliability and validity of the results.

5.7 FUTURE RESEARCH DIRECTIONS:

The study of consumer behaviour in the context of mobile commerce (m-commerce) is an evolving field, influenced by rapid technological advancements and shifts in consumer lifestyles. While existing research has identified critical factors such as attitude, perceived behavioural control, and subjective norms and its impact on intention and behaviour of consumers towards m-commerce, as per the theory of planned behaviour, there remain significant areas that warrant further exploration. Below are some promising avenues for future research:

I. Technological Advancements: Examine the role of emerging technologies such as artificial intelligence (AI), and augmented reality (AR) in shaping consumer behaviour towards m-commerce

II. Psychological and Emotional Factors: Analyse how emotions, such as anxiety or excitement, triggered by m-commerce experiences influence purchase behaviour of consumers.

III. Social media Influencers: Study the impact of social media influencers on m-commerce consumer behaviour.

IV. **Privacy and Security Concerns:** Assess how concerns over cybersecurity influence consumer trust and willingness to engage in m-commerce.

V. **Demographic and Psychographic Segmentation:** Conduct studies focused on specific demographic groups, such as Gen Z or senior citizens, to understand their unique m-commerce behaviours.

By addressing these gaps, future research can provide a deeper understanding of the antecedents to consumer behaviour in m-commerce, thereby enabling businesses to design strategies that better meet the needs of their mobile-centric customers.

5.8 SUMMARY OF KEY CONTRIBUTIONS:

This research provides an evidence-based assessment of the Theory of Planned Behaviour in the context of mobile commerce. Its key contributions include:

I. Validating the structure and significance of TPB constructs through empirical SEM analysis.

II. Demonstrating the stronger role of Attitude and Subjective Norms over Perceived Behavioural Control in predicting Mobile Commerce Intention.

III. Identifying demographic distinctions, especially the rural-urban divide, in shaping consumer behaviour.

IV. Offering practical and policy-driven recommendations grounded in quantitative findings.

These contributions not only reinforce the TPB as a theoretical model but also extend its utility in guiding strategic decisions in the m-commerce space.

5.9 CONCLUSIONS:

The present study was undertaken with the primary objective of examining the antecedents of consumer behaviour towards mobile commerce (m-commerce) adoption by applying the Theory of Planned Behaviour (TPB) as the guiding theoretical framework. As digital technologies increasingly shape the patterns of consumer decision-making, m-commerce has emerged as a transformative force redefining the way individuals engage with products, services, and marketplaces. Against this backdrop, the research sought to understand how consumers' psychological factors namely attitude, subjective norms, and perceived behavioural control influence their intention to adopt m-commerce and, ultimately, their actual purchase behaviour towards m-commerce. The findings of this study provide valuable

insights into the dynamics of m-commerce adoption in the state of Goa, while also extending the applicability of TPB to the domain of digital consumer behaviour in a broader context.

The empirical results highlight that among the three central antecedents of TPB, attitude emerges as the most powerful determinant of consumer intention to adopt m-commerce. Attitude, which reflects an individual's positive or negative evaluation of using mobile platforms for shopping, strongly influences whether a consumer is willing to engage in such transactions. The findings confirm that consumers who perceive m-commerce as convenient, secure, efficient, and reliable develop more favourable attitudes, which in turn strengthen their intention to use such platforms. This insight highlights that consumer perceptions of value, trustworthiness, and utility play a vital role in driving digital adoption. In the context of m-commerce, where issues of security, privacy, and ease of transaction remain central concerns, a positive attitude serves as a crucial gateway for shaping behavioural intentions. Thus, the results reaffirm the TPB proposition that attitudes act as a cornerstone of behavioural prediction within the unique setting of mobile-commerce.

Closely linked to attitude, the findings also emphasise the significant role of subjective norms in shaping intention. Subjective norms, defined as the perceived social pressure from important others to perform or not perform a behaviour, emerged as a noteworthy determinant of m-commerce adoption. Consumers were found to be strongly influenced by the opinions, encouragement, and behaviours of peers, family members, and broader social groups. The results indicate that when consumers perceive mobile commerce as widely accepted and endorsed by their social networks, they are more likely to develop favourable intentions to engage in such practices. This insight reflects the inherently social nature of technology adoption, where the influence of peers and social circles increases the use of digital practices. Moreover, with the explosion of social media platforms, online communities, and influencer-driven content, subjective norms emerge not only as a theoretical construct within TPB but also as a practical driver of consumer adoption in the contemporary digital era.

In contrast, perceived behavioural control was not found to significantly influence intention in this study. Traditionally, perceived behavioural control refers to the extent to which individuals feel capable of performing a behaviour based on their resources, opportunities, and self-efficacy. However, the findings suggest that in the current context, technical skills, access to smartphones, and availability of internet services are no longer substantial barriers

to adoption. With the rapid growth of mobile technologies, affordable data services, and user-friendly application interfaces, consumers increasingly perceive themselves as capable of engaging in mobile commerce without significant constraints. This diminishing relevance of perceived behavioural control marks an important shift in the digital adoption landscape. While TPB suggests behavioural control as an important determinant of intention, the present findings suggest that in contexts where technological barriers are minimal, the construct may exert limited influence. This result offers an important refinement to the application of TPB in digital environments, signalling the need to reassess the relative weight of its constructs in contexts characterised by high levels of technological accessibility.

Beyond the individual antecedents, the study also underscores the central role of intention as the mediating variable between psychological constructs and actual behaviour. The results clearly demonstrate that intention is the strongest predictor of actual adoption, while the direct effects of attitude, subjective norms, and perceived behavioural control on behaviour were found to be insignificant. This reinforces the conceptualisation within TPB that behavioural intention serves as the most important determinant of actual behaviour. In the context of m-commerce, consumers may hold favourable attitudes and perceive social endorsement; however, it is only when these factors translate into concrete behavioural intentions that actual adoption takes place. This finding highlights the importance of developing strong consumer intentions, as these serve as the critical link between attitude and purchase behavioural outcomes. By confirming the mediating role of intention, the study contributes empirical evidence supporting the theoretical foundations of TPB while adapting them towards use of mobile-commerce.

The analysis of demographic variables provided further depth to the understanding of consumer adoption patterns. Age was found to play a significant role, with younger consumers—particularly those between the ages of 21 and 40—demonstrating the highest levels of intention to adopt m-commerce. This finding reflects the digital orientation of younger generations, who are more familiar with mobile technologies and more open to integrating them into their daily shopping practices. Education emerged as another significant factor, with respondents possessing higher levels of education displaying stronger subjective norms and greater intention to adopt. This can be attributed to the role

of education in fostering digital literacy, critical thinking, and openness to technological innovations.

Marital status was also found to influence adoption behaviour, with unmarried individuals exhibiting greater willingness to engage in m-commerce compared to their married counterparts. This may be explained by differences in lifestyle, consumption preferences, and financial decision-making patterns. Occupation similarly shaped adoption, as professionals in the service sector displayed higher levels of intention, likely due to greater exposure to digital technologies in their work environments. Income was observed to affect attitudes towards m-commerce, with higher-income groups perceiving greater value in such platforms, though income did not consistently predict intention. Location also played an important role, as urban consumers reported higher adoption intentions compared to rural consumers, though the gap is gradually narrowing with increasing mobile penetration in semi-urban and rural areas. Collectively, these demographic insights highlight that m-commerce adoption is shaped by a complex interplay of psychological and socio-demographic factors, highlighting the importance of segment-specific strategies to understand consumer behaviour.

A notable insight emerging from the study concerns the barriers to adoption. Among non-users of m-commerce, lack of knowledge emerged as the most prominent obstacle. Many individuals reported security features associated with mobile commerce, which lacks their participation. This points to the importance of addressing knowledge gaps and creating awareness as a critical step towards expanding adoption. Psychological barriers also played a role, as individuals with negative attitudes or weak intentions were significantly less likely to engage in mobile transactions. Interestingly, perceived behavioural control did not emerge as a significant barrier for non-users, further reinforcing the observation that technological accessibility is no longer a major obstacle in the current context. Together, these findings highlight that adoption barriers are primarily psychological rather than infrastructural, suggesting that efforts to promote m-commerce should focus on improving knowledge and shaping positive attitudes.

From a theoretical point of view, this research makes important contributions by validating and extending the application of TPB in the context of m-commerce. The study affirms the robustness of TPB in predicting consumer behaviour while also highlighting the differential influence of its constructs. Specifically, attitude and subjective norms emerged as stronger

predictors of intention compared to perceived behavioural control, signalling the relative importance of evaluative and social factors over control-related considerations in digital environments. The mediating role of intention was also reinforced, confirming its significance in linking antecedents to actual behaviour. Furthermore, by integrating demographic variables into the analysis, the study extends the explanatory power of TPB, demonstrating how socio-demographic contexts interact with psychological constructs to shape adoption patterns.

The contributions of this study also extend to a broader understanding of digital consumer behaviour in emerging markets. Unlike developed economies, where digital adoption is often taken for granted, the findings reveal that in developing contexts, adoption is shaped by a combination of favourable attitudes, social influence, and demographic characteristics. The research provides empirical evidence that mobile commerce adoption in such settings is not uniform but varies across age groups, educational backgrounds, and urban–rural divides. Study enriches the theoretical discourse and provides a more comprehensive understanding of the dynamics of digital adoption.

To conclude, this research has provided a detailed examination of the antecedents of consumer behaviour towards m-commerce, confirming that attitude and subjective norms are the most critical drivers of intention, and intention itself is the strongest predictor of actual adoption behaviour towards mobile commerce. The findings validate the applicability of TPB while also extending its scope by highlighting the subtle role of its constructs and the influence of demographic factors. By identifying knowledge gaps and psychological barriers among non-users, the study also sheds light on the challenges that remain in expanding m-commerce adoption. Ultimately, the research contributes both to theoretical advancement and to the practical understanding of consumer behaviour in the digital age.As mobile commerce continues to reshape consumer lifestyles and redefine the retail landscape, the insights derived from this study offer a valuable foundation for academics, policymakers, and industry stakeholders seeking to understand and leverage the drivers of adoption. By highlighting the antecedents of consumer behaviour towards m-commerce, validating the importance of intention, and situating these insights within the socio- demographic realities, the study advances both knowledge and understanding of this rapidly evolving domain of mobile commerce.

BIBLIOGRAPHY

Agarwal, S., & Prasad, J. (2018). Adoption of mobile commerce: Influencing factors and consumer behaviour in India. International Journal of Mobile Marketing, 13(2), 23–36.

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. Journal of Applied Social Psychology, 32(4), 665-683.

Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Prentice-Hall.

Ajzen, I., & Fishbein, M. (2005). The influence of attitudes on behavior. In D. Albarracín, B. T. Johnson & M. P. Zanna (Eds.), The Handbook of Attitudes (pp. 173–221). Mahwah, NJ: Lawrence Erlbaum Associates.

Amin, M. (2020). Examining the role of customer satisfaction within mobile shopping apps on customer relationship performance. Journal of Retailing and Consumer Services, 56, 102207.

Anderson, J. C. (2020). *Structural equation modeling: A second course* (2nd ed.). Information Age Publishing.

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems, 8*(4), 244–254.

Bagozzi, R. P., & Yi, Y. (1989). *On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16*(1), 74–94.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly, 25*(3), 351–370.

Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.

Bansal, A., & Sharma, P. (2020). Examining trust and security dimensions in mobile commerce: An Indian consumer perspective. Journal of Internet Commerce, 19(3), 263–284. https://doi.org/10.1080/15332861.2020.1772890

Bansal, S., & Bharti, K. (2020). Impact of social media advertisements on consumer buying behavior: An empirical study using theory of planned behavior. International Journal of Management Studies, 7(3), 24–34. https://doi.org/10.18843/ijms/v7i3/04

Barnes, S. J., & Corbitt, B. J. (2004). Mobile commerce: Beyond retail – A vision of future developments and research. International Journal of Electronic Commerce, 8(3), 7-23.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182.

Beldad, A., de Jong, M., & Steehouder, M. (2010). How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust. Computers in Human Behavior, 26(5),

857–869.

Chang, H. H., & Chen, S. W. (2012). *The impact of online store environment cues on purchase intention: Trust and perceived risk as a mediator*. *Online Information Review, 36*(6), 1036–1056.

Chaffey, D., & Ellis-Chadwick, F. (2019). Digital Marketing: Strategy, Implementation, and Practice. Pearson.

Chauhan, A., & Verma, H. V. (2018). The influence of trust and perceived risk on consumer purchase intention in online shopping: A study of Indian e-commerce market. International Journal of Retail & Distribution Management, 46(3), 301–322. https://doi.org/10.1108/IJRDM-11-2016-0213

Chang, H. H., & Chen, S. W. (2010). *The impact of online store environment cues on purchase intention: Perceived playfulness and perceived flow*. *Online Information Review, 34*(6), 1185–1207.

Chau, P. Y. K., & Lai, V. S. (2003). *An empirical investigation of the determinants of user acceptance of Internet banking*. *Journal of Organizational Computing and Electronic Commerce, 13*(2), 123–145.

Cheng, Y., & Chen, S. (2015). *Exploring the factors influencing the adoption of mobile commerce: An empirical study in Taiwan*. *Journal of Electronic Commerce Research, 16*(2), 108–118.

Choi, J., Lee, H., & Kim, H. (2013). *The moderating effect of gender in the adoption of mobile banking*. *International Journal of Bank Marketing, 28*(5), 328–341.

Chopdar, P. K., & Sivakumar, V. J. (2019).Understanding continuance usage of mobile shopping applications in India: The role of espoused cultural values and perceived risk. *Behaviour & Information Technology, 38*(1), 42–64.

Chopdar, P. K., & Sivakumar, V. J. (2024). Customization at a glance: Investigating consumer experiences in mobile commerce applications. *Journal of Retailing and Consumer Services, 76*, 103602.

Chew (2006), defining behavioral intention: "the power of an individual's intention to perform a certain behaviour."

Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. Decision Support Systems, 54(1), 461–470. https://doi.org/10.1016/j.dss.2012.06.008

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. Journal of Marketing Research, 43(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Chiu, C. M., Lin, H. Y., & Tang, L. L. (2005). Gender differs: Assessing a model of online purchase intentions in e-tail service. International Journal of Service Industry Management, 16(5), 416-435.

Chong, A. Y. L. (2013). Mobile commerce usage activities: The roles of demographic and motivation variables. Technological Forecasting and Social Change, 80(7), 1350-1359.

Chong, A. Y. L. (2013). Understanding mobile commerce continuance intentions: An empirical analysis of Chinese consumers. Journal of Computer Information Systems, 53(4), 22-30.

Chu, S.-C., & Kim, Y. (2011). Determinants of consumer engagement in electronic word-of-mouth (eWOM) in social networking sites. International Journal of Advertising, 30(1), 47–75. https://doi.org/10.2501/IJA-30-1-047-075

Conner, M., & Armitage, C. J. (1998). Extending the theory of planned behavior: A review and avenues for further research. Journal of Applied Social Psychology, 28(15), 1429–1464. https://doi.org/10.1111/j.1559-1816.1998.tb01685.x

Coakes, S. J., & Steed, L. (2009). *SPSS: Analysis without anguish: Version 14.0 for Windows* (3rd ed.). Willey

Cyr, D., Kindra, G., & Head, M. (2006). The influence of website structure on perceived trust in online information. Information & Management, 43(2), 196–207. https://doi.org/10.1016/j.im.2005.01.002

Dahlberg, T., Mallat, N., & Öörni, A. (2008). Consumer acceptance of mobile payment solutions: A literature review. *Electronic Commerce Research and Applications, 7*(2), 165–181.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. Management Science, 35(8), 982-1003.

Deshmukh, N., & Patel, R. (2022). The impact of mobile promotional strategies on consumer behaviour in m-commerce. Journal of Consumer Marketing, 39(4), 394–406. https://doi.org/10.1108/JCM-10-2021-491

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., (2020). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management, 102168*.

Eagly, A. H., & Chaiken, S. (1993). The psychology of attitudes. Harcourt Brace Jovanovich College Publishers.

Fogg, B. J., Soohoo, C., Danielson, D. R., Marable, L., Stanford, J., & Tauber, E. R. (2001). *How do users evaluate the credibility of Web sites? A study with over 2,500 participants*. *Proceedings of the 2001 Conference on Designing for User Experiences*, 1–15.

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. Addison-Wesley.

Fishbein, M., & Ajzen, I. (2010). Predicting and changing behavior: The reasoned action approach. Psychology Press.

Fowler, F. J. (2013). Survey research methods (5th ed.). Sage Publications.

Gao, L., & Bai, X. (2014). A unified perspective on the factors influencing consumer acceptance of internet of things technology. Asia Pacific Journal of Marketing and Logistics, 26(2), 211-231.

Gao, L., Waechter, K. A., & Bai, X. (2015). Understanding consumers' continuance intention towards mobile purchase: A theoretical framework and empirical study – A case of China. Computers in Human Behavior, 53, 249-262.

Gefen, D. (2003). TAM or just plain habit: A look at experienced online shoppers. Journal of End User Computing, 15(3), 1-13.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90. https://doi.org/10.2307/30036519

George, A., & Kumar, G. G. (2014). Antecedents of customer satisfaction in online shopping: An integrated framework and research propositions. Journal of Internet Commerce, 13(3-4), 281–305. https://doi.org/10.1080/15332861.2014.961346

George, J. F. (2004). The theory of planned behavior and Internet purchasing. Internet Research, 14(3), 198–212. https://doi.org/10.1108/10662240410542634

Ghazali, E. M., Zolkepli, I. A., & Ramayah, T. (2018).Do consumers want mobile commerce? A closer look at m-shopping and technology adoption in Malaysia. *Computers in Human Behavior, 84*, 1–13.

Hajli, M. N. (2014). *A study of the impact of social media on consumers*. *International Journal of Market Research, 56*(3), 387–404.

Hanafizadeh, P., Keating, B. W., & Khedmatgozar, H. R. (2014). *A systematic review of Internet banking adoption*. *Telematics and Informatics, 31*(3), 492–510.

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations* (2nd ed.). Sage Publications.

Hsieh, Y. H., Rai, A., & Keil, M. (2012). *Understanding digital inequality: Comparing continued use behavioral models of the 'digital haves' and 'have-nots'*. *Information Systems Research, 23*(3), 542–559.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (1998). *Multivariate data analysis* (5th ed.). Prentice Hall.

Hamzah, M. I., Othman, A. K., & Hassan, F. (2020). Mediating effects of individual market orientation on the link between learning orientation and job performance. Journal of Business & Industrial Marketing, 35(4), 655-668.

Hernandez, B., Jimenez, J., & Martin, M. J. (2009). Adoption vs acceptance of e-commerce: Two different decisions. European Journal of Marketing, 43(9/10), 1232-1245.

Huang, Z., Huang, S., & Zhang, C. (2015). Trust in m-commerce: The impact of consumer's trust in supply chain management and service quality. Industrial Management & Data Systems, 115(2), 231-252.

IAMAI. (2023). Internet and Mobile Association of India.

Karjaluoto, H., Mattila, M., & Pento, T. (2007). *Factors underlying attitude formation towards online banking in Finland*. *International Journal of Bank Marketing, 25*(2), 105–121.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10.

Kumar, A., & Mukherjee, A. (2018). *Understanding the role of millennials in mobile commerce adoption*. *Journal of Retailing and Consumer Services, 45*, 1–10.

Kanchan, U., Kumar, R., & Gupta, A. (2015). A study of online purchase behaviour of consumers in India. International Journal of Advanced Research in Computer Science and Management

Studies, 3(6), 79–85.

Kaplan, D., & Graziano, W. G. (2009). The subjective norm as a mediator of the attitude-behavior relationship: A meta-analysis review. Journal of Social Psychology, 149(3), 231-244.

Kapoor, A. P., & Vij, M. (2021). Following you wherever you go: Mobile shopping 'cart-checkout'abandonment. Journal of Retailing and Consumer Services, 61, 102553.

Kapoor, K. K., Dwivedi, Y. K., & Williams, M. D. (2014). Examining the role of three sets of innovation attributes for determining adoption of the interbank mobile payment service. Information Systems Frontiers, 16(5), 1039-1056.

Kasuma, J., Razak, F. L. A., Omar, N., Naim, A. S. A., Naimullah, B. S. S., & Darma, D. C. (2020). Attitude, Perceived Usefulness and Perceived Ease of Use towards Intention to Use M-Commerce: A Case of Grocery Shoppers in Kuching, Sarawak. Journal of Entrepreneurship & Business, 8(1).

Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. Computers in Human Behavior, 26(3), 310-322.

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems, 44(2), 544-564.

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2009). Trust and satisfaction, two stepping stones for successful e-commerce relationships: A longitudinal exploration. Information Systems Research, 20(2), 237-257.

Kim, H.-W., Chan, H. C., & Gupta, S. (2007). Value-based adoption of mobile internet: An empirical investigation. Decision Support Systems, 43(1), 111–126. https://doi.org/10.1016/j.dss.2005.05.009

Kim, J., & Lennon, S. J. (2013). Effects of reputation and website quality on online consumers' emotion, perceived risk, and purchase intention. Journal of Research in Interactive Marketing, 7(1), 33-56.

Kim, S. H., Kim, H. W., & Wang, H. (2010). Understanding key drivers of m-commerce adoption in South Korea. International Journal of Mobile Communications, 8(3), 298-315.

Kim, S. J., Wang, R. J. H., Maslowska, E., & Malthouse, E. C. (2016). "Understanding a fury in your words": The effects of posting and viewing electronic negative word-of-mouth on purchase behaviors. Computers in Human Behavior, 54, 511-521.

Kim, Y. G., Shin, D. H., & Lee, J. H. (2008). Understanding dynamics between initial trust and usage intentions of mobile banking. Information Systems Journal, 18(6), 545-580.

Kotler, P., & Armstrong, G. (2016). Principles of marketing (16th ed.). Pearson.

Kumar, V., & Roy, S. (2019). Lifestyle and demographic factors influencing m-commerce usage: Evidence from Indian consumers. Journal of Retailing and Consumer Services, 50, 8–17. https://doi.org/10.1016/j.jretconser.2019.04.010

Lee, M. C. (2011). *Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation-confirmation model*. *Computers & Education, 57*(2), 1362–1376.

Lim, W. M., Tan, G. W. H., & Lee, S. H. (2016).*Online shopping: A review of the literature. International Journal of Economics and Management, 10*(2), 1–20.

Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2014). The moderating effect of experience in the adoption of mobile payment tools in virtual social networks: The m-payment acceptance model in a virtual social network context. International Journal of Information Management, 34(2), 151-166.

Lim, H., & Dubinsky, A. J. (2004). Consumers' perceptions of e-shopping characteristics: An expectancy-value approach. Journal of Services Marketing, 18(7), 500-513.

Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How habit limits the predictive power of intention: The case of information systems continuance. MIS Quarterly, 31(4), 705-737.

Lu, J. (2014). Are personal innovativeness and social influence critical to continue with mobile commerce? Internet Research, 24(2), 134-159.

Lu, J., & Su, P. (2009). Factors affecting purchase intention on mobile shopping web. International Journal of Business and Management, 4(1), 87–95. https://doi.org/10.5539/ijbm.v4n1p87

Lu, J., Yao, J. E., & Yu, C. S. (2005). Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. Journal of Strategic Information Systems, 14(3), 245-268.

Luarn, P., & Lin, H. H. (2005). Toward an understanding of the behavioral intention to use mobile banking. Computers in Human Behavior, 21(6), 873-891.

Mallat, N. (2007). Exploring consumer adoption of mobile payments – A qualitative study. *The Journal of Strategic Information Systems, 16*(4), 413–432.

Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.

Miniard, P. W., & Cohen, J. B. (1981). *Modeling personal and normative influences on behavior. Journal of Consumer Research, 8*(2), 169–177.

Mital, M., Chang, V., Choudhary, P., Papa, A., & Pani, A. K. (2021). Adoption of Internet of Things in India: A test of competing models using a structured equation modeling approach. *Technological Forecasting and Social Change, 173*, 121073.

Molla, A., & Licker, P. S. (2005). *E-commerce adoption in developing countries: A model and instrument*. *Information & Management, 42*(6), 877–899.

Moon, J. W., & Kim, Y. G. (2001). *Extending the TAM for a World-Wide-Web context*. *Information & Management, 38*(4), 217–230.

Morosan, C., & DeFranco, A. (2016). It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *International Journal of Hospitality Management, 53*, 17–29.

Mathieson, K. (1991). Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. Information Systems Research, 2(3), 173-191.

Mclean, G., Al-Nabhani, K., & Wilson, A. (2020). Developing a mobile applications customer experience model (MACE) – Implications for retailers. Journal of Business Research, 109, 104-115.

Mehta, P., & Chatterjee, R. (2022). Green consumer behaviour in India: A study of eco-conscious purchase intentions. Journal of Cleaner Production, 367, 132823.

Mehta, R., & Shah, S. (2021). Promotional strategies and consumer impulsive buying behaviour: Evidence from Indian e-commerce platforms. Indian Journal of Marketing, 51(3), 15–27. https://doi.org/10.17010/ijom/2021/v51/i3/157394

Mitchell, A. A., & Olson, J. C. (1981). Are product attribute beliefs the only mediator of advertising effects on brand attitude? Journal of Marketing Research, 18(3), 318–332. https://doi.org/10.2307/3150973

Mortimer, G., Fazal e Hasan, S. M., Andrews, L., & Martin, J. (2016). Online grocery shopping: The impact of shopping frequency on perceived risk. The International Review of Retail, Distribution and Consumer Research, 26(2), 202-223.

Nguyen, T. D., Ngo, L. V., & Ruël, H. (2020). Social capital, knowledge sharing, and innovation: Evidence from Vietnam's information technology industry. *Journal of Innovation & Knowledge, 5*(4), 282–290.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Nysveen, H., Pedersen, P. E., & Thorbjørnsen, H. (2005).Intentions to use mobile services: Antecedents and cross-service comparisons. *Journal of the Academy of Marketing Science, 33*(3), 330–346.

Ooi, K. B., & Tan, G. W. H. (2016). Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card. Expert Systems with Applications, 59, 33-46.

Pallant, J. (2020). *SPSS survival manual: A step-by-step guide to data analysis using IBM SPSS* (7th ed.). McGraw-Hill Education

Pappas, I. O. (2016). Marketing strategies and tactics in the age of digital transformation. *Journal of Strategic and International Studies, 12*(2), 1–11.

Park, C., & Kim, Y. (2003). Identifying key factors affecting consumer purchase behavior in an online shopping context. International Journal of Retail & Distribution Management, 31(1), 16-29.

Park, D. H., Lee, J., & Han, I. (2007). The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement. International Journal of Electronic Commerce, 11(4), 125–148. https://doi.org/10.2753/JEC1086-4415110405

Patil, D., & Bansal, A. (2018). Understanding rural consumer behaviour in India. International Journal of Rural Management, 14(1), 62–78. https://doi.org/10.1177/0973005218763507

Patil, P., & Rani, S. (2021). Factors affecting intention to adopt mobile wallets in India: An application of TPB. International Journal of Management Studies, 8(2), 112–125. https://doi.org/10.18843/ijms/v8i2/12

Paul, J., Modi, A., & Patel, J. (2016). Predicting green product consumption using theory of planned behavior and reasoned action. Journal of Retailing and Consumer Services, 29, 123–134. https://doi.org/10.1016/j.jretconser.2015.11.006

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce, 7(3), 101-134.

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. MIS Quarterly, 30(1), 115-143.

Petty, R. E., Cacioppo, J. T., & Schumann, D. (1983). Central and peripheral routes to advertising effectiveness: The mediating role of involvement. Journal of Consumer Research, 10(2), 135-146.

Rogers, E. M. (1962). *Diffusion of innovations* (1st ed.). New York: Free Press of Glencoe.

Ryan, E. H., & Bonfield, E. H. (1980). *The Fishbein-Ajzen model of attitude-behavior relations: A meta-analysis. Journal of Consumer Research, 7*(3), 307–316.

Rana, R., & Singh, J. (2021). App quality, user satisfaction and m-commerce engagement: An empirical investigation. International Journal of Information Management, 58, 102321. https://doi.org/10.1016/j.ijinfomgt.2020.102321

Rao, K., & Sinha, M. (2020). Online consumer behaviour in tier II and III cities in India: A study on emerging digital markets. Journal of Business and Retail ManagementResearch,14(3),120130.https://doi.org/10.24052/JBRMR/V14IS03/ART-11

Riquelme, H. E., & Rios, R. E. (2010). The mediating effect of gender in the adoption of mobile banking. International Journal of Bank Marketing, 28(5), 328-341.

Rogers, E. M. (2003). Diffusion of Innovations (5th ed.). Free Press.

Russo, I., Confente, I., Gligor, D. M., & Cobelli, N. (2017). The combined effect of product returns experience and switching costs on B2B customer re-purchase intent. Journal of Business & Industrial Marketing, 32(5), 664-676.

Schiffman, L. G., & Wisenblit, J. (2019). *Consumer behavior* (12th ed.). Pearson Education.

Shareef, M. A., Baabdullah, A. M., Dutta, S., Kumar, V., & Dwivedi, Y. K. (2021). Consumer adoption of mobile banking services: An empirical examination of factors according to adoption stages. *Journal of Retailing and Consumer Services, 61*, 102554.

Sheth, J. N. (2021). Impact of demographic factors on consumer behavior in digital markets. *Journal of Business Research, 124*, 1–9.

Shin, D. H. (2010). The effects of trust, risk, and privacy concern on users' acceptance of location-based services. *International Journal of Mobile Communications, 8*(4), 393–411.

Shin, D., & Kang, M. (2016). Understanding the role of cultural differences in the adoption of mobile commerce: A cross-national study. *Information & Management, 53*(4), 499–510.

Simon, H. A. (1955). A behavioral model of rational choice. The Quarterly Journal of Economics, 69(1), 99–118.

Sadi, A. S. (2012). Modeling the Factors Affecting the Adoption of Mobile Commerce in Malaysia Higher Institutions (Doctoral dissertation, Kulliyyah of Information and Communication Technology, International Islamic University Malaysia).

Saxena, S., & Khanna, M. (2019). Influence of website quality on consumer online purchase

behaviour: Evidence from Indian fashion e-commerce. Indian Journal of Marketing, 49(5), 37–49. https://doi.org/10.17010/ijom/2019/v49/i5/143363

Saxena, S., & Yadav, R. (2019). Investigating the role of subjective norm and brand consciousness in brand loyalty: Evidence from Indian fashion retail. Journal of Retailing and Consumer Services, 51, 234–240. https://doi.org/10.1016/j.jretconser.2019.06.010

Sharma, R., & Kapoor, S. (2021). Impact of digital media on youth consumer behaviour in India. Journal of Retailing and Consumer Services, 59, 102400. https://doi.org/10.1016/j.jretconser.2020.102400

Sharma, S., & Gupta, V. (2020). Influence of subjective norms and attitude on online shopping behaviour in India: An extension of the TPB model. Indian Journal of Marketing, 50(7), 8–20. https://doi.org/10.17010/ijom/2020/v50/i7/155026

Singh, A., & Kaur, G. (2019). Cultural values and consumer behaviour: A study of Indian consumers. Asian Journal of Business Research, 9(2), 78–90. https://doi.org/10.14707/ajbr.190065

Sivathanu, B. (2019). Adoption of digital payment systems in the era of demonetization in India: An empirical study. Journal of Science and Technology Policy Management, 10(1), 143-171.

Slade, E. L., Williams, M. D., Dwivedi, Y. K., & Piercy, N. C. (2015). Exploring consumer adoption of proximity mobile payments. Journal of Strategic Marketing, 23(3), 209-223.

Smith, J. (2019). *Marketing to Gen Z: Understanding the preferences and behaviors of the next generation*. ResearchGate.

Sunita, C. (2023). Consumer Perception Towards Sustainable Packaging in E-Commerce Industry: A Factor Analytic Approach. Quing: International Journal of Commerce and Management, 3(2), 177-185.

Tan, G. W. H., Ooi, K. B., & Lin, B. (2014). Predicting the drivers of behavioral intention to use mobile learning. *Computers in Human Behavior, 35*, 1–10.

Tarkiainen, A., & Sundqvist, S. (2005). Subjective norms, attitudes and intentions of Finnish consumers in buying organic food. British Food Journal, 107(11), 808-822.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144-176.

Thakur, R. (2013). Customer adoption of mobile payment services by professionals across two cities in India: An empirical study using modified technology acceptance model. Business Perspectives and Research, 1(2), 17-29.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2012). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.

Venkatesh, V., Thong, J.Y.L., & Xu, X. (2012). Consumer acceptance and use of information

technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157-178.

Vermeir, I., & Verbeke, W. (2006). Sustainable food consumption: Exploring the consumer "attitude–behavioral intention" gap. Journal of Agricultural and Environmental Ethics, 19(2), 169–194. https://doi.org/10.1007/s10806-005-5485-3

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. MIS Quarterly, 26(2), iii–xiii.

Wedel, M., & Kamakura, W. A. (2012). *Market segmentation: Conceptual and methodological foundations* (2nd ed.). Springer Science & Business Media.

Wang, R. J. H., Malthouse, E. C., & Krishnamurthi, L. (2015). On the go: How mobile shopping affects customer purchase behavior. Journal of retailing, 91(2), 217-234.

Wang, Y., & Lin, C. A. (2009). Consumer attitudes toward marketing and consumerism in China and the United States. International Journal of Advertising, 28(1), 125–146. https://doi.org/10.2501/S026504870920014X

Wang, Y.-S., & Lin, H.-H. (2012). Determinants of user acceptance of mobile banking: An empirical study. International Journal of Mobile Communications, 10(6), 578–597. https://doi.org/10.1504/IJMC.2012.049238

Wei, K. K., Teo, H. H., Chan, H. C., & Tan, B. C. Y. (2011). Conceptualizing and testing a social cognitive model of the digital divide. Information Systems Research, 22(1), 170-187.

Wei, R., Lo, V. H., & Wang, H. Y. (2011). The antecedents of mobile shopping behavior: An empirical study in China. Journal of Information Technology Management, 22(1), 1-12.

Xu, H., & Gupta, S. (2009). The effects of privacy concerns and personal innovativeness on potential and experienced customers' adoption of location-based services. Electronic Markets, 19(2-3), 137-149.

Yadav, R., & Pathak, G. S. (2016). Intention to purchase organic food among young consumers: Evidences from a developing nation. Appetite, 96, 122–128. https://doi.org/10.1016/j.appet.2015.09.017

Yadav, R., & Pathak, G. S. (2016). Young consumers' intention towards buying green products in a developing nation: Extending the theory of planned behavior. Journal of Cleaner Production, 135, 732–739. https://doi.org/10.1016/j.jclepro.2016.06.120

Yang, K. (2010). Determinants of US consumer mobile shopping services adoption: Implications for designing mobile shopping services. Journal of Consumer Marketing, 27(3), 262–270. https://doi.org/10.1108/07363761011038338

Yang, K. C. (2005). Exploring factors affecting the adoption of mobile commerce in Taiwan. Journal of CyberPsychology & Behavior, 8(2), 222–231. https://doi.org/10.1089/cpb.2005.8.222

Yang, K., & Forney, J. C. (2013). The moderating role of consumer technology anxiety in mobile shopping adoption: Differential effects of facilitating conditions and social influences. Journal of Electronic Commerce Research, 14(4), 334-347.

Yousafzai, S. Y., Foxall, G. R., & Pallister, J. G. (2010). Explaining Internet banking behavior: Theory of Reasoned Action, Theory of Planned Behavior, or Technology Acceptance Model? Journal of Applied Social Psychology, 40(5), 1172–1202.

https://doi.org/10.1111/j.1559-1816.2010.00615.x

Zeithaml, V. A. (1985). *Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence*. *Journal of Marketing*, 52(3), 2–22.

Zhou, T. (2011). *An empirical examination of users' post-adoption behavior of mobile services*. *Behaviour & Information Technology, 30*(4), 319–330.

Zhang, L., Zhu, J., & Liu, Q. (2012). A meta-analysis of mobile commerce adoption and the moderating effect of culture. Computers in Human Behavior, 28(5), 1902–1911. https://doi.org/10.1016/j.chb.2012.05.008

Zhou, T. (2011). An empirical examination of initial trust in mobile banking. Internet Research, 21(5), 527–540. https://doi.org/10.1108/10662241111176353

Zhou, T. (2011). Understanding mobile internet continuance usage from the perspectives of UTAUT and flow. Information Development, 27(3), 207-218.

Zhou, T. (2012). Examining mobile banking user adoption from the perspectives of trust and flow experience. Information Technology and Management, 13(1), 27–37. https://doi.org/10.1007/s10799-011-0111-8

Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. Decision Support Systems, 54(2), 1085-1091.

QUESTIONNAIRE FOR STUDY

Greetings Sir/Madam,

I am Roopa Acharya alias Pooja Prabhudesai, Assistant Professor, C.E.S. College of Arts & Commerce, Cuncolim, Goa. I am conducting a survey on Consumer behaviour towards use of Mobile Commerce for shopping, as a part of my Ph.D. study.

The title of my Study is **"Antecedents to Consumer Behaviour towards M-Commerce: An Empirical Study"**

M-commerce which is also termed as mobile commerce is the buying and selling of goods and services through mobile devices like smartphone and tablets

Kindly answer all the questions given below. Information provided by you will be kept confidential and will be used only for academic purpose.

Please co-operate and spare 15 minutes of your valuable time to respond to this survey.

Thank you for your precious time.

PART 1

This part of the questionnaire deals with **"Demographic" and "Socio-Economic Factors" of the respondents**.

Kindly answer the following questions.

Q.1 Name----------

Q.2 Gender:

- Male
- Female

Q.3 Age:

- Less than 20 years
- 21 to 40 years
- 41 to 60 years
- 61 years and above

Q.4 Education:

- Up to HSSC
- Graduation
- Post-Graduation and above
- Professional
- Other

Q.5 Area of location

- Municipal Area
- Panchayat Area

Q.6 Marital Status

- Married
- Unmarried

Q.7 Occupation

- Unemployed
- Service
- Business
- Home Maker
- Retired

Q.8 Monthly family income

- Less than Rs 25,000
- Rs 25,000 to Rs 50,000

- Rs 50,000 to Rs.75.000
- Rs 75,000 to Rs 1,00,000
- More than Rs 1,00.000

PART-2

This part of the questionnaire is to collect information on **"Attitude towards mobile commerce"**. Your responses to this part of the questionnaire will help to understand your views about benefits and limitations of using M-commerce for shopping.

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	Opinion	1	2	3	4	5
1	I think there is wide choice of products at reasonable prices on mobile commerce shopping platforms					
2	I feel M-commerce shopping platforms offer quick customer care service					
3	I think M-commerce lacks physical shopping experience					
4	I feel M-commerce is very convenient(Useful) for shopping from anywhere, anytime					
5	I think M-commerce transactions are not safe & secure					

6	I feel using mobile commerce without good knowledge and understanding of mobile technology is not safe					
7	I think customer reviews and ratings on M-commerce shopping portals are not reliable to make shopping decisions					
8	I think user friendly M-commerce apps make shopping simple and enjoyable					
9	I think use of M-commerce leads to shopping addiction					
10	I think M-commerce gives privacy in shopping personal products					

PART-3

This part of the questionnaire is to collect information on **"Perceived Behavioural Control Towards M-Commerce"**. Your responses to this part of the questionnaire will tell whether you need to take permission before using m-commerce for shopping.

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	**Opinion**	**1**	**2**	**3**	**4**	**5**
1	I need to take permission from family members to buy products on mobile commerce sites					
2	I have full freedom to spend any amount of money while shopping on m-commerce sites					

3	I can make my decision to shop anytime on mobile commerce shopping sites whenever I feel like shopping					
4	I don't need to take permission from anyone to shop using mobile commerce sites					

PART-4

This part of the questionnaire is to collect information on **'Subjective Norm'.** Your responses to this part of the questionnaire will tell whether, you give importance to other people's opinion for taking decisions to use or not to use mobile commerce for shopping

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	**Opinion**	**1**	**2**	**3**	**4**	**5**
1	I use mobile commerce for shopping since, most people who are important to me prefer mobile commerce for shopping					
2	I use mobile commerce for shopping since, most people who are important to me have recommended it to me					
3	I don't use mobile commerce for shopping since, most people who are important to me think that using mobile commerce for shopping is not safe					
4	I use mobile commerce for shopping since, most of my followers on social networking sites encourage me to use mobile commerce for shopping					
5	I use mobile commerce for shopping, even when people who are close to me are not in favour of it					

6	I always depend on other people's opinion for shopping on mobile commerce sites					

PART-5

This part of the questionnaire is to collect information on '**Mobile Commerce Intention'.**

Your responses to this part of the questionnaire, will make your intentions clear whether you will give preference to mobile commerce while shopping in future or not.

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	**Opinion**	**1**	**2**	**3**	**4**	**5**
1	I intend to use mobile commerce to keep my shopping private and confidential					
2	I intend to use mobile commerce as I believe that it is convenient (Useful)					
3	I intend to use mobile commerce as I believe that it is safe to use					
4	I intend to use mobile commerce as it is cheaper than offline shopping					
5	I don't intend to use mobile commerce due to my past experience with it					
6	I intend to use mobile commerce since people who are important to me have recommended it to me					
7	I intend to use mobile commerce since I believe that it is easy to use					
8	I don't intend to use mobile commerce due to lack of knowledge of using mobile commerce					

Q.9. Please share at least one good/ bad experience of yours with mobile commerce, if you have used it for shopping

---

Q.10. What are your expectations from mobile commerce shopping platforms, for improving future shopping experiences with mobile commerce?

PART-6

This part of the questionnaire is to collect information on **'Mobile Commerce Purchase Behaviour'.**

Your response to this part of the questionnaire will tell your actual use of mobile commerce for the purchase of different categories of products listed in the statements below.

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	Opinion	1	2	3	4	5
1	In the past few years, I have been using mobile commerce for shopping electronic products					
2	In the past few years, I have been using mobile commerce for shopping sports products.					
3	In the past few years, I have been using mobile commerce for shopping clothing, shoes and Jewellery items					

4	In the past few years, I have been using mobile commerce for shopping beauty and personal care products					
5	In the past few years, I have been using mobile commerce for shopping home and kitchen appliances					
6	I have never used mobile commerce for shopping					
7	In the past few years, I have been using mobile commerce for shopping for Books, Magazines and Newspapers					
8	In the past few years, I have been using mobile commerce for shopping for healthcare and medicines					
9	In the past few years, I have been using mobile commerce for shopping for stationary items and games					
10	In the past few years, I have been using mobile commerce for shopping for groceries					

Q.11 Do you enjoy shopping on mobile commerce sites?

- Yes
- No

Q.12 Do you require other people's help while using mobile commerce for shopping?(e.g. while completing shopping transaction/ while using mobile commerce for shopping)

- Yes
- No

Q.13 If yes, please state the reason. ----------

----------THE END----------

"ANTECEDENTS TO CONSUMER BEHAVIOUR TOWARDS M-COMMERCE: AN EMPIRICAL STUDY"

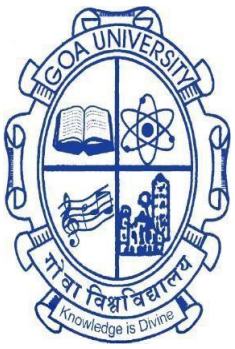
A THESIS SUBMITTED IN PARTIAL FULFILLMENT FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

in Commerce

IN THE GOA BUSINESS SCHOOL

GOA UNIVERSITY



By

Roopa Arvind Acharya

Research Centre in Sant Sohirobanath Ambiye, Government College, Pernem, Goa Business School, Goa University, Goa

September 2025

DECLARATION

I, Roopa Arvind Acharya hereby declare that this thesis represents work which has been carried out by me and that it has not been submitted, either in part or full, to any other University or Institution for the award of any research degree.

Place: Taleigao Plateau. Roopa Arvind Acharya

Date:27-09-2025

CERTIFICATE

I hereby certify that the above Declaration of the candidate, name of the candidate is true and the work carried out under my supervision.

Prof. (Dr.) Achut P. Pednekar

Research Guide

Professor and Principal, Swami Vivekanand Vidyaprasarak Mandal's, College of Commerce, Borim, Ponda, Goa.

ACKNOWLEDEMENT

As I reflect on my academic journey, I am deeply humbled by the kindness and goodwill extended to me at every stage. It is indeed a privilege to acknowledge all those whose contributions have played an instrumental role in shaping my research and in helping me reach this milestone of my life.

At the very outset, I bow my head in gratitude to the God for granting me good health, inner strength, resilience, and spiritual guidance throughout the course of my doctoral studies. His blessings sustained me in moments of challenge, uncertainty, and self-doubt, and His grace enabled me to persist with determination. Without His divine support, this journey would not have been possible.

I am profoundly indebted to my esteemed research guide, Prof. Achut P. Pednekar, whose invaluable mentorship has been the cornerstone of this work. From the very day of my registration, he has been a constant source of inspiration. His untiring support, patience, constructive criticism, and faith in my abilities provided me with clarity and direction at every step. I owe the successful completion of this thesis to his dedicated supervision and advice.

I wish to record my sincere appreciation to Prof. Filipe Rodrigues e'Melo**,** whose motivation and encouragement consistently inspired me to put forth my best efforts. I am equally grateful to Prof. Nilesh Borde**,** who, despite his demanding schedule, generously shared his expertise and guided me with valuable insights and suggestions. His intellectual guidance was instrumental in refining my study, and I hold his contribution in the highest regard. I also wish to thank the Principal and administrative staff of my research centre at Sant Sohirobanath Ambiye, Government College, Pernem and Goa Business School, administrative staff at Goa University specially Ms. Aditi for their cooperation and support in completing administrative procedures smoothly .I also wish to extend my gratitude to the distinguished experts who participated in the scale development process by providing their expert ratings, and to the respondents who took part in the qualitative study**.** Their contribution of time and effort was vital to the

empirical foundation of this research. I acknowledge their willingness to share their perspectives, which significantly enriched the study and helped me achieve the objectives of this thesis.

My heartfelt thanks go to Prof. Sandesh Dessai, Librarian, Goa University, and Dr. Nandkishor Bandekar, Assistant Librarian, Goa University, for their cooperation and assistance during my numerous visits to the university library. I am also grateful to the office staff of the Goa Business School, Goa University, for their constant cooperation and support during the administrative processes.

Special appreciation is due to Dr. Bhavesh Vanpariya and Ms. Nidhi Gajera, whose insightful guidance on academic writing and data analysis helped me with the necessary tools to organize my research more effectively. Their readiness to engage in meaningful discussions and to offer assistance whenever sought greatly helped my work. Their contribution has been invaluable in enhancing the quality of this thesis.

I also remain indebted to Mr. Vishal Gaonkar, Dr. Suraj Velip, Dr. Virendra Amonkar, and Dr. Sadanand Gaonkar for their constant encouragement and willingness to extend support whenever required. My heartfelt thanks are also due to my fellow research scholars, Shri Jayesh Mayekar and Mr. Yogeshwar Bhosle, whose academic companionship and constructive feedback made my research journey personally enriching.

I extend my deep gratitude to Mr. Virendra (Videsh) Dessai, Chairman of Cuncolim Education Society, and to all the members of the Management for their cooperation in sanctioning my study leave, which enabled me to pursue and complete my doctoral studies in a timely manner. I am equally thankful to our former Principal, Shri Laximan Naik, Prof. Sanjay Sawant Dessai, Dr. Sarala Ketegari, Prof. Avinash Raikar, and my Principal Prof. Brahma Edwin Barreto, whose consistent encouragement and moral support motivated me to register for Ph.D. and remain focused on my academic goals.

My sincere thanks are also due to all my colleagues and friends at C.E.S. College, and also to Assistant Professor Vibha Angle from Dempo College, for their cooperation, encouragement, and support throughout this journey. I am also grateful to the administrative staff of C.E.S. College, Cuncolim, who extended their assistance whenever required and helped me in fulfilling the necessary formalities with efficiency.

Beyond my academic circle, my deepest gratitude is reserved for my family**,** who have been the foundation of my strength. Whatever I am today is a reflection of their unconditional love, sacrifices, and firm belief in me.

I owe my achievements to the blessings and encouragement of my parents, Shri Arvind Acharya and Smt. Rekha Acharya**,** who have been my guiding light. Their moral support during this long journey of over six years gave me courage and determination when I needed it most.

I also wish to acknowledge the invaluable technical support extended by my nephew, Mr. Neel Prabhudesai**,** who stood by me until the final stages of thesis writing. I am equally grateful to my brother**,** Mr. Prasanna Acharya (I.A.S.)**,** and my sisters-in-law, Dr. Puja Acharya and Ms. Cristine Prabhudesai**,** as well as to Mr. Raj Prabhudesai and Ms. Isha Kurade, for their constant encouragement and Support.

My heartfelt thanks also go to my husband, Mr. Jitendra Prabhudesai**,** and my son, Mr. Deep Prabhudesai, for their patience, support, and sacrifices throughout my research journey.

Finally, I acknowledge with gratitude the contributions of numerous other individuals whose names may not find a place here but whose support, prayers, and encouragement have in some way contributed to the successful completion of this thesis. I sincerely pray that God bless them all abundantly. To each and every person who has supported me in this journey. **Thank You.**

DEDICATION

This thesis is dedicated with profound love and deepest gratitude to my beloved parents, Mr. Arvind S. Acharya and Mrs. Rekha A. Acharya. Their sacrifices, wisdom and constant faith in me have shaped my journey and given me the strength to pursue my aspirations.

This thesis is also dedicated to my dear son, Mr. Deep Prabhudesai, whose constant support has been an invaluable part of my research journey. I am deeply grateful for his thoughtful assistance in accompanying me to the Research Centre Pernem and Goa University, often driving me with patience and care. His timely help with various research-related tasks, including printing and other essential work, has made this journey smoother and less burdensome.

Beyond his practical support, his understanding, encouragement, and willingness to stand by me during challenging times have been a true source of strength. This achievement is as much his as it is mine, and I dedicate this work to him with heartfelt appreciation and love.

Antecedents to Consumer Behaviour towards M-Commerce:

An Empirical Study

By

Roopa Arvind Acharya

Research Guide: Prof. (Dr.) Achut P.Pednekar

Professor and Principal, Swami Vivekanand Vidya Prasarak Mandal's,
College of Commerce, Borim, Ponda, Goa.

ABSTRACT

The rapid advancement of mobile technologies has significantly reshaped the domain of electronic commerce, leading to the emergence of mobile commerce (M-commerce) as a prominent channel for digital transactions. Although existing literature grounded in the Theory of Planned Behaviour (TPB) has highlighted the impact of factors such as attitude, perceived usefulness, ease of use, and trust on consumers' behavioural intentions towards mobile technologies, there remains a notable gap in comprehensive empirical investigations that specifically examine the antecedents of consumer behaviour within the M-commerce context. This study seeks to address this gap by empirically analysing the influence of core TPB constructs 'Attitude', 'Subjective Norms', and 'Perceived Behavioural Control on consumers' intentions towards mobile commerce and their actual mobile commerce purchase behaviour while shopping different categories of product.

This study investigated the antecedents of consumer behaviour towards mobile commerce (m-commerce) using the Theory of Planned Behaviour (TPB) as the conceptual framework. Based on structural equation modeling (SEM), the research validates the key TPB constructs Attitude, Subjective Norms, Perceived Behavioural. Control (PBC), and Intention to assess their influence on m-commerce adoption across diverse consumer segments.

The measurement model demonstrated strong validity, with significant factor loadings confirming construct reliability. Attitude emerged as a multidimensional construct, shaped by both positive aspects (e.g., convenience, user-friendliness) and negative concerns (e.g., safety, past experiences). Subjective Norms were largely influenced by peer and societal expectations, though some resistance due to negative social cues were evident. Perceived Behavioural Control showed limited influence, with ease of use and knowledge contributing positively but perceived risks negatively.

Demographic analysis revealed nuanced influences. Age, education, location, and marital status significantly impacted attitudes and intentions, with younger, urban, and more educated users showing greater adoption likelihood. Occupation influenced intention but not attitudes or subjective norms, while gender and income showed minimal effects. Importantly, non-adoption was strongly associated with lack of knowledge, negative attitudes, and low intention, highlighting barriers to digital inclusion.

SEM findings confirmed that Attitude and Subjective Norms are the strongest predictors of intention, whereas Perceived Behavioural Control had no significant effect on intention. Intention, in turn, significantly mediated the relationship between these antecedents and actual purchase behaviour, confirming its central role. The model displayed robust fit indices, validating its application to m-commerce research.

Overall, the findings reinforce the applicability of the TPB model in explaining m-commerce behaviour. The study highlights the dominance of consumer attitudes and social influence in shaping behavioural intentions, while also revealing demographic disparities. Strategic implications suggest the need for targeted awareness campaigns, user-centric design, and rural outreach to enhance m-commerce engagement across varied consumer groups.

Keywords: Electronic commerce, M-commerce, Attitude, Subjective Norms, Perceived Behavioural Control, Intention, Mobile commerce purchase behaviour

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CHAPTER-1
INTRODUCTION

1.1 INTRODUCTION:

Mobile commerce (m-commerce) in India has experienced rapid growth, transforming the way consumers shop and businesses operate. With the increasing penetration of smartphones and internet connectivity, m-commerce is poised to become the dominant force in the Indian e-commerce landscape. Unlike e-commerce, m-commerce offers the convenience of on-the-go shopping, personalized user experiences, and real-time access to products and services. However, consumer adoption is not solely determined by accessibility. Several other factors such as perceived usefulness, ease of use, trust and security concerns, significantly shape consumer intentions and actual usage (Jain et al., 2023). Moreover, younger consumers and digital natives show higher engagement with m-commerce due to their comfort with mobile technologies and demand for instant gratification (Gupta & Pathak, 2023). In contrast, resistance among older consumers and users in rural regions often stems from concerns about data privacy & lack of digital literacy (Kumar et al., 2019). Understanding these factors provide businesses with insights into how to tailor their M-commerce strategies effectively to meet consumer needs and preferences.

1.2 BACKGROUND OF THE STUDY:

Technology and innovation have become a significant part of our lives in recent years. Despite this fact several innovation-based technologies, businesses have never arrived at their fullest capacity due to lack of acceptance by users. Hence several researchers are working very hard over the years towards testing and proposing extended models of various technology adoption theories like, Theory of Reasoned action (TRA) (Fishbein and Ajzen, 1975), Technology Acceptance Model (TAM) (Davis, 1989), Diffusion of Innovation (DOI) (Rogers, 1962), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et.al,2003) and many others, in order to know the reasons behind acceptance of innovation by the consumers and also to know the factors determining behavioural intention towards adoption and use of technology.

This study aims to investigate both the reasons behind acceptance and rejection of use of mobile devices for shopping. The behavioural intention to use mobile commerce for shopping is the basic construct of this model. Chew (2006) defined behavioural intention as "the power of an individual's intention to perform a certain behaviour". In the context of

m-commerce, this construct can be described as an individual's intention to perform online shopping through mobile wireless devices (Yang, 2005).

Extensive research based on the review of literature, supports the notion that ultimate behaviour of consumers' is important for the survival of any business, which is 'adoption and use of mobile commerce'. The theory of planned behaviour (Ajzen,1991), is one of the preferred technology adoption theories for the research in social science as well as behavioural sciences. Hence researcher have decided to use it for predicting consumer behaviour towards m-commerce in the state of Goa. This study has been conducted primarily to test the usage behaviour of m-commerce applications by consumers for shopping.

This study integrates the Theory of Planned Behaviour with the study of consumer behaviour towards M-commerce, highlighting the theoretical underpinnings and empirical applications in understanding consumers' attitudes, subjective norms, and perceived behavioural control in adopting mobile commerce services for shopping .The Theory of Planned Behaviour (TPB), developed by Ajzen (1991), provides a robust framework for understanding and predicting human behaviour in various contexts, including consumer behaviour towards M-commerce. According to TPB, consumer behaviour is influenced by three primary factors: attitudes towards the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991).

Attitudes towards M-commerce refer to consumers' overall evaluation of engaging in mobile commerce activities such as purchasing goods or services through mobile applications. Positive attitudes towards M-commerce are likely to increase the intention to engage in such behaviours (Ajzen, 1991). For instance, if consumers perceive M-commerce as convenient, time-saving, and offering a wide variety of choices, their attitudes towards using M-commerce are likely to be favourable (Davis, 1989).

Subjective norms reflect the perceived social pressures and expectations that influence individuals' decisions to adopt M-commerce. This includes the influence of significant others, such as friends, family, and peers, who may encourage or discourage the use of mobile commerce services (Ajzen, 1991). Social influence plays a crucial role in shaping consumer behaviour, as individuals are likely to confirm to perceived norms regarding M-commerce usage (Venkatesh et al., 2003).

Perceived behavioural control refers to consumers' perceptions of their ability to successfully perform the behaviour of using m-commerce applications. Factors such as perceived ease of use, technical skills, and confidence in conducting secure transactions on mobile platforms influence perceived behavioural control (Ajzen, 1991; Gefen, 2003). Higher levels of perceived behavioural control enhance consumers' intention to adopt and use M-commerce services.

In the context of M-commerce, empirical studies grounded in TPB have shown that attitudes towards mobile technology, perceived usefulness, ease of use, and trust in mobile transactions significantly influence consumers' behavioural intentions (Venkatesh et al., 2003; Kim et al., 2008). For example, research indicates that consumers who perceive M-commerce as convenient and secure are more likely to develop positive attitudes and intentions towards using mobile commerce services (Kim et al., 2008).

Despite the theoretical insights provided by TPB, there remains a need for empirical research that applies this framework to investigate specific antecedents influencing consumer behaviour towards M-commerce comprehensively. This study aims to address this gap by examining the relationships between attitudes, subjective norms, perceived behavioural control, and consumer behaviour towards M-commerce, utilizing a quantitative research approach to gather and analyse data from a diverse sample of mobile users.

By applying TPB to the study of M-commerce, this research seeks to enhance our understanding of the psychological factors driving consumer adoption and usage of mobile commerce applications. The findings of this study are expected to provide valuable insights for businesses and policymakers aiming to optimize strategies for promoting M-commerce adoption and improving consumer engagement in mobile transactions.

1.3 THE E-COMMERCE INDUSTRY: A GLOBAL AND INDIAN PERSPECTIVE:

The e-commerce industry continues to evolve rapidly, driven by technological advancements and changing consumer preferences. Globally, regions like Asia-Pacific and North America lead the market, while India emerges as a significant player with immense growth potential. Businesses must stay alert, leveraging trends like mobile commerce, AI-driven personalization, and social commerce, while addressing challenges related to

logistics, infrastructure, and regulatory environments. By doing so, they can capitalize on the growing opportunities in the global and Indian e-commerce markets.

E-commerce has transformed consumer interactions with businesses by providing unmatched convenience and accessibility via electronic devices. Over the past decade, the global e-commerce sector has experienced significant growth, reshaping both consumer shopping behaviour and business operations. In 2023, global e-commerce sales reached approximately $5.8 trillion, accounting for nearly 20% of total retail sales worldwide (Statista, 2023). This growth is driven by increasing internet penetration, the proliferation of smartphones, and improvements in logistics and payment systems. The COVID-19 pandemic further accelerated e-commerce adoption, with more consumers turning to online shopping for convenience and safety**.**

Table 1.1: Recent Data and Projections of Global E-commerce Sales (2018-2025)

Year	**Sales (in Trillion USD)**
2018	2.8
2019	3.5
2020	4.2
2021	4.9
2022	5.2
2023	5.8
2024	6.5
2025	7.4

Source: IAMAI. (2023). Digital India and Mobile Commerce Report. Retrieved from IAMAI

In India, the e-commerce industry has experienced amazing growth, making it one of the fastest-growing e-commerce markets globally. In 2023, the Indian e-commerce market was valued at approximately $90 billion and is projected to reach $120 billion by 2025 (IBEF, 2023). This surge is attributed to a fast-growing net user base and increasing smartphone penetration (TRAI, 2023). Government initiatives like Digital India campaign and improvements in digital infrastructure have also played an important role in fostering this growth.

Table 1.2: Recent Data and Projections of Indian E-commerce Sales (2018-2025)

Year	Sales (in Billion USD)
2018	39
2019	51
2020	60
2021	67
2022	75
2023	90
2024	105
2025	120

Source: Statista. (2023). E-commerce market size in India. Retrieved from Statista

1.4 M-COMMERCE: AN INDIAN PERSPECTIVE:

Mobile commerce (m-commerce), has become an essential component of the e-commerce industry, driving significant changes in consumer behaviour and business strategies. With the explosion of smartphones and the increasing availability of high-speed internet, consumers now prefer to shop via mobile devices than ever before (Statista, 2023). This shift has compelled e-commerce platforms to optimize their interfaces for mobile use, enhancing user experiences through responsive design and mobile-specific features (Kumar & Mukherjee, 2022).

The growth of m-commerce is particularly noticeable in India, with mobile transactions accounting for nearly 60% of e-commerce sales, reflecting importance of mobile-first strategies in capturing the Indian market (Forrester, 2023). By 2023, India had one of the largest smartphone user bases globally, with more than 750 million users of smartphone,and this number is expected to surpass 1 billion by 2026 (Statista, 2023). This surge has made m-commerce a central factor of digital economy.

According to the Ministry of Electronics & Information Technology (MeitY, 2022), smartphone penetration in Goa is above the national average, yet there remain considerable differences in adoption of digital payment and m-commerce systems. Factors like socio-economic status, digital literacy, local business practices, and trust in mobile platforms can vary significantly, impacting the overall acceptance of m-commerce in the state of Goa. (Shirodkar et al., 2020).

Table 1.3: Recent Data and Projections of M-commerce Sales in India (2020-2025)

Year	Sales (in Billion USD)
2020	25
2021	30
2022	35
2023	40
2024	55
2025	75

Source: Statista. (2023)

1.5 MEANING OF M-COMMERCE:

Mobile commerce also known as m-commerce, involves using wireless handheld devices like cell phones and tablets to conduct commercial transactions online, including Mobile shopping (purchase and sale of products), Mobile Banking, Mobile Payments and Mobile Advertising.

1.6 DEFINITIONS OF M-COMMERCE:

1.6.1 “Mobile e-commerce, commonly referred to as m-commerce, is the ability to purchase goods anywhere through a wireless Internet-enabled devices.” **(Clarke)**

1.6.2 “M-commerce refers to any transaction of monetary value that is conducted through a mobile network, using devices such as mobile phones, pagers, personal digital assistants, or laptops.” **(Varshney & Vetter)**

1.7 CHALLENGES AND OPPORTUNITIES FOR M-COMMERCE IN INDIA:

The m-commerce industry in India is on a rapid growth trajectory, driven by increasing mobile internet penetration, the proliferation of mobile payment systems, and changing consumer behaviour. While there are challenges to address, the opportunities for growth are immense. Businesses that can effectively leverage technology, understand consumer preferences, and navigate logistical challenges will be well-positioned to succeed in this dynamic market.

1.7.1 Challenges for M-Commerce in India:

a. Logistics and Delivery Infrastructure: Despite improvements, logistics and delivery infrastructure remain a significant challenge for m-commerce in India, particularly in rural and remote areas. According to the Indian Logistics Report 2023, the logistics sector in India is expected to grow at a CAGR of 10.5% from 2020 to 2025. However, the average delivery time for rural areas is 2-3 days longer compared to urban areas.

Table 1.4: Average Delivery Time for M-commerce in India

Location	Average Delivery Time (Days)
Urban	2
Semi-Urban	3
Rural	5

Source: Indian Logistics Report 2023, KPMG.

Implication: Improving the logistics and delivery infrastructure is crucial for ensuring timely deliveries and enhancing customer satisfaction in rural and semi-urban areas.

b. Digital Literacy and Internet Penetration: While internet penetration is increasing, digital literacy remains low in certain segments of the population, particularly among older

adults and those in rural areas. As per the Internet and Mobile Association of India (IAMAI), the number of internet users in India reached 700 million in 2023. However, digital literacy in rural areas is only about 25%, compared to 61% in urban areas.

Table 1.5: Digital Literacy Rate in India

Area	Digital Literacy Rate (%)
Urban	61
Rural	25
National	38

Source: Internet and Mobile Association of India (IAMAI, 2023)

Implication: Enhancing digital literacy through educational programs and awareness campaigns is essential for increasing the adoption of m-commerce across all demographic segments.

c. Cybersecurity Concerns: Ensuring secure transactions and protecting consumer data are critical concerns that need continuous attention. According to the CERT-In (Indian Computer Emergency Response Team), there were over 1.16 million cybersecurity incidents in India in the year, 2022, a 20% increase from 2021.

Table 1.6: Cybersecurity Incidents in India (2020-2022)

Year	**Cybersecurity Incidents (Million)**
2020	0.93
2021	0.97
2022	1.16

Source: CERT-In (Indian Computer Emergency Response Team)

Implication: Investing in robust cybersecurity measures and educating consumers about safe online practices are crucial for building trust in m-commerce platforms.

1.7.2 Opportunities for M-Commerce in India:

a. Rural Market Penetration:

With the majority of India's population residing in rural areas, there is significant potential for m-commerce growth through targeted strategies and improved logistics. The rural e-commerce market in India is projected to 38 billion USD in 2028.

Table 1.7: Rural E-commerce Market Size Projection in India (2023-2028)

Year	Rural E-commerce Market Size (Billion USD)
2023	10
2024	13
2025	17
2026	22
2027	29
2028	38

Source: Statista, (2024)

Implication: Companies can tap into this vast market by developing localized strategies, improving rural connectivity, and creating mobile-friendly platforms that cater to the unique needs of rural consumers.

b. Rise of Mobile Payment Systems in India: The increasing adoption of mobile payment systems like UPI, Paytm, Google Pay, and PhonePe has facilitated the growth of m-commerce by simplifying transactions. UPI transactions reached a record high of 9.36 billion in December 2023, according to the National Payments Corporation of India (NPCI). The total value of UPI transactions for 2023 was approximately $1.8 trillion.

Table 1.8: UPI Transactions (Billion) in India

Year	UPI Transactions (Billion)	Total Transaction Value (Trillion USD)

2020	2.2	0.54
2021	3.8	0.93
2022	6.5	1.4
2023	9.36	1.8

Source: National Payments Corporation of India (NPCI).

Implication: The continued growth of mobile payment systems offers an opportunity for m-commerce platforms to enhance user experience by providing seamless and secure payment options, thus encouraging more consumers to use m-commerce for shopping.

c. AI and Personalization: Leveraging: Artificial Intelligence (AI) offering personalized shopping experiences can enhance customer satisfaction and drive sales. A report by McKinsey & Company indicates that companies using AI-driven personalization can achieve up to a 15% increase in sales. AI applications in m-commerce, such as chatbots and recommendation engines, are expected to grow by 25% annually in India through 2025.

Table 1.9: AI Applications Growth Rate Projection (%) In India

Year	**AI Applications Growth Rate (%)**
2020	10
2021	15
2022	20
2023	25
2024	25
2025	25

Source: McKinsey & Company. "AI-driven Personalization in E-commerce."

Implication: By integrating AI technologies, m-commerce platforms can provide tailored recommendations, personalized marketing, and efficient customer service, thereby improving user engagement and retention.

d. Augmented Reality (AR):

Augmented Reality (AR) can revolutionize the shopping experience, particularly in segments like fashion and home decor, by allowing customers to virtually try products before purchasing. According to a report by PwC, the AR market in India is projected to grow at a CAGR of 55% from 2023 to 2028.By 2028, AR is expected to influence up to $15 billion in m-commerce sales.

Table 1.10: AR Market Size Projections (Billion USD) in India

Year	AR Market Size (Billion USD)
2023	2
2024	3.5
2025	5
2026	7.8
2027	11.5
2028	15

Source: PwC. "Augmented Reality Market Projections for India."

Implication: Incorporating AR technology can enhance the shopping experience by providing interactive and immersive product demonstrations, which can increase consumer confidence and reduce return rates.

1.8 SIGNIFICANCE OF THE STUDY:

This study highlights the theoretical and practical significance of applying the Theory of Planned Behaviour to investigate consumer's behavioural intentions and its impact on actual usage behaviour in the context of M-commerce, emphasizing its relevance for business strategy, consumer education, and theoretical advancements in the field.

The Theory of Planned Behaviour (TPB), developed by Ajzen (1991), provides a structured framework for understanding and predicting consumer behaviour towards M-commerce. This theory suggests that consumer intentions and behaviours are influenced by three key factors: attitudes towards the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991).

1.8.1 Predictive Power of Attitudes, Subjective Norms, and Perceived Behavioural Control:

This study is significant as it applies TPB to investigate how attitudes towards M-commerce, subjective norms, and perceived behavioural control collectively influence consumers' intentions and actual behaviour towards using mobile commerce applications for shopping purpose. By empirically testing these relationships, the study aims to provide insights into which factors are most influential in shaping consumer adoption and usage of M-commerce applications (Ajzen, 1991; Venkatesh et al., 2003).

1.8.2 Practical Implications for Businesses and Policy Makers:

Understanding the factors influencing consumer behaviour towards M-commerce is crucial for businesses and policymakers. Insights gained from this study can help businesses design and implement effective marketing strategies that will adjust with consumers' attitudes and preferences towards mobile transactions (Gefen, 2003).

1.8.3 Contribution to Theoretical Advancement:

Empirical validation of TPB in the context of M-commerce contributes to theoretical advancements in consumer behaviour research. By testing TPB constructs in a specific domain like M-commerce, this study expands our understanding of how general theories of behaviour can be applied to contemporary technological contexts. Such advancements are essential for developing robust theoretical frameworks that can guide future research and practical applications in mobile commerce (Venkatesh et al., 2003).

1.8.4 Insights for Consumer Education and Trust Building:

The study's findings can also suggest initiatives aimed at educating consumers about the benefits and safety of M-commerce. By identifying factors that influence perceived behavioural control and trust in mobile transactions, policymakers can develop policies and

guidelines that promote consumer confidence in using mobile commerce platforms securely and effectively (Kim et al., 2008).

1.9 RESEARCH PROBLEM:

The rapid evolution of mobile technologies and the spread of smartphones have catalysed the emergence and growth of mobile commerce (m-commerce), creating significant changes in consumer purchasing behaviour. M-commerce, as a subset of e-commerce, allows consumers to engage in real-time transactions anytime and anywhere, offering unprecedented convenience and personalization (Chopdar & Sivakumar, 2024). However, despite the technological advancements and the increasing penetration of mobile internet, m-commerce adoption varies significantly across demographic segments. Many consumers remain hesitant or inconsistent in their usage of mobile platforms for shopping, suggesting that key behavioural antecedents are still not fully understood or optimized by businesses.

A critical research problem, therefore, lies in identifying and empirically examining the antecedents that shape consumer behaviour towards use of m-commerce for shopping. While numerous studies have attempted to apply frameworks such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Theory of Planned Behaviour (TPB) to understand technology adoption, there remains a research gap in contextualizing these frameworks specifically to mobile commerce with a consumer-centric lens (Zhou, 2013; Chong, 2013).

Hence, the core research problem is: "What are the key antecedents that influence consumer behaviour towards m-commerce, and how do these antecedents interact to impact their intention to adopt m-commerce applications for shopping"

1.10 THE SCOPE OF THE STUDY:

This study is set within the field of consumer behaviour and digital marketing, specifically focusing on Mobile Commerce (M-commerce). It aims to apply the Theory of Planned Behaviour (TPB) (Ajzen, 1991) to understand and predict consumer intentions and behaviours towards use of M-commerce applications for shopping. The scope of the study consists of theoretical scope, empirical scope, managerial and policy scope, and educational scope:

1.10.1 Theoretical Scope: The study applies TPB as its theoretical framework, which suggests that attitudes, subjective norms, and perceived behavioural control are central determinants of behavioural intention (Ajzen, 1991). By employing TPB, the study examines the cognitive and social factors influencing M-commerce adoption. (Mital et al., 2021).

1.10.2 Empirical Scope: The research will be empirical in nature, using quantitative methods to measure the strength and significance of the three TPB constructs in predicting consumer intention and behaviour. Data will be collected through structured surveys administered to users of smartphones across the state of Goa. Analytical tools like regression analysis and structural equation modelling (SEM) will be employed to establish relationships among variables (Dwivedi et al., 2020).

1.10.3 Managerial and Policy Scope: This study holds practical relevance for businesses, marketers, and policymakers by identifying the psychological and behavioural factors that affect M-commerce adoption. Businesses can leverage these insights to develop targeted marketing strategies, personalized mobile interfaces, and trust-building mechanisms. Moreover, the findings can guide policymakers in formulating digital literacy campaigns, data privacy frameworks, and consumer protection measures that enhance user confidence in mobile platforms (Shareef et al., 2021).

1.10.4 Educational Scope: The study also examines the role of **consumer education** in influencing trust and perceived behavioural control in M-commerce usage. It investigates how digital awareness, mobile literacy, and understanding of online transaction security can affect user attitudes and behavioural outcomes. This can contribute to designing effective educational interventions aimed at improving digital participation across different demographic segments of society (Nguyen et al., 2020).

1.11 PURPOSE OF THE STUDY:

The study aims to provide a comprehensive understanding of the factors influencing consumer intention and usage behaviour towards mobile commerce applications for shopping. By examining attitudes, subjective norms, and perceived behavioural control, the study seeks to contribute both theoretically and practically to the field of M-commerce research, offering insights that can inform business strategies and policy initiatives aimed at promoting the growth and acceptance of mobile commerce platforms.

The Theory of Planned Behaviour (TPB), developed by Ajzen (1991), provides a structured framework for understanding consumer behaviour, particularly in the context of decision-making processes related to technology adoption such as use of M-commerce for shopping. This study aims to explore and analyse the factors influencing consumer behaviour towards M-commerce through the lens of TPB, focusing on three primary constructs: attitudes towards M-commerce, subjective norms, and perceived behavioural control (Ajzen, 1991).

1.11.1 Attitudes towards M-Commerce:

The study will investigate how consumers' attitudes towards M-commerce influences their intentions and behaviours towards use of m-commerce for shopping. Attitudes include consumers' overall evaluations and perceptions of using mobile devices for m-commerce activities, such as purchasing goods or services using mobile devices. (Davis, 1989; Ajzen, 1991).

1.11.2 Subjective Norms:

The research will explore the influence of subjective norms on consumer behaviour towards M-commerce. Subjective norms refer to the perceived social pressures and expectations from significant others, including family, and peers, regarding the adoption and usage of M-commerce services. This study will analyse how social influences impact consumers' intentions and behaviours in adopting mobile commerce (Ajzen, 1991; Venkatesh et al., 2003).

1.11.3 Perceived Behavioural Control:

The study will assess consumers' perceived behavioural control over using M-commerce platforms. This construct includes factors such as perceived ease of use, technical skills, and confidence in conducting secure transactions via mobile devices independently. Understanding perceived behavioural control is crucial for predicting consumers' intentions and actual behaviours towards M-commerce adoption and usage (Ajzen, 1991; Gefen, 2003).

1.11.4 Methodological Approach:

To achieve its objectives, the study will employ a quantitative research methodology, involving survey instruments designed to measure attitudes, subjective norms, perceived behavioural control, and actual purchase behaviour towards m-commerce among a diverse sample of mobile users from the state of Goa. Statistical analyses such as regression analysis and structural equation modelling (SEM) will be used to examine the relationships between TPB constructs and consumer behaviour (Venkatesh et al., 2003; Kim et al., 2008).

1.12 RESEARCH QUESTIONS:

I. How do the respective measurement variables contribute to the relevance and validity of their latent constructs in the proposed model of the “Theory of Planned Behaviour"?

II. How do the constructs of “The Theory of Planned Behaviour” influence the intentions to use m-commerce among consumers?

III. How do the ‘Demographic Variables’ influence ‘Attitude’, ‘Subjective Norms’, ‘Perceived Behaviour Control’, and ‘Intention’ regarding the use of m-commerce among consumers?

IV. How does intention mediate the relationship between ‘Attitude’, ‘Subjective Norms’, ‘Perceived Behavioural Control’, and consumer behaviour towards purchasing specified products through m-commerce?

V. How does “The Theory of Planned Behaviour" explain the factors influencing consumers’ adoption of m-commerce, and whether the empirical evidence supports the validity of this conceptual model in this specific context?

VI. What are the factors influencing an individual's likelihood of non-adoption of m-commerce?

1.13 OBJECTIVES OF THE STUDY:

I. To evaluate the relevance and validity of the measurement variables to their respective latent constructs in the proposed structural model of the “Theory of Planned Behaviour”

II. To evaluate the significance and extent to which the constructs of the ‘Theory of Planned Behaviour’ influence the intentions to use mobile commerce.

III. To examine the impact of ‘Demographic Variables’ on consumers' ‘Attitude’, ‘Perceived Behaviour Control’, ‘Subjective Norms’ and ‘Intention’ to use m-commerce.

IV. To investigate the mediating role of 'Intention' in the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories, through m-commerce.

V. To validate the conceptual model based on "The Theory of Planned Behaviour".

VI. To identify and analyse the factors influencing an individual's likelihood of non-adoption of m-commerce.

1.14 ORGANISATION OF THE THESIS:

Chapter 1: Introduction: This chapter includes Introduction, Background of the study, The E-commerce Industry: A Global and Indian Perspective, M-commerce(m-commerce) An Indian Perspective, meaning and definitions of M-commerce, Challenges and Opportunities for M-Commerce in India, Significance of the Study, Research Problem, The scope of the Study, Purpose of the Study, Research Questions, Objectives of the study, Organization of the Thesis and Conclusions

Chapter 2: Literature Review: Introduction, Theoretical Background, Indian study on consumer behaviour, Impact of antecedents of planned behaviour: Indian study, Global Study on consumer behaviour, Impact of antecedents of planned behaviour: Global study, Research Gap, the logical explanation of each research question, research objective and research hypothesis development with supporting literature review and citations and Conclusions.

Chapter 3: Research Methodology: This chapter includes introduction, research methodology based on the research ONION, development of measurement instruments, Operational definitions, development of scale, Pilot Test, population, Unit of analysis, sampling and sample size, Statistical Test Used, Ethical Considerations of the study.

Chapter 4: Data Analysis and Interpretation: This chapter includes introduction, data screening, demographic profile of respondents, Descriptive Statistics, objectives and hypothesis testing, Conclusions

Chapter 5: Findings and Conclusions: This chapter includes: introduction, objective wise findings of the study, findings of demographic insights, implications for theory and practice, recommendations, limitations of the study, future research directions, summary of key contributions and conclusions.

1.15 CONCLUSIONS:

In conclusion, this chapter has provided the conceptual and theoretical foundation necessary for the research study. It has brought together insights from literature, industry reports, and theoretical frameworks to establish the relevance and necessity of exploring consumer behaviour towards m-commerce through the lens of the Theory of Planned Behaviour. With this groundwork laid, the subsequent chapters will focus on review of literature, research methodology, data analysis, and interpretation of findings to answer the research questions and fulfil the stated objectives of the study.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION:

The review of literature serves as a foundational pillar in any scholarly research. This chapter aims to critically synthesize existing scholarly contributions, identify gaps, and establish the theoretical framework necessary for the current study. A well-structured review of literature not only anchors the research within the broader academic discourse but also justifies the research questions and methodology adopted (Webster & Watson, 2002).

For this study, the review focuses on key themes such as consumer behaviour theories, e-commerce and mobile commerce trends, technological acceptance models, and strategic marketing practices. By analysing important works and contemporary studies, this chapter aims to map out the evolution of concepts and their application in various contexts.

Furthermore, this chapter critically examines both conceptual and empirical contributions, identifying methodological strengths and limitations that inform the design of the present study. Attention is also given to recent systematic and analytical reviews in the field of m-commerce to identify underexplored areas (Palmatier et al., 2018). In doing so, the review not only provides context for the study's hypotheses but also guides the development of a conceptual framework and operational variables. Ultimately, this chapter highlights the importance of revisiting existing theoretical constructs in light of current market realities and consumer expectations.

The chapter is organised under following sections:

- Theoretical Background
- Indian Study on Consumer Behaviour
- Impact of Antecedents of Planned Behaviour: Indian Study
- Global Study on Consumer Behaviour
- Impact of Antecedents of Planned Behaviour: Global Study
- Research Gaps Literature Review of Research Questions, Research Objectives, Hypothesis, Summary and Conclusions.

2.2 THEORETICAL BACKGROUND:

Consumer Behaviour Theories:

Understanding consumer behaviour has long been a focal point in marketing research, as it provides valuable insights into how individuals make purchasing decisions and respond to marketing stimuli. Over the decades, various theoretical frameworks have been developed to explain consumer decision-making processes. This section critically reviews major consumer behaviour theories that have significantly contributed to the academic and practical understanding of consumption patterns.

2.2.1 Traditional Economic and Psychological Foundations

Early conceptualizations of consumer behaviour were rooted in economic theory, particularly the notion of the rational consumer, who is assumed to make decisions based on utility maximization and cost-benefit analysis (Simon, 1955). However, this model was criticized for oversimplifying human behaviour and ignoring psychological and emotional factors. As a result, psychological models gained prominence, incorporating cognitive and affective processes into consumer decision-making.

The Stimulus-Organism-Response (S-O-R) Model (Mehrabian & Russell, 1974) introduced the role of internal states such as emotions and moods in mediating external stimuli (e.g., advertisements) and behavioural responses (e.g., purchase intentions). This model laid the foundation for more sophisticated psychological frameworks that consider both environmental and internal influences.

2.2.2 The Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (Fishbein & Ajzen, 1975) was one of the first models to formalize the role of attitudes and subjective norms in predicting behavioural intentions. TRA suggests that a consumer's behavioural intention is influenced by their attitude toward the behaviour and the perceived social pressure to perform it (subjective norm). These constructs together influence the intention to perform a behaviour, which is considered the immediate antecedent to actual behaviour. TRA assumes that if a person intends to perform a behaviour, they are likely to do so, provided they have the necessary resources and opportunities.

TRA has been widely adopted in marketing research to explain various consumer actions such as purchase intention, brand choice, online shopping, and technology adoption. Studies have found that attitudes and subjective norms consistently predict behavioural intentions across a variety of consumer contexts (Ryan & Bonfield, 1980; Miniard & Cohen, 1981). Similarly, in product innovation studies, researchers have employed TRA to understand how new product perceptions and social influence affect consumers' willingness to try innovations (Taylor & Todd, 1995). In digital marketing, TRA has been instrumental in understanding online purchase behaviour. For example, Lim et al. (2016) utilized TRA to study online shopping intentions and found that subjective norms, especially peer reviews and social media influence, strongly impact consumer intentions in e-commerce environments.

Despite its wide use, TRA has been critiqued for its inability to explain behaviours that are not under complete volitional control. Many consumer behaviours such as impulse buying or habitual consumption are not always deliberate or planned. As a response, Ajzen (1991) extended the model into the Theory of Planned Behaviour (TPB) by adding the perceived behavioural control (PBC) component to account for non-volitional factors.

Moreover, empirical studies have shown that TRA's explanatory power can be limited in contexts where external barriers, emotions, or situational constraints play a major role (Bagozzi & Yi, 1989).

2.2.3 The Theory of Planned Behaviour (TPB):

To address the limitations of TRA, Ajzen (1991) introduced the Theory of Planned Behaviour (TPB) by incorporating a third construct perceived behavioural control (PBC) which captures the individual's perception of ease or difficulty in performing a behaviour. TPB has been extensively used in marketing research to predict behaviours such as online shopping (Pavlou & Fygenson, 2006), green purchasing (Paul et al., 2016), and mobile commerce adoption (Yang, 2005). TPB's strength lies in its comprehensive structure and predictive validity, especially when combined with contextual or demographic mediators.

2.2.4 The Technology Acceptance Model (TAM) and Its Extensions:

Originally developed in the context of information systems, the Technology Acceptance Model (TAM) by Davis (1989) has gained widespread adoption in marketing, particularly in digital environments. TAM suggests that perceived usefulness and perceived ease of use are the primary predictors of technology adoption behaviour. The model has been extended into TAM2, TAM3, and eventually integrated into the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003).

These models are particularly useful in understanding consumer behaviour in tech-driven contexts such as e-commerce, mobile applications, and social media marketing. Nonetheless, critics argue that TAM and its variants often overlook emotional, cultural, and social influences (Bagozzi, 2007).

While TAM has contributed immensely to understanding user interaction with technology, its narrow focus on system-related beliefs limits its utility in diverse marketing contexts. The TPB, with its incorporation of subjective norms and perceived behavioural control, offers a more comprehensive, flexible, and empirically robust model.

2.3 INDIAN STUDY ON CONSUMER BEHAVIOUR:

The consumer landscape in urban India has undergone a significant transformation due to globalization, digitalization, and rising disposable income. A study by (Gupta and Verma ,2020) examined how lifestyle changes and digital access affect urban Indian consumers' decision-making processes. Their research focused on factors such as convenience, brand perception, and product innovation. The study revealed that urban consumers are highly influenced by digital advertisements and social media reviews, emphasizing the importance of digital touchpoints in consumer journeys. India’s cultural diversity plays a critical role in shaping consumer preferences. (Singh and Kaur ,2019) investigated how cultural values, traditions, and social norms influence buying behaviour across different Indian regions. The study employed a qualitative design through focus group discussions and found that collectivism, family influence, and religious beliefs significantly affect purchase decisions, especially in categories such as food, clothing, and lifestyle products. While urban markets have matured, rural India represents an evolving consumer segment. (Patil and Bansal ,2018) explored consumer behaviour in rural regions, focusing on awareness levels, purchasing power, and brand loyalty. The study concluded that rural consumers are increasingly aspirational, showing interest in branded products, but are constrained by limited income

and poor access to organized retail. The research highlights the need for affordable pricing and effective distribution networks to penetrate rural markets. The digital revolution has significantly influenced the buying behaviour of millennials and Gen Z in India. In a study conducted by (Sharma and Kapoor ,2021), the authors examined the role of social media platforms, influencers, and e-WOM (electronic word-of-mouth) in shaping young consumers' choices. The study used a quantitative approach with 500 college students in metropolitan cities. Results indicated that trust in influencers and peer recommendations had a significant impact on brand preferences and buying intentions. As environmental awareness grows, so does interest in sustainable consumption. (Mehta and Chatterjee ,2022) explored the emergence of green consumer behaviour in India by examining how eco-labels, environmental knowledge, and corporate social responsibility (CSR) practices influence buying behaviour. The research revealed a gap between consumer attitudes and actual green purchasing behaviour, often due to higher prices and limited availability of eco-friendly alternatives.

2.3.1 Consumer Behaviour and E-Commerce:

Trust and perceived risk are major determinants in online consumer behaviour. (Chauhan and Verma, 2018) explored how these two factors influence online purchase intentions among Indian consumers. Using a structured questionnaire survey with 400 respondents, the study revealed that concerns about data privacy, product authenticity, and payment security significantly shape trust and risk perceptions. Consumers with higher trust in the e-commerce platform showed greater intention to purchase online. Demographic variables such as age, income, education, and gender significantly influence online shopping behaviour in India. (Kanchan, Kumar, and Gupta,2015) investigated how these variables affect consumer attitudes and frequency of online purchases. The study found that young, educated, and urban consumers with moderate to high income were more likely to shop online. Gender differences also emerged, with males engaging more frequently in tech-based and high-value purchases. Website aesthetics, ease of navigation, loading speed, and product display are vital in influencing Indian consumer satisfaction and purchase behaviour. (Saxena and Khanna, 2019) evaluated the impact of website design on consumer engagement and loyalty in India’s online fashion retail segment. The study used SEM analysis and concluded that good website design leads to greater user trust, reduced bounce rates, and higher conversions. With the expansion of internet access and smartphone

penetration, consumers from Tier II and III cities in India have emerged as active participants in the e-commerce ecosystem. (Rao and Sinha, 2020) examined behavioural shifts among consumers in semi-urban and rural India. The study found that factors like COD (Cash on Delivery), regional language support, and local influencer marketing drive trust and adoption among this segment. Promotional strategies such as flash sales, discounts, cashback, and free delivery play a critical role in influencing impulsive buying behaviour among Indian online shoppers. (Mehta and Shah, 2021) conducted a quantitative study on the impact of online promotions on impulsive purchases, particularly during festive seasons. Their findings confirmed that time-limited deals and mobile app notifications significantly increased the frequency of unplanned purchases.

2.3.2 Consumer Behaviour and M-Commerce:

M-commerce adoption is closely linked to consumers' perceptions of ease of use and usefulness, as described by the Technology Acceptance Model (TAM). (Agarwal and Prasad, 2018) examined mobile shopping behaviour among urban Indian consumers and found that perceived ease of use and perceived usefulness were the two most significant predictors of mobile shopping adoption. Their quantitative study, conducted using a structured questionnaire, emphasized that user-friendly app interfaces and utility-driven features significantly influence consumer decision-making in the mobile environment. Trust is a critical determinant in shaping mobile shopping behaviour. (Bansal and Sharma, 2020) investigated the impact of trust, security, and privacy on Indian consumers' willingness to engage in m-commerce transactions. Their study revealed that perceived risk is a significant barrier, and consumers often hesitate to enter personal and financial information via mobile platforms. To mitigate these concerns, the authors recommended secure payment gateways and transparent return policies. Consumer lifestyle and demographic factors have a significant impact on m-commerce usage. In their study, (Kumar and Roy, 2019) analysed the influence of age, income, and lifestyle orientation on mobile shopping habits. They found that younger consumers (ages 18–35), particularly those with higher disposable incomes and tech-savvy lifestyles, are more likely to make frequent mobile purchases. Their findings support the importance of lifestyle segmentation in mobile marketing strategies. The quality of mobile applications significantly affects consumer engagement and loyalty. (Rana and Singh, 2021) explored how app design, ease of navigation, responsiveness, and personalized content influence repeat usage in the Indian m-commerce sector. Their structural equation modeling (SEM) analysis confirmed that mobile app quality directly enhances consumer

satisfaction and indirectly impacts continued purchasing behaviour. Promotional tools such as discounts, cashback offers, and flash sales are powerful motivators for consumer engagement in mobile commerce. (Deshmukh and Patel, 2022) conducted a mixed-method study to evaluate how such marketing strategies affect impulse buying and brand switching behaviour in m-commerce. Their findings showed that time-sensitive promotions and personalized notifications can trigger instant purchases, especially among young Indian consumers.

2.4 IMPACT OF ANTECEDENTS OF PLANNED BEHAVIOR:AN INDIAN STUDY:

Attitude toward behaviour is a key antecedent in the Theory of Planned Behaviour (TPB). In a study by (Ajzen and Fishbein, 2005), attitude was found to have a direct and significant influence on consumers' intentions to engage in online shopping. Positive evaluations of online buying (e.g., convenience, time-saving, and variety) lead to a stronger intention to shop online. This finding is supported by various marketing studies that align with the TPB model in explaining online consumer behaviour. Subjective norms refer to the perceived social pressure to perform or not perform a behaviour. (Armitage and Conner,2001) conducted a meta-analytic review of TPB studies and found that subjective norms significantly influence intention, particularly in collectivist cultures where social approval and family opinions play a dominant role. In the context of Indian consumers, the influence of family, friends, and social groups has been noted to be especially impactful in categories such as fashion, technology, and food. Perceived Behavioural Control (PBC) reflects an individual's perception of their ability to perform a behaviour. (Pavlou and Fygenson, 2006) applied the TPB model to e-commerce and found PBC to be a strong predictor of both intention and actual usage of mobile shopping. Factors such as internet literacy, mobile access, and ease of transaction influenced PBC levels. For marketing managers, enhancing the user's control over the buying process (e.g., through mobile UX and customer support) can positively impact outcomes. (Ajzen, 1991) emphasized that intention serves as a mediator between attitude, subjective norms, PBC, and actual behaviour. Several studies confirm that the predictive power of TPB depends on how strongly intention is formed by these antecedents. In marketing contexts such as environmental or ethical consumerism, although attitudes are favourable, unless PBC and subjective norms are also strong, actual purchase behaviour often does not occur—highlighting the mediating role of intention.

(Paul, Modi, and Patel ,2016) applied TPB to investigate Indian consumers' intentions toward buying green products. Their study revealed that attitude (e.g., environmental concern), subjective norms (peer influence), and PBC (availability and affordability of green products) all significantly contributed to purchase intention. Among these, attitude had the strongest influence. This suggests that pro-environmental marketing campaigns should not only raise awareness but also address perceived control and social desirability.

2.4.1 Study on Impact of Attitude Dimension of Planned Behaviour:

George and Kumar (2014). examined the influence of attitude on online purchase intention using TPB. Their study revealed that attitude was the most significant predictor among the three antecedents, especially among young urban consumers. The research showed that positive perceptions of convenience, time-saving, and value deals in e-commerce formed strong attitudes that translated into higher purchase intentions. (Yadav and Pathak, 2016) studied green consumer behaviour in India and found that attitude toward environmentally friendly products significantly affected consumer intention to buy them. Their study employed the TPB framework and demonstrated that consumers with positive environmental attitudes were more likely to express intention and follow through with purchasing green products. However, the attitude-behaviour gap was moderated by factors such as price and availability. (Venkatesh, Thong, and Xu, 2012) found that user attitude plays a pivotal role in mobile commerce adoption decisions. Positive attitudes toward using mobile apps for shopping—driven by perceived enjoyment, ease, and convenience—significantly influenced behavioural intentions. Marketers leveraging app design, personalization, and gamification strategies can therefore directly influence consumer attitudes and drive mobile commerce growth. (Bansal and Bharti, 2020) investigated the impact of consumer attitude toward social media advertisements on purchase intention in India. The study, grounded in the TPB framework, found that a positive attitude toward social media ads based on relevance, entertainment, and credibility—strongly influenced behavioural intention to engage with brands online. This highlights how digital marketers can shape consumer attitudes through targeted, value-driven ad content.

2.4.2 Impact of Subjective Norm Dimension of Planned Behaviour:

In a study on Indian e-commerce, (Sharma and Gupta, 2020) examined how subjective norms affect online buying intentions. They found that recommendations from family and

friends significantly influenced product choices, especially in the case of first-time online buyers. Peer influence was more pronounced among younger demographics, who rely heavily on reviews, social media, and influencer endorsements. This underscores the need for marketers to build trust and social validation through word-of-mouth and user-generated content. (Yadav and Pathak, 2016) investigated the role of subjective norms in promoting green purchasing behaviour among young Indian consumers. Their study revealed that peer and parental encouragement positively influenced intention to buy eco-friendly products. However, while subjective norm shaped intention, the actual purchase behaviour was still moderated by other factors like perceived behavioural control and product availability. (Patil and Rani, 2021) studied the acceptance of mobile wallets in India using the TPB framework. They found subjective norm to be a strong predictor of intention, particularly among users influenced by peer groups and social media trends. Social acceptance and normative beliefs about digital payment safety were crucial in encouraging users to adopt platforms like Paytm and Google Pay, particularly during and after the COVID-19 pandemic. (Saxena and Yadav, 2019) explored the impact of subjective norms on brand loyalty in the Indian fashion retail sector. Their findings indicated that consumers were significantly influenced by peer opinions and societal expectations regarding fashion choices, especially in metropolitan cities. The study suggested that brands should leverage influencer marketing and celebrity endorsements to align consumer identity with social approval, thus enhancing loyalty.

2.4.3 Study on Impact of Perceived Behavioural Control Dimension of Planned Behaviour:

Gupta and Arora (2017) studied online shopping behaviour in India and found that PBC was a significant predictor of online purchase intention, second only to attitude. Factors such as internet access, mobile phone usage proficiency, and secure payment options enhanced consumers' perceived control over online transactions. The study suggested that reducing technological and logistical barriers can increase consumers' online engagement and purchase frequency. (Zhou, 2011) investigated mobile commerce adoption in emerging markets using an extended TPB model. The study found that PBC had the strongest impact on consumer intention to adopt m-commerce, particularly due to its relationship with self-efficacy and facilitating conditions (like smartphone usability and mobile data access). The findings are particularly relevant in the Indian context, where mobile-based transactions are rapidly increasing but often constrained by network and payment infrastructure. (Paul,

Modi, and Patel, 2016) used TPB to investigate sustainable consumer behaviour in India. Their study highlighted PBC as a critical barrier to the adoption of sustainable products and practices, despite positive attitudes and social norms. High cost, lack of availability, and limited information reduced perceived control, weakening the link between intention and behaviour. The study recommended policy-level interventions to reduce these barriers and improve market accessibility. (Yadav and Pathak, 2016) examined the purchase intention of green products among Indian youth and found that PBC played a mediating role between intention and actual purchase behaviour. Although consumers had favourable attitudes and normative support, many did not purchase due to high prices and limited product availability. Enhancing consumer control (via affordability and accessibility) was identified as essential to translate positive intention into real buying behaviour.

2.5 GLOBAL STUDY ON CONSUMER BEHAVIOUR:

The digital revolution has profoundly transformed consumer behaviour across the globe, influencing how individuals search for, evaluate, and purchase products. With the proliferation of digital devices, internet accessibility, and interactive technologies, the decision-making journey of global consumers is increasingly shaped by online experiences, digital advertising, social media, and e-commerce platforms. According to (Cheung and Thadani ,2012), electronic word-of-mouth (e-WOM) has become a key factor influencing online consumer behaviour. Their comprehensive review found that consumers rely heavily on peer-generated content across global digital platforms such as Facebook, Twitter, and YouTube. e-WOM contributes significantly to trust formation, especially when brand communication is perceived as biased or untrustworthy. (Grewal, Roggeveen, and Nordfält ,2017) studied the impact of mobile technologies on in-store and online shopping across countries. Their research indicated that mobile apps and location-based services significantly affect consumer engagement, real-time decision-making, and impulse purchases. Globally, consumers now expect seamless integration between physical and digital retail experiences. (Park, Lee, and Han ,2007) demonstrated that online product reviews serve as influential decision aids for global consumers. Their research found that the quality and quantity of reviews significantly influence purchase intentions, particularly in high-involvement product categories. Review credibility and perceived helpfulness were shown to affect trust and buying behaviour across diverse consumer segments. (Arora et al. ,2008) emphasized the significance of digital personalization in enhancing consumer

satisfaction and loyalty. Their study across several Western markets highlighted that consumers respond positively to personalized emails, recommendations, and advertisements, which enhance perceived relevance and engagement. However, over-personalization may raise privacy concerns, especially in regions with strict data protection regulations. (Beldad, de Jong and Steehouder ,2010) explored how trust in online platforms is shaped across different cultures. Their findings reveal that perceived security, website usability, and reputation are central to digital trust. Trust-building mechanisms such as third-party certifications, clear privacy policies, and customer service transparency were particularly valued in both Western and Eastern consumer markets.

2.5.1 Consumer Behaviour and E-Commerce:

Trust remains a critical factor influencing consumer behaviour in e-commerce. (Gefen et al., 2003) found that perceived trust in online vendors significantly affects consumers' willingness to engage in e-commerce transactions. Elements like secure payment systems, privacy assurances, and positive reviews enhance trust and reduce perceived risk. The design and usability of an e-commerce platform play a pivotal role in shaping consumer behaviour. According to (Cyr et al., 2006), aesthetic appeal, navigation ease, and information quality on a website positively affect consumer satisfaction and purchase intentions. A user-friendly interface can reduce bounce rates and improve conversion. Social proof and peer influence drive online shopping decisions. (Chevalier and Mayzlin, 2006) illustrated how consumer-generated reviews on e-commerce platforms (e.g., Amazon) influence buyer behaviour, especially when the reviews are detailed and perceived as credible. This aligns with the rise of user-generated content in shaping online consumer perception. Mobile commerce (m-commerce) has revolutionized consumer behaviour by enabling real-time, location-independent shopping. (Yang, 2010) emphasized that convenience, personalization, and time-saving are key motivators for mobile shoppers. However, mobile app design and performance are crucial in ensuring a smooth user experience. Online consumers exhibit high price sensitivity due to the ease of price comparison. (Brynjolfsson and Smith, 2000) showed that digital markets have more price transparency, which compels consumers to seek value and compare alternatives. E-tailers respond with dynamic pricing, flash sales, and discount strategies to attract bargain-driven shoppers. Despite the growth in e-commerce, privacy concerns remain a significant deterrent. (Pavlou, 2003) argued that perceived privacy risks negatively affect consumer attitudes and online purchase intentions.

ensuring data security, transparent privacy policies, and ethical data use are essential for fostering consumer confidence.

2.5.2 Consumer Behaviour And M-Commerce:

According to the Technology Acceptance Model (TAM), perceived usefulness and ease of use are key predictors of consumer behaviour in mobile commerce. (Davis, 1989) originally introduced this model, and it has since been widely applied to m-commerce settings. Users are more likely to adopt mobile shopping apps if they find them efficient and simple to use. Research by (Zhang et al., 2012) highlighted that consumer attitudes shaped by personalization, entertainment, and utility significantly influence behavioural intentions toward m-commerce platforms. Positive consumer attitude toward mobile shopping apps increases the likelihood of repeated usage and brand loyalty. Trust and perceived security continue to be critical issues in mobile commerce. (Zhou, 2012) argued that trust in the mobile platform and vendor is a strong antecedent of purchase intention, especially when personal and financial data is involved. Enhancing data encryption and transparency builds consumer trust. Consumer motivations in m-commerce can be both hedonic (fun, enjoyment) and utilitarian (useful, efficient). A study by (Kim et al., 2007) showed that while utilitarian factors dominate initial adoption, hedonic factors play a key role in sustained engagement and loyalty to mobile commerce apps. Mobile application design quality significantly affects consumer satisfaction and loyalty. According to (Wang and Lin, 2012), intuitive navigation, aesthetic design, and responsiveness positively influence user perceptions and behaviour. A well-designed app improves the customer experience and purchase likelihood. Social influence through reviews, recommendations, and social media has a strong effect on mobile shopping. (Lu and Su, 2009) found that peer influence and online word-of-mouth shape perceptions of credibility and brand image, thus affecting mobile shopping behaviour.

2.6 IMPACT OF ANTECEDENTS OF PLANNED BEHAVIOUR: GLOBAL STUDY:

Attitude toward a behaviour is one of the strongest predictors of consumer intention in the Theory of Planned Behaviour. (Ajzen, 1991) emphasized that individuals evaluate the

outcomes of a behaviour before forming intentions. In marketing, favourable consumer attitudes toward a brand or product often led to a higher likelihood of purchase intention.

Subjective norms, or perceived social pressure, significantly impact consumers' behavioural intentions. According to (Fishbein and Ajzen, 2010), people are more likely to engage in a behaviour if they believe important others (family, peers, influencers) approve of it. This is particularly relevant in the context of social media marketing and peer-influenced purchase decisions.

Perceived Behavioural Control (PBC), which reflects the ease or difficulty of performing a behaviour, acts both as a direct and indirect predictor of consumer behaviour. (Armitage and Conner, 2001) noted that high PBC increases the likelihood of intention translating into action, especially in digital commerce, where ease of transaction matters.
(Taylor and Todd, 1995) extended TPB by incorporating e-commerce behaviours, finding that PBC (such as confidence in using technology) is a more significant determinant in online settings than in traditional settings. Their findings validate the flexibility of TPB across digital platforms in understanding online consumer behaviour.

Many studies have confirmed that the effect of TPB antecedents on actual behaviour is largely mediated by intention. A study by (George, 2004) in the online banking sector revealed that while attitude and PBC strongly influence intention, the actual behaviour depends on the stability of that intention over time. Culture can moderate the strength of TPB components. (Yousafzai et al., 2010) demonstrated that in collectivist cultures, subjective norms have a stronger effect than in individualist societies, where attitudes and PBC dominate. This has critical implications for global marketing strategies and behavioural prediction across cultures.

2.6.1 Impact of Attitude on behavioural intention:

Attitude as a core determinant in the Theory of Planned Behaviour (Ajzen, 1991) identified attitude as a key antecedent of behavioural intention in the Theory of Planned Behaviour (TPB). A positive attitude toward a product or behaviour increases the likelihood that consumers will intend to engage in related behaviour. This framework has become foundational in understanding consumer actions across various marketing contexts. According to (Keller, 1993), consumer attitudes significantly shape brand perception and brand equity. Positive attitudes toward a brand, driven by past experiences, advertising, or

word-of-mouth, create stronger brand associations, thereby increasing brand loyalty and long-term customer retention. In the e-commerce domain, (Pavlou, 2003) demonstrated that consumers' attitudes toward online transactions strongly affect their intention to purchase. A favourable attitude is influenced by website trustworthiness, ease of use, and perceived usefulness. Attitude plays a critical role in consumers' intention to purchase environmentally friendly products. According to (Chen and Chai, 2010), positive environmental attitudes significantly increase the likelihood of green product consumption. However, the attitude-behaviour gap may still occur due to price sensitivity and limited product availability. (Mitchell and Olson, 1981) distinguished between cognitive (rational) and affective (emotional) components of attitude in advertising. Both influences how consumers respond to marketing messages. Emotional appeals often produce stronger attitude change, which is essential for campaigns targeting lifestyle or identity-based products. Attitude formation is also subject to cultural context. (Wang and Lin, 2009) showed that in collectivist cultures, social conformity influences attitudes more than in individualist societies, where personal experience and values dominate. This has implications for global branding and segmentation strategies.

2.6.2 Impact of Subjective Norm on Behavioural Intention:

According to (Hansen et al., 2004), subjective norms significantly affect online consumer purchase intentions, especially when the product is socially visible or the consumer is uncertain. Positive social influence from peers and social media reinforces the consumer's intention to engage in online purchases. Subjective norms are particularly influential in green marketing and ethical consumption. (Dean et al., 2008) found that social norms strongly shape consumers' intentions to purchase organic food and eco-friendly products. Consumers are more likely to buy such products when they believe it is socially expected or valued in their community. (Yousafzai et al., 2010) observed that subjective norm has a stronger impact in collectivist cultures (e.g., India, China) than in individualistic ones (e.g., USA, UK). In collectivist settings, consumers are more motivated by social approval and conforming to group expectations when making purchasing decisions.

(Chu and Kim, 2011) showed that subjective norm plays a pivotal role in e WOM (electronic word-of-mouth) and brand advocacy on social media platforms. Consumers are more likely to share and endorse brands when they perceive that their peers approve or expect such engagement, making subjective norm a strategic variable in digital marketing. Research by (Conner and Armitage, 1998) suggested that subjective norm can moderate the gap between

intention and behaviour. For example, if a consumer intends to buy a health supplement but perceives disapproval from family or friends, the actual behaviour may be inhibited despite strong intention.

2.6.3 Impact of Perceived Behavioural Control on Behavioural Intention:

PBC has been found to influence sustainable behaviour such as buying eco-friendly products. (Vermeir and Verbeke, 2006) reported that consumers may hold favourable attitudes toward green products but only purchase them when they perceive behavioural control such as availability, affordability, and knowledge of use. In service marketing, (Taylor and Todd, 1995) found that PBC was especially important in predicting intentions to use self-service technologies. For example, consumers are more likely to use ATMs, kiosks, or online banking if they believe they are capable of doing so without assistance. Moderating Effect of PBC in the Intention-Behaviour Relationship (Armitage and Conner, 2001) conducted a meta-analysis and concluded that PBC moderates the relationship between intention and actual behaviour. Where perceived control is high, intentions are more likely to translate into actions. This insight is particularly valuable in designing marketing strategies for new product adoption.

2.7 RESEARCH GAP:

Despite the growing body of literature on m-commerce, several research gaps persist that warrant further investigation:

2.7.1 Gap1: Comprehensive Examination of Antecedents: There is a lack of integrated empirical model that consider a wide and multidimensional range of antecedents that influence consumer behaviour towards m-commerce.

While several studies have investigated individual predictors of m-commerce adoption such as perceived ease of use, trust, and security most research is fragmented, focusing on isolated variables or frameworks such as the Technology Acceptance Model (TAM) or Theory of Planned Behaviour (TPB). There is a noticeable lack of integrated models that simultaneously examine multiple categories of behavioural factors, in a unified framework.

For instance, (Chopdar and Sivakumar ,2019) integrated cultural values and perceived risk into mobile app usage behaviour, but did not include technological or hedonic factors. Similarly, (Liébana-Cabanillas et al. 2014) incorporated machine learning and structural equation modelling but focused more on user intention, leaving out interpersonal influences like subjective norms or peer recommendations.

This gap in holistic modelling limits our understanding of how these antecedents interact with one another. A comprehensive examination is essential to design well-rounded strategies for consumer engagement and long-term retention in m-commerce.

2.7.2 Gap 2: Behavioural Intention versus Actual Usage: There is a critical gap in distinguishing and empirically validating the relationship between behavioural intention and actual usage behaviour in the context of m-commerce, leading to limitations in predicting consumer conversion and retention.

Most empirical research on m-commerce continues to emphasize behavioural intention as a proxy for actual consumer behaviour. However, behavioural intention does not always translate into actual usage, especially in m-commerce, where external factors may hinder execution.

Studies like (Zhou ,2013 and Chong ,2013) have applied models like TPB and UTAUT to predict intention but did not measure actual purchase data. This results in a conceptual gap between what consumers intend to do and what they actually do. This also raises concerns about the validity of findings in real-world application, especially when businesses rely on behavioural data for strategy and personalization.

Addressing these research gaps will provide a deeper understanding of the antecedents to consumer behaviour towards m-commerce in Goa. This study aims to fill these gaps by conducting a comprehensive empirical investigation, considering regional specificities, a wide range of antecedents, the gap between behavioural intention and actual usage, the influence of attitude, perceived behavioural control and subjective norms on intentions and behaviour of consumers towards m-commerce. Such an investigation will contribute to the existing body of knowledge and provide valuable insights for stakeholders in the m-commerce ecosystem in Goa.

2.8 LITERATURE REVIEW OF RESEARCH QUESTIONS, RESEARCH OBJECTIVES AND HYPOTHESIS:

2.8.1 Research Question, Objective and Hypothesis 1:

Background of Research Question 1:

Understanding consumer behaviour involves analyzing various constructs such as Attitude, Perceived Behavioural Control (PBC), Subjective Norms (SN), and Intention, which are

central to predicting consumer intentions and actions as per the “Theory of Planned Behaviour". This literature review explores how specific measurement variables contribute to these constructs within the context of consumer behaviour in Goa.

Attitude: Attitude refers to consumers' overall evaluation or affective response towards a product, service, or brand (Ajzen & Fishbein, 1980). Measurement variables that contribute to attitude typically include affective, cognitive, and conative components (Fishbein & Ajzen, 1975). For instance, affective variables may assess consumers' emotional responses, while cognitive variables evaluate their beliefs and perceptions about a product's attributes (Eagly & Chaiken, 1993). Research has shown that these components collectively influence consumers' overall attitude formation and subsequent behavioural intentions (Ajzen, 1991).

Perceived Behavioural Control (PBC): PBC refers to consumers' perceptions of the ease or difficulty of performing a behaviour (Ajzen, 1991). Measurement variables contributing to PBC include self-efficacy, perceived resources, and perceived barriers (Ajzen, 2002). For example, consumers' confidence in their ability to afford a product or their perception of external obstacles can significantly influence their perceived control over purchasing decisions (Bandura, 1986). Understanding these variables helps predict consumers' ability to enact their intentions effectively (Ajzen, 1991).

Subjective Norms (SN): SN reflects consumers' perceptions of social pressures or expectations regarding a specific behaviour (Ajzen, 1991). Measurement variables contributing to SN include normative beliefs and motivation to comply (Fishbein & Ajzen, 1975). For instance, consumers' beliefs about the opinions of significant others and their motivation to conform to those expectations play a crucial role in shaping their behavioural intentions (Ajzen, 1991). Research indicates that SN significantly influences consumers' decisions by integrating social influences into their decision-making process (Kaplan & Graziano, 2009).

Intention: Intention represents consumers' readiness to perform a specific behaviour and is a direct precursor to actual behaviour (Ajzen, 1991). Measurement variables contributing to intention typically include attitude towards the behaviour, PBC, and SN (Ajzen, 1991). For example, a positive attitude towards a product, combined with a strong belief in one's ability to purchase it (PBC) and a perceived social expectation to do so (SN), increases the likelihood of forming a strong intention to purchase (Ajzen, 1991). Intention is considered a critical determinant of actual consumer behaviour across various contexts (Ajzen, 1991).

Research Question 1: How do the respective measurement variables contribute to the relevance and validity of their latent constructs in the proposed model of the "Theory of Planned Behaviour"?

The measurement variables associated with 'Attitude', 'Perceived Behavioural Control', 'Subjective Norms', and 'Intention' are important in understanding and predicting consumer behaviour in Goa. By examining these constructs and their respective measurement variables, researchers can develop comprehensive structural models that explain the factors influencing consumer decision-making processes in this specific region. Based on this argument, researcher developed the following objective and hypothesis to be studied.

Background of Research Objective 1:

Numerous existing studies provide a comprehensive analysis of measurement variables contributing to TPB constructs in m-commerce. (Ajzen, I. 1991). (Gefen et al. 2003) found 'Trust' to be a significant predictor of attitudes toward online commerce. In m-commerce, trust includes security and privacy measures, shaping users' positive or negative attitudes. (Taylor and Todd ,1995) found that, Self-efficacy, or the user's 'Confidence' in performing tasks on a mobile platform, strongly predicts PBC. High self-efficacy is linked to greater control and intention to adopt m-commerce. (Fishbein and Ajzen ,1975), this foundational work highlights those normative beliefs, such as approval from family and peers, shape subjective norms. For m-commerce, peer recommendations and family encouragement are critical normative measures. (Bhattacharjee ,2001) concluded that the post-adoption context, user satisfaction with prior m-commerce transactions can influence intention, which aligns with attitudinal feedback loops, where satisfaction reinforces positive attitudes. (Pavlou and Fygenson,2006) argued that perceived risk negatively affects attitudes toward m-commerce. Consumers wary of fraud or data breaches are less likely to form positive attitudes toward such platforms. (Luarn and Lin ,2005) found that monetary costs, such as transaction fees, negatively influence intention by affecting attitudes. When perceived costs outweigh benefits, users are less likely to adopt m- commerce. (Liébana-Cabanillas et al. 2014) revealed that perceived enjoyment enhances attitudes toward m-commerce, especially in entertainment-based applications. Platforms emphasizing user enjoyment are more likely to gain adoption. (Zhou et al. 2012) demonstrated that trust mediates the relationship between PBC and intention. Users who trust the platform perceive fewer obstacles in engaging with m-commerce. (Mallat,2007) emphasized the importance of contextual control variables,

such as the ability to perform transactions “on-the-go.”. Study found that, for m-commerce, mobility is a vital factor which enhances PBC. (Kim et al. ,2010) opined that, social influence, including opinions shared on social media, enhances subjective norms and younger users are particularly influenced by this variable when considering m-commerce adoption. (Chong, 2013) investigated that, personal innovativeness, a consumer trait, significantly contributes to attitudes toward m-commerce and innovative users are more open to adopting new platforms, creating a positive influence on attitude. (Zhou ,2013) found that Compatibility between m-commerce and users’ existing habits positively affects attitudes, especially when the m-commerce platform aligns with daily routines and expectations. (Slade et al. 2015) found that mobile literacy, or users’ ability to navigate mobile interfaces, strongly predicts PBC. Users with high mobile literacy perceive fewer barriers to adopting m-commerce. (Hajli ,2014) investigated that electronic Word of Mouth (eWOM) significantly shapes SNs and Positive reviews and recommendations enhance consumer perceptions of social approval for m-commerce platforms. (Chang et al. 2012) study revealed that, habitual behaviours, such as using smartphones for tasks, contribute to intention indirectly by influencing attitudes and SNs. (Mathieson, 1991) found that high-quality relevant information on m-commerce platforms enhances users' attitudes by reducing uncertainty and perceived risk. (Zhou and Wang ,2010) opined that, Concerns over privacy strongly mediates relationship between trust and attitude. Platforms addressing privacy concerns create more positive user attitudes.

Objective 1: To evaluate the relevance and validity of the measurement variables to their respective latent constructs in the proposed structural model of the “Theory of Planned Behaviour”

The objective of this study is to examine how each measurement variable included in the conceptual model influences and contributes to the latent constructs of Attitude, Perceived Behavioural Control (PBC), Subjective Norms, and Intention within the proposed structural equation model (SEM). The study aims to assess the strength and significance of these relationships, thereby validating the measurement model and providing insights into the determinants of behavioural intentions related to the studied phenomenon.

Key Components of the Objective:

Measurement Variables: To identify and analyze each measurement variable specified in the conceptual model. These variables serve as indicators or proxies for the underlying

constructs of Attitude, Perceived Behavioural Control, Subjective Norms, and Intention.

Contribution to Constructs: To evaluate the extent to which each measurement variable contributes to the variance of the respective constructs (Attitude, PBC, Subjective Norms, Intention) within the SEM framework. This involves examining the factor loadings or path coefficients between the measurement variables and their corresponding latent constructs.

Validation of Structural Model: To validate the proposed structural model by confirming that all measurement variables significantly contribute to the specified constructs. This validation ensures the reliability and validity of the measurement model, supporting the overall theoretical framework and providing a basis for interpreting the relationships between variables.

Implications: To discuss the implications of the findings for theory and practice. Understanding how these measurement variables influence attitudes, perceived control, social norms, and behavioural intentions can inform strategies for promoting desired behaviours or outcomes in relevant contexts.

By pursuing this objective, the study aims to advance understanding of the complex interrelationships between variables and contribute valuable insights to the field of consumer behaviour, and help:

- To validate the measurement model of the Theory of Planned Behaviour (TPB) by examining the relationships between measurement variables and latent constructs (Attitude, Subjective Norms, Perceived Behavioural Control, and Behavioural Intention) among individuals in Goa.

- To investigate the impact of the Theory of Planned Behaviour (TPB) constructs (Attitude, Subjective Norms, and Perceived Behavioural Control) on the buying intentions towards mobile commerce.

Based on the objective following hypothesis has been framed:

Hypothesis-1:

H1: The measurement variables are relevant and valid to their respective latent constructs in the proposed structural model of the "Theory of Planned Behaviour"

Sub-hypothesis:

H1a: All measurement variables are relevant and valid to the 'Attitude' construct in the proposed structural model of the "Theory of Planned Behaviour".

H1b: All measurement variables are relevant and valid to the 'Perceived Behavioural Control' construct in the proposed structural model of the "Theory of Planned Behaviour".

H1c: All measurement variables are relevant and valid to the 'Subjective Norms' construct in the proposed structural model of the "Theory of Planned Behaviour".

H1d: All measurement variables are relevant and valid to the 'Mobile Commerce Intention' construct in the proposed structural model of the "Theory of Planned Behaviour".

H1e: Measurement model is having goodness-of-fit indices.

Explanation:

This hypothesis suggests that each measurement variable included in the TPB model effectively measures and contributes to its corresponding latent construct: Attitude, Subjective Norms, Perceived Behavioural Control, and Behavioural Intention. In TPB, these constructs represent key determinants influencing individuals' intentions and behaviours.

2.8.2 Research Question, Objective and Hypothesis 2:

Background of Research Question 2:

Understanding consumer behaviour through the lens of the Theory of Planned Behaviour (TPB) provides insights into how attitudes, subjective norms, and perceived behavioural control influence buying intentions. This literature review synthesizes existing research to explore these relationships specifically within the context of consumers in Goa.

Attitude: Attitude in the context of TPB refers to consumers' overall evaluation or affective response towards purchasing a product or service (Ajzen, 1991). Positive attitudes are associated with favourable beliefs about the product's features, benefits, and quality (Fishbein & Ajzen, 1975). Research has consistently demonstrated that stronger positive attitudes towards a product or service correlate positively with higher buying intentions (Ajzen, 1991; Tarkiainen & Sundqvist, 2005). For example, consumers in Goa may develop positive attitudes towards products that are culturally relevant or align with their lifestyle preferences, influencing their intention to purchase (Verlegh & Steenkamp, 1999).

Subjective Norms: Subjective norms refer to consumers' perceptions of social pressures or expectations regarding purchasing behaviour (Ajzen, 1991). These norms are shaped by the

beliefs about what significant others think they should do and the motivation to comply with those opinions (Fishbein & Ajzen, 1975). In Goa, where social networks and cultural influences play significant roles in consumer decision-making, subjective norms can exert a strong influence on buying intentions (Kaplan & Graziano, 2009). For instance, recommendations from family members, peers, or opinion leaders within the Goan community can impact consumers' intentions to purchase specific products or brands (Ajzen, 1991; Verplanken & Holland, 2002).

Perceived Behavioural Control (PBC): Perceived behavioural control reflects consumers' beliefs about the ease or difficulty of performing the purchasing behaviour (Ajzen, 1991). Factors influencing PBC include perceived resources, skills, and situational constraints (Ajzen, 2002). In Goa, where economic conditions and accessibility to products and services vary, PBC becomes crucial in determining buying intentions (Ajzen, 1991; Venkatesh & Davis, 2000). Higher levels of perceived control over the purchasing process increase the likelihood that consumers will translate their intentions into actual purchases (Ajzen, 1991; Taylor & Todd, 1995).

Integration of Constructs and Buying Intention: The TPB suggests that attitudes, subjective norms, and PBC collectively determine individuals' intentions to engage in specific behaviours, including purchasing decisions (Ajzen, 1991). Studies have consistently shown that stronger positive attitudes, perceived social pressures, and greater perceived control over the buying process led to higher buying intentions (Ajzen, 1991; Venkatesh & Morris, 2000). In Goa, where consumer behaviour is influenced by cultural values, social norms, and economic factors, understanding these relationships is essential for marketers and policymakers aiming to predict and influence consumer decisions (Ajzen, 1991; Trafimow et al., 2002).

Research Question 2: How do the constructs of "The Theory of Planned Behaviour" influence the intentions to use m-commerce among consumers?

The constructs of the Theory of Planned Behaviour attitude, subjective norms, and perceived behavioural control play significant roles in shaping buying intentions among consumers in Goa. By examining these constructs, researchers can develop targeted strategies to enhance consumer engagement and satisfaction in this unique cultural context. Based on the given understanding, researcher has framed the following objective and hypothesis to be studied.

Background of Research Objective 2:

Some of the previous studies demonstrate the applicability of TPB to m-commerce, highlighting the dynamic interaction of attitudes, subjective norms, and perceived behavioural control in driving consumer behaviour. (Ajzen, I.1991) theory provides the foundation for understanding human intentions and behaviour. The TPB identifies attitudes, subjective norms, and perceived behavioural control (PBC) as predictors of intention. This framework is applicable in analysing consumer adoption of m-commerce. (Yang ,2012) investigated young consumers' intention to adopt mobile shopping using TPB. It revealed that attitudes and perceived ease of use significantly enhance intention, while subjective norms had a moderate effect. Findings suggest that positive attitudes toward convenience and security drive m-commerce adoption. (Chong et al. 2013) integrated perceived risk into TPB to examine m-commerce adoption. Perceived behavioural control was significantly influenced by perceived risks like transaction safety. As per study findings perceived risk strengthens PBC and increases m-commerce intention. (Slade et al. 2015) studied m-commerce with a focus on mobile payment systems. Subjective norms played a critical role, especially in collectivist cultures, where peer and family recommendations significantly influenced intention and found that social influence enhances subjective norms and purchase intention in mobile payments. (Kim et al. 2010) analysed attitudes toward m-commerce platforms, emphasizing usability, interface design, and personalization and found that positive user experiences significantly shaped attitudes and purchase intentions. (Nysveen et al. ,2005) extended the Theory of Planned Behaviour (TPB) by incorporating perceived ease of use and enjoyment as key factors influencing perceived behavioural control (PBC). Their findings highlighted the significance of these constructs in the context of mobile application-based shopping, demonstrating that ease of use has a positive impact on perceived behavioural control in m-commerce. (Gefen et al.2003) studied the mediating role of trust in m-commerce adoption. Trust was found to positively influence all TPB constructs, particularly attitudes and PBC and also enhances consumer intention to adopt m-commerce. (Ghazali et al. 2018) explored how app features influence attitudes and perceived behavioural control, in m-commerce. Features like seamless navigation, responsive design, and speed were significant contributors to attitudes. Study found that ‘m-commerce App quality’ positively influences attitudes and perceived behavioural control. (Dahlberg et al. 2008) examined the effect of PBC in the adoption of mobile payment systems, a critical component of m-commerce. The study found that PBC significantly impacts intention, influenced by transaction simplicity and simplified payment systems enhance PBC. (Shin and Kang ,2016) analysed cultural differences in TPB’s application to m-commerce

adoption. Subjective norms were found more critical in Asian cultures than in Western cultures. (Limayem et al. 2007) extended TPB by including habit as a predictor. Habit strongly influenced purchase intentions in mobile shopping contexts, particularly for frequent users and as per study findings, it also moderates the influence of TPB constructs.

Objective 2: To evaluate the significance and extent to which the constructs of the 'Theory of Planned Behaviour' influence the intentions to use mobile commerce.

The Theory of Planned Behaviour (TPB), developed by Ajzen in 1985, is a widely recognized psychological theory that predicts deliberate behaviour based on three key constructs: attitude, subjective norm, and perceived behavioural control. These constructs collectively shape an individual's behavioural intentions, which are strong predictors of actual behaviour.

Relevance to the Context of Goa

Goa, a prominent tourist destination in India, has a unique consumer market. Understanding the buying intentions of consumers in Goa, therefore, requires a tailored approach that considers these distinct sociocultural dynamics. The TPB provides a comprehensive framework for this purpose, allowing for the examination of external influences shaping consumer behaviour. This research aims to explore how these TPB constructs impact consumers' intentions to engage with m-commerce in Goa, a region with unique characteristics and a growing digital landscape.

Research Hypothesis-2:

H2: Theory of Planned Behaviour constructs significantly influence the intentions to use m-commerce.

Sub-hypothesis:

H2a: Attitude towards mobile commerce significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that a positive attitude towards using mobile commerce (e.g., perception of convenience, trustworthiness of mobile platforms) leads to a higher intention to make purchases via mobile devices.

H2b: Subjective norms significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that perceived social influences regarding mobile commerce usage (e.g., recommendations from friends, social media influencers) affect consumers' intention to engage in mobile commerce transactions.

H2c: Perceived behavioural control significantly influences the intentions to use m-commerce.

Explanation: This hypothesis proposes that consumers' perception of their ability to control and use mobile commerce applications (e.g., ease of use, technical skills required) impacts their intention to purchase goods or services via mobile devices.

H2d: Attitude, subjective norms, and perceived behavioural control significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that all three constructs, attitude, subjective norms, and perceived behavioural control, collectively influence consumers' buying intention in the context of mobile commerce.

2.8.3 Research Question, Objective and Hypothesis-3

Background of Research Question 3:

Understanding the demographic profile of respondents is crucial in various fields of research, including marketing, social sciences and education. This literature review explores the significance of demographic profiling and its implications for research outcomes:

Demographic segmentation continues to serve as a fundamental component of e-marketing strategies due to its effectiveness in guiding resource allocation, message customization, and market targeting (Kotler & Armstrong, 2016). By categorizing consumers based on variables such as age, gender, income, education level, and geographic location, marketers can design more personalized campaigns that resonate with specific audience groups (Schiffman & Wisenblit, 2019). For instance, age-based segmentation often helps tailor content and platform choice, while income segmentation influences product pricing strategies and promotional offers.

Despite its widespread application, the predictive power of demographic segmentation in explaining or influencing actual online consumer behaviour is not always robust. Its

effectiveness varies significantly depending on contextual factors, such as cultural background, digital literacy, and regional market maturity (Sheth, 2021). Moreover, the relationship between demographic variables and consumer decision-making is often complex and nonlinear, requiring sophisticated modeling techniques such as multivariate analysis, structural equation modeling, or machine learning algorithms to capture the nuances of consumer behaviour accurately (Harris & Goode, 2010; Pappas, 2016). As a result, while demographic segmentation offers a starting point for strategy formulation, its explanatory strength is greatly enhanced when combined with psychographic, behavioral, and technographic data in integrated marketing models (Wedel & Kamakura, 2012). Based on the given logical support, we have developed the following objective to be studied.

Research Question 3: How do the 'Demographic Variables' influence 'Attitude', 'Subjective Norms', 'Perceived Behaviour Control', and 'Intention' regarding the use of m-commerce among consumers?

Background of Research Objective 3:

Previous studies highlight the importance of demographic variables in shaping TPB constructs in m-commerce adoption. (Kim et al. 2010) highlighted the impact of age on PBC, showing that older users struggle with complex mobile applications, reducing their intention to use m-commerce. Despite favourable attitudes, the lack of perceived control over technology hinders adoption. Accessible design, including larger fonts, simplified navigation, and voice-activated commands, significantly improves PBC for older users. (Karjaluoto et al. 2007) examined the role of trust in m-commerce adoption, noting that older users place greater emphasis on trust than younger ones. For older adults, trust was a critical determinant of attitudes and SNs, moderating the relationship between PBC and intention. Younger consumers, however, relied more on peer recommendations. (Chong,2013) analysed the role of age in shaping mobile shopping behaviours, particularly attitudes and PBC. The findings discovered that young consumers are more likely to accept m-commerce, driven by their familiarity and comfort with mobile devices. Older adults, however, demonstrated lower PBC due to challenges with technology usability and security concerns. Despite favourable attitudes, the reduced sense of control hindered their intention to adopt. (Kumar and Mukherjee,2018) focused on millennials, emphasizing their openness to adopting m-commerce due to favourable attitudes toward technology. Millennials valued convenience, customization, and quick service, which positively influenced their intention.

Additionally, peer influence was a significant factor in shaping SNs among this demographic. (Riquelme and Rios ,2010) explored gender differences in trust and perceived risk in mobile shopping adoption. They found that women are more sensitive to security and trust concerns than men, directly impacting their attitudes and intention to adopt m-commerce. (Gefen and Straub,1997) explored how gender influences technology adoption by examining PBC and perceived ease of use. Women were found to rely more on external system support to feel confident using technology, highlighting the significance of PBC. Men, on the other hand, exhibited higher intrinsic confidence in navigating technology, translating to higher PBC with less reliance on system support. (Slade et al. 2015) investigated the influence of socioeconomic status on subjective norms in mobile payment adoption. They found that lower-income groups are more influenced by recommendations from peers, family, and community, as trust in technology is lower within this demographic. These social endorsements compensate for the lack of personal experience with mobile payments. (Hanafizadeh et al. 2014) explored how educational attainment affects attitudes toward mobile banking, a critical aspect of m-commerce. study found that consumers with higher educational levels are associated with stronger positive attitudes, as educated individuals better understand the benefits and risks associated with mobile transactions. This understanding fosters trust and reduces anxiety, which are key components of attitudes and intention. (Hofstede, 2001) emphasized the role of collectivist vs. individualist cultures in shaping subjective norms (SNs). In collectivist cultures, SNs are stronger as individuals are heavily influenced by societal expectations, family recommendations, and peer behaviour. These norms significantly drive m-commerce adoption in such societies. Conversely, in individualist cultures, attitudes and PBC play a more prominent role in shaping intention. (Zhou et al. 2012) examined gender differences in attitudes toward mobile shopping. Women demonstrated a stronger preference for secure and trustworthy platforms, which significantly influenced their attitudes. Men, on the other hand, were less concerned about security and more influenced by the platform's functionality and speed. (Cheung et al. 2012) examined the role of peer pressure in SNs for younger consumers. Their study discovered that younger demographics are more susceptible to peer influence, with recommendations from friends and influencers heavily driving their m-commerce intentions. (Cheung et al. 2012) analyzed the role of peer influence and electronic word of mouth (eWOM) in shaping subjective norms (SNs) for younger demographics. Younger users rely more on social recommendations and peer reviews when deciding to adopt m-commerce platforms. Positive eWOM significantly increased SNs, leading to higher intention to adopt. (Taylor and Todd

,1995) investigated how education level enhances PBC by improving technological self-efficacy. Educated users were more confident in their ability to navigate m-commerce platforms, leading to higher adoption intentions. (Davis et al. 1989) found that demographics like education significantly moderate ease of use. Educated individuals exhibit positive attitudes toward m-commerce due to their ability to navigate complex interfaces. (Barnes and Scornavacca, 2004) investigated the role of income levels in determining PBC for m-commerce. Wealthier individuals showed higher PBC due to access to advanced mobile devices and reliable internet connections. Lower-income groups faced technological barriers, reducing their perceived control over the adoption process (Pavlou ,2003) analysed the interplay between culture and perceived risk in shaping m-commerce intention. In collectivist cultures, SNs play a dominant role as users look to trusted peers for recommendations. Individualist cultures, however, focus more on attitudes and personal control over the process (PBC). (Choi et al. 2008) investigated gender-specific differences in SNs and PBC and found that women were more influenced by social proof (e.g., friend recommendations), while men were more self-reliant in making decisions. This aligns with the stronger effect of SNs on female users and higher intrinsic PBC in male users. (Liébana-Cabanillas et al. 2014) analysed the impact of geographical location on m-commerce adoption. Urban consumers exhibited higher PBC due to better access to infrastructure and technology, while rural users struggled with limited resources, affecting their PBC and intention.

Objective 3: To examine the impact of 'Demographic Variables' on consumers' 'Attitude', 'Perceived Behaviour Control', 'Subjective Norms' and 'Intention' to use m-commerce.

Studying the objective of describing the demographic characteristics of individuals in Goa who use smartphone is important for several reasons:

Understanding User Profiles: It provides insights into who is currently using mobile commerce services in Goa. By identifying demographic characteristics such as age, gender, education level, occupation, income, and location, researchers can create detailed user profiles. This understanding helps in targeting and tailoring mobile commerce platforms, services, and marketing strategies to better meet the needs and preferences of different demographic segments.

Market Segmentation: Demographic profiling allows for segmentation of the market based on user characteristics. This segmentation helps businesses and policymakers understand the diversity within the mobile commerce user base in Goa. It enables them to differentiate their offerings and develop targeted approaches for engaging specific demographic groups more effectively.

Predicting Adoption Trends: By studying demographic characteristics, researchers can predict future trends in mobile commerce adoption and usage patterns in Goa. For instance, understanding which age groups or income brackets are more likely to adopt mobile commerce can inform strategic planning and resource allocation for businesses and policymakers.

Policy Formulation: Demographic insights can inform policy decisions related to mobile commerce infrastructure, regulations, and incentives. For example, policies aimed at improving digital literacy or expanding mobile network coverage can be targeted based on demographic data to maximize impact and accessibility.

Comparative Analysis: Comparative analysis across different demographic groups allows for a deeper understanding of disparities in mobile commerce adoption and usage. It helps identify barriers or facilitators specific to certain demographic segments, guiding efforts to promote more equitable access and usage of mobile commerce services.

Academic Research: This objective provides a foundational dataset for academic research on mobile commerce behaviors and trends in Goa. Researchers can use demographic data to investigate broader questions related to consumer behavior, technology adoption, socio-economic impacts, and digital inclusion.

Business Strategy: Businesses can use demographic insights to refine their product offerings, user experience design, pricing strategies, and customer support initiatives. Understanding the demographic profile of mobile commerce users helps businesses align their strategies with the preferences and needs of their target audience.

Hypothesis-3:

H3: Demographic variables significantly influence consumers' attitudes, Perceived Behaviour Control, Subjective Norms and intention towards m-commerce.

Sub-Hypotheses:

H3a: There is no statistically significant difference between male and female consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3b: There is no statistically significant difference between Area of Location of consumers and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3c: There is no statistically significant difference between 'Marital Status' of consumers and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3d: There is no statistically significant difference between consumers 'Age' and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3e: There is no statistically significant difference between 'Educational level' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3f: There is no statistically significant difference between 'Occupation' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

H3g: There is no statistically significant difference between 'Monthly Family Income' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Explanation: By exploring these hypotheses and objectives, the research will provide a comprehensive understanding of how demographic factors shape the adoption and usage of m-commerce, offering valuable insights for businesses and policymakers aiming to enhance m-commerce experiences and adoption rates.

2.8.4 Research Question, Objective and Hypothesis-4

Background of Research Question-4:

Understanding the dynamics of '**Intention'** as a mediator between attitude, subjective norms, perceived behavioural control (PBC), and consumer behaviour in mobile commerce is essential for comprehending the decision-making processes of consumers in Goa. This literature review synthesizes relevant studies to explain these relationships.

Attitude and Intention: Attitude towards mobile commerce influences consumers' intentions to purchase products through this platform. Positive attitudes, characterized by favourable evaluations of mobile commerce (Ajzen, 1991), are likely to increase the intention to engage in such behaviours (Taylor & Todd, 1995).

In Goa, where technological adoption varies across demographic groups, consumers with positive attitudes towards the convenience and accessibility of mobile commerce are more inclined to express intentions to buy products through this channel (Venkatesh et al., 2012). For instance, perceptions of ease of use and trust in mobile payment systems positively influence intention formation (Venkatesh & Davis, 2000).

Subjective Norms and Intention: Subjective norms reflect consumers' perceptions of social pressures or expectations regarding mobile commerce adoption (Ajzen, 1991). These norms are influenced by cultural factors, peer influence, and family expectations (Riquelme & Rios, 2010). In Goa, where social networks and communal ties play significant roles in decision-making, subjective norms can strengthen or weaken intentions to engage in mobile commerce (Kaplan & Graziano, 2009). Consumers who perceive strong social approval or encouragement from significant others are more likely to form intentions aligned with these norms (Ajzen, 1991).

Perceived Behavioural Control (PBC) and Intention: PBC refers to consumers' beliefs about their ability to perform mobile commerce activities effectively (Ajzen, 1991). Higher levels of PBC, driven by factors such as technological literacy, internet access, and financial resources, increase the likelihood of forming strong intentions (Venkatesh & Davis, 2000). In Goa, where digital infrastructure and technological readiness vary, perceived control over mobile commerce usage can significantly influence intention formation (Hernandez et al., 2009). Consumers who feel confident in taking independent decisions with regards to shopping using m-commerce are more likely to translate intentions into actual buying behaviour (Ajzen, 1991).

Intention as a Mediator in Consumer Behaviour: Intention mediates the relationship between attitude, subjective norms, perceived behavioural control, and actual consumer behaviour in mobile commerce (Ajzen, 1991). Strong intentions driven by positive attitudes, supportive subjective norms, and perceived control over actions lead to higher levels of engagement with mobile commerce platforms (Venkatesh & Morris, 2000). Studies suggest that intention plays a pivotal role in bridging cognitive processes (attitude and norms) with behavioural outcomes (Ajzen, 1991). In Goa, understanding how these constructs interact through intention helps marketers predict and influence consumer behaviours effectively (Venkatesh et al., 2012).

Research Question 4: How does intention mediate the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and consumer behaviour towards purchasing specified products through m-commerce?

Intention serves as a crucial mediator between attitude, subjective norms, perceived behavioural control, and M-commerce purchase behaviour in Goa. By examining these relationships, researchers can develop strategies to enhance consumer engagement and facilitate adoption of mobile commerce platforms in this dynamic market.

Background of Objective 4:

Extensive review of previous study describes the mediating role of 'Intention' in the relationship between 'Attitude', 'Subjective Norms (SN), Perceived Behavioural Control (PBC) and actual purchase behaviour across various product categories. (Ajzen ,1991) Ajzen's foundational study on the Theory of Planned Behaviour proposes that intention is a critical mediator between constructs (ATT, SNs, PBC) and actual behaviour. He argued that without intention, the effect of ATT, SNs, and PBC on APB is weakened. (Pavlou and Fygenson ,2006) this study extends TPB to electronic commerce, emphasizing the role of intention as a mediator in the purchase of electronic goods. Intention fully mediates ATT, SNs, and PBC, making it a necessary construct for translating attitudes into actions. (Mallat ,2007) investigated that, for stationery items and newspapers, mobility-related purchase behavioural control enhances intention, mediating actual purchase behaviour. (Cheung et al. 2012) study examined subjective norms (via electronic word of mouth) for purchasing products like books and stationery and fond that intention mediates the relationship between SNs and APB. (Gupta and Arora ,2017) study concluded that, for low-involvement products like groceries, PBC strongly influences intention, which acts as a significant mediator for APB in m-commerce. (Luarn and Lin ,2005) investigated, ATT to be a significant predictor of intention, fully mediating the relationship with actual purchase behaviour. Similar mechanisms apply to high-value categories like jewellery and healthcare products in m-commerce. (Taylor and Todd ,1995) findings suggest that PBC has both direct and mediated effects (via intention) on APB, with healthcare items showing the strongest mediation effect due to higher perceived risk. (Zhou and Wang ,2010) study reveals that, privacy concerns act as a barrier to ATT and SNs, mediated by intention for products like healthcare and medicines and strong intention reduces the adverse effects of perceived risks. (Mathieson ,1991) concluded that high-quality information on mobile platforms enhances attitude,

mediated by intention, for healthcare products. (Kim et al. 2010) found that social influence enhances intention, which mediates SNs and APB for grocery and healthcare items. (Chiu et al. 2005) study shows that for games and jewellery, hedonic attitudes strongly predict intention, which mediates the effect on actual purchase behaviour. (Riquelme and Rios, 2010) found that perceived risk negatively influences attitude but is mitigated by strong intentions for jewellery and home appliances. (Hajli ,2014) study concluded that subjective norms via social media positively influence intention, especially for fashion items like clothing and shoes, which in turn drives actual purchase behaviour. (Liébana-Cabanillas et al. 2014) opined that, compatibility with mobile platforms increases attitude towards m-commerce, leading to higher intention and subsequent purchase behaviour for categories like home and kitchen appliances (Chang et al. 2012) found that, habitual use of mobile devices influences intention, mediating 'Attitude' and 'PBC' for books and magazines. (Slade et al. ,2015) found that mobile literacy enhances purchase behavioural control, leading to higher intention and actual purchase behaviour for grocery purchases. (Chong ,2013) opined that personal innovativeness enhances attitude, increasing intention and actual purchase behaviour for electronics and games.

Objective 4: To investigate the mediating role of 'Intention' in the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories, through m-commerce.

The research objective focuses on investigating how intention mediates the relationships between attitude, subjective norms, perceived behavioural control (PBC), and actual purchasing behaviour across various product categories through mobile commerce in Goa. Here's an explanation of each component:

Attitude: This refers to consumers' overall evaluation or perception of mobile commerce as a platform for purchasing different product categories. Positive attitudes are likely to lead to favourable intentions and subsequent purchasing behaviours (Ajzen, 1991).

Subjective Norms: This reflects consumers' perceptions of social pressures or expectations regarding the use of mobile commerce for shopping. They include influences from family, friends, and other significant others in the Goan context (Fishbein & Ajzen, 1975).

Perceived Behavioural Control: PBC refers to consumers' beliefs about their ability to perform actions related to mobile commerce effectively. Factors influencing PBC include technological skills, ease of use of mobile platforms, and trust in online transactions (Venkatesh & Davis, 2000).

Intention as a Mediator: Intention mediates the relationships between 'Attitude', 'Subjective Norms', Perceived Behavioural Control, and actual purchasing 'Behaviour'. It represents consumers' readiness or willingness to engage in mobile commerce for purchasing specific product categories (Ajzen, 1991). Strong intentions, influenced by positive attitudes, supportive social norms, and perceived control, are expected to lead to actual buying behaviour in Goa's mobile commerce environment (Ajzen, 1991; Venkatesh et al., 2012).

Actual Purchasing Behaviour: This refers to the real-world actions of consumers in Goa, where they use mobile commerce platforms to purchase electronic products, sports items, clothing, shoes, jewelry, home and kitchen appliances, books, magazines, newspapers, healthcare products, medicines, stationary items, games, and groceries. The study aims to observe how actual behaviors correspond with consumers' intentions, attitudes, subjective norms, and perceived behavioural control.

Explanation: By exploring these relationships across a wide range of product categories, the research aims to provide insights into the decision-making processes of Goan consumers in adopting mobile commerce in purchasing different categories of products. It seeks to understand how cognitive factors (attitude, subjective norms, PBC) influence behavioural outcomes (intention and actual purchase behaviour), thereby contributing to the broader understanding of consumer behaviour in digital commerce contexts.

Hypothesis-4:

H4: 'Intention' mediates the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories through m-commerce.

Sub-Hypotheses:

H4a: Attitude positively influences the intention to purchase various products through mobile commerce.

H4b: Subjective norms positively influence the intention to purchase various products through mobile commerce.

H4c: Perceived behavioural control positively influences the intention to purchase various products through mobile commerce.

H4d: Intention positively influences consumer behaviour towards buying electronic products, sports items, clothing, shoes, jewellery, home and kitchen appliances, books, magazines, newspapers, healthcare and medicines, stationary items, games, and grocery products through mobile commerce.

H4e: Intention mediates the relationship between attitude and consumer behaviour towards purchasing various products through mobile commerce.

H4f: Intention mediates the relationship between subjective norms and consumer behaviour towards purchasing various products through mobile commerce.

H4g: Intention mediates the relationship between perceived behavioural control and consumer behaviour towards purchasing various products through mobile commerce.

Explanation: By exploring this hypothesis, study will examine the mediating role of *intention* in the Theory of Planned Behaviour (TPB) framework within the context of mobile commerce (m-commerce) purchase behaviour towards specified product categories. and also, will investigate, whether *intention* significantly mediates the effect of each antecedent on purchase behaviour towards specified product categories, thereby validating the central belief of TPB that behavioural intention is a key predictor of actual behaviour.

2.8.5 Research Question, Objective and Hypothesis-5

Background of Research Question-5:

The Theory of Planned Behaviour (TPB), proposed by Icek Ajzen (1991), has been widely utilized to understand and predict various behaviours, including technology adoption and usage. TPB suggests that an individual's intention to perform a specific behaviour is influenced by three key components: attitudes towards the behaviour, subjective norms, and perceived behavioural control. This literature review explores how TPB explains the factors influencing consumer adoption and usage of mobile commerce (m-commerce) and examines empirical evidence supporting the validity of this model in the specific context of Goa.

Attitude towards Mobile Commerce:

Attitude refers to the degree to which a person has a favourable or unfavourable evaluation of the behaviour in question. In the context of m-commerce, attitudes encompass positive or negative beliefs about using mobile platforms for shopping, such as convenience, time-saving, and access to a wide range of products, risky, time consuming etc. Several studies have highlighted the positive correlation between favourable attitudes and the intention to adopt m-commerce (Kim, Mirusmonov, & Lee, 2010; Yang, 2010).

For instance, (Kim et al. 2010) found that perceived usefulness and ease of use significantly impact consumers' attitudes towards m-commerce, which in turn influence their behavioural intentions. Similarly, studies specific to Indian contexts, such as that by Gupta and Arora (2017), have demonstrated that perceived advantages like convenience and availability of diverse products positively affect consumer attitudes towards m-commerce.

Subjective Norms:

Subjective norms refer to the perceived social pressure to perform or not to perform a particular behaviour. In the domain of m-commerce, this includes the influence of peers, family, and societal trends on an individual's decision to use mobile platforms for shopping. Empirical studies have shown that subjective norms play a significant role in shaping consumer intentions towards technology adoption (Taylor & Todd, 1995; Venkatesh & Davis, 2000).

Research by (Lu, Yao, and Yu ,2005) indicates that social influence is a critical factor in m-commerce adoption, especially in collectivist cultures like India, where societal approval and peer influence are highly valued.

Perceived Behavioural Control:

Perceived behavioural control refers to an individual's perception of their ability to perform a specific behaviour, considering facilitating conditions and obstacles. In the context of m-commerce, this includes factors such as technological literacy, freedom to access mobile devices. Studies have consistently shown that perceived ease of use and control over technology significantly influence adoption intentions (Mathieson, 1991; Venkatesh, Morris, Davis, & Davis, 2003).

For example, research by Chong (2013) on mobile commerce adoption in Malaysia highlights that perceived ease of use and self-efficacy are significant predictors of behavioural intention. Similarly, (Tan et.al ,2014) found that perceived behavioural control, including factors like mobile internet experience and facilitating conditions, significantly impacts m-commerce adoption in developing countries.

Empirical Evidence from Goa:

While specific studies on m-commerce adoption in Goa are limited, broader research on Indian m-commerce provides valuable insights. A study by (Kapoor et.al ,2014) on mobile commerce adoption in India emphasizes the role of consumer attitudes, social influence, and perceived behavioural control, aligning with the TPB framework.

Furthermore, regional studies, such as those by (Singh et.al, 2019), indicate that the proliferation of smartphones and improved internet connectivity in Goa have positively impacted m-commerce adoption. However, challenges such as digital literacy and trust in online transactions remain significant barriers, highlighting the need for targeted interventions to enhance perceived behavioural control among consumers.

Research Question 5: How does "The Theory of Planned Behaviour" explain the factors influencing consumers' adoption of m-commerce, and whether the empirical evidence supports the validity of this conceptual model in this specific context?

The Theory of Planned Behaviour provides a robust framework for understanding the factors influencing consumer adoption and usage of mobile commerce in Goa. Attitudes towards m-commerce, subjective norms, and perceived behavioural control are critical determinants of consumer intentions and behaviours. Empirical evidence from broader Indian contexts supports the validity of the TPB model, suggesting its applicability to the state of Goa.

Background of Objective 5:

Majority of previous studies provide detailed insights into how the 'TPB' has been applied, validated, and extended to understand the adoption of m-commerce. (Ajzen ,1991) Ajzen's pivotal work on TPB provides the theoretical foundation for studying consumer behaviour across a variety of domains, including mobile commerce. The study suggests that 'Attitude', 'SNs', and 'PBC' are key determinants of behavioural intention, which subsequently affects actual behaviour. (Taylor & Todd ,1995) validated the TPB in the context of information technology adoption by incorporating perceived ease of use and perceived usefulness. The TPB model is confirmed as an effective framework for predicting mobile commerce adoption, demonstrating the impact of attitudes, subjective norms, and PBC on consumers' intention to use m-commerce platforms. (Lu et al.,2014) applied the TPB framework to mobile commerce adoption and validated its relevance. Their study confirms that attitudes, subjective norms, and perceived behavioural control significantly influence the intention to use m-commerce, which subsequently drives actual use. The study also finds that these

factors vary based on demographic and technological factors. (Hsu et al.,2004) investigated the role of perceived risk in m-commerce adoption and validated the TPB model's applicability in the mobile context. Their findings suggest that perceived behavioural control, attitude, and subjective norms influence the decision to adopt m-commerce, with perception of risk moderating these relationships. (Al-Qeisi et al.,2014) study validates the TPB constructs in the context of mobile commerce adoption. As per the findings of the study, attitudes toward mobile shopping, subjective norms, and perceived behavioural control directly impact intention to use mobile commerce, with consumer habits playing a significant role in moderating these relationships. (Cheng et al. ,2015) extend the TPB framework to explore how subjective norms, attitudes, and perceived behavioural control shape consumers' intention to adopt mobile commerce. Study demonstrates that social influences and perceived behavioural control have a significant effect on the intention to use mobile commerce. (Pavlou & Fygenson ,2006) applied the TPB model in the context of e-commerce, validating its constructs in predicting the adoption of mobile commerce. The study found that social influence, attitude, and perceived control are essential in determining behavioural intentions toward using m-commerce platforms. (Lee et al. ,2011) applied the TPB model in the context of mobile commerce adoption and found that attitude, subjective norms, and perceived behavioural control significantly predict the intention to adopt mobile commerce. The study also finds that trust and security concerns moderate these relationships. (Zhou et al. ,2011) extend the Theory of Planned Behaviour to investigate how attitudes, subjective norms, and perceived behavioural control is affecting the intention to adopt mobile commerce. Their findings validate the TPB model in predicting consumer m-commerce behaviours for product categories such as electronics and clothing. (Wang et al. ,2010) explored the application of the TPB in predicting m-commerce adoption in the Chinese market. The study concluded that perceived behavioural control, subjective norms, and attitudes significantly influence consumer intention to use mobile shopping applications. (Park et al. ,2003) studied the role of subjective norms in predicting m-commerce adoption using the TPB model. As per the findings, the influence of family and friends significantly moderates the intention to use m-commerce, particularly in purchasing products like healthcare items. (Zhou ,2011) tested the applicability of Theory of Planned Behaviour in understanding the adoption of mobile commerce in China. The study validates the influence of attitudes, perceived behavioural control, and subjective norms in shaping purchase intentions in the mobile retail space. (Kim & Park ,2012) found that subjective norms and perceived behavioural control influence consumers' purchase intentions toward m-

commerce platforms. Study suggests that attitude towards mobile shopping directly affect purchase intentions for product categories like clothing and electronics. (Choi et al. ,2013) validates the TPB framework in predicting m-commerce adoption, highlighting that attitudes, subjective norms, and perceived behavioural control are critical in forming intention to use mobile shopping services. Study also explored how gender and income moderate these relationships. (Liu et al. ,2022) validates TPB in predicting mobile commerce adoption in the context of purchasing healthcare products. The study found that attitudes and subjective norms significantly affect purchase intentions, with perceived control playing a mediating role. (Riquelme ,2010) applied the 'TPB' to study the adoption of mobile commerce in the UAE, and validated that attitudes, subjective norms, and perceived behavioural control significantly influence intention to use m-commerce platforms for purchasing electronics and sports items. (Moon & Kim ,2001) validated the integration of TPB with the Technology Acceptance Model (TAM), and found that attitude and subjective norms influence mobile commerce adoption in a similar manner to traditional e-commerce. (Zhou et al. ,2011) extended the Theory of Planned Behaviour by incorporating trust and perceived risk as additional constructs and validated this model and showed that attitudes, perceived control, and subjective norms strongly influence m-commerce intentions. (Chiu et al. 2005) study focused on Taiwan's m-commerce adoption through TPB and validated that subjective norms, attitudes, and perceived behavioural control contribute significantly to m-commerce usage in various product categories like electronics and clothing.

Objective 5: To validate the conceptual model based on "The Theory of Planned Behaviour".

The objective involves a systematic approach to verifying the effectiveness and applicability of a conceptual model for the mobile commerce (m-commerce) industry in Goa, grounded in the Theory of Planned Behaviour (TPB). The TPB, developed by Icek Ajzen, is a psychological framework that predicts individual behaviour based on three key factors: attitudes, subjective norms, and perceived behavioral control. Here's a detailed breakdown of what this objective entails:

Conceptual Model Development:

- **Theory of Planned Behaviour (TPB):** The model is constructed using the TPB framework, which suggests that an individual's intention to perform a behaviour is

influenced by their attitude towards the behaviour, the subjective norms surrounding it, and their perceived control over performing the behaviour.

❖ **Application to M-commerce:** This model will be tailored to fit the specific context of m-commerce in the state of Goa, considering unique regional factors that might influence consumer behaviour, such as local culture, technological infrastructure and economic conditions.

❖ **Components of the Model:**

a. **Attitudes:** Consumer attitudes towards m-commerce, including their beliefs about the advantages and disadvantages of using mobile platforms for shopping.

b. **Subjective Norms:** The perceived social pressure to engage or not to engage in m-commerce, influenced by peers, family, and societal trends.

c. **Perceived Behavioural Control:** The perceived ease or difficulty of using m-commerce, considering factors such as technological literacy, access to mobile devices, and internet connectivity.

❖ **Validation Process:**

- **Empirical Testing:** The model will be validated through empirical research, involving the collection and analysis of data from consumers in Goa. Surveys and interviews may be used to gather relevant data.
- **Statistical Analysis:** Advanced statistical techniques, such as Structural Equation Modeling (SEM), will be employed to test the relationships between the constructs of the TPB and their influence on m-commerce adoption and usage.
- **Hypothesis Testing:** Specific hypotheses derived from the TPB will be tested to determine their validity in the context of Goa's m-commerce industry. For example, hypotheses might examine whether positive attitudes towards m-commerce significantly increase the intention to use it.

❖ **Contextual Considerations:**

- **Regional Specificity:** The validation process will consider the unique characteristics of consumers of Goa, such as demographic profile, economic conditions, and technological landscape, ensuring the model is contextually relevant.

❖ **Outcomes and Implications:**

- **Model Refinement:** Based on the validation results, the conceptual model may be refined to better reflect the realities of the Goan m-commerce market.

- **Strategic Insights:** The validated model will provide valuable insights for businesses and policymakers, helping them understand the key drivers of m-commerce adoption and how to leverage them effectively.

Hypothesis-5:

H5: The "Theory of Planned Behaviour" describes consumers 'Attitude ", 'Subjective Norms', and 'Perceived Behavioural Control', influencing consumers' intentions and behaviour towards adoption of m-commerce.

Explanation: By exploring this hypothesis, the study will contribute to the academic literature by demonstrating the applicability and robustness of the TPB in the context of m-commerce, potentially offering a framework that can be adapted to other regions and contexts.

2.8.6 Research Question, Objective and Hypothesis-6

Background of Research Question-6:

The rapid growth of mobile commerce (m-commerce) has transformed retail landscapes globally. However, despite the widespread adoption, a significant portion of the population remains hesitant or unwilling to engage with m-commerce. This literature review explores the factors influencing an individual's likelihood of never using m-commerce, focusing on knowledge, education level, area of location, occupation, monthly family income, perceived behavioural control, attitude, and subjective norms.

Knowledge and M-Commerce Usage:

Knowledge about m-commerce plays a critical role in its adoption. Consumers with a higher level of awareness and understanding of m-commerce are more likely to use it (Liébana-Cabanillas et al., 2014). Lack of knowledge can result in apprehension towards the technology, leading to non-use (Yang, 2010). For instance, consumers who are not familiar with the functionalities and benefits of m-commerce are less likely to trust and use it (Gefen, Karahanna, & Straub, 2003).

Educational Level:

Educational level is a significant predictor of technology adoption, including m-commerce. Higher educational levels are associated with greater technological literacy and the ability to understand and use new technologies (Venkatesh, Thong, & Xu, 2012). Studies have shown that individuals with higher education are more likely to adopt m-commerce due to their ability to navigate and understand the complexities of mobile applications (Riquelme

& Rios, 2010). Conversely, lower education levels may correlate with higher likelihoods of never using m-commerce.

Area of Location:

The area of location, such as urban versus rural settings, significantly impacts m-commerce adoption. Urban areas typically have better internet infrastructure and higher smartphone penetration rates, facilitating easier access to m-commerce (Wei et al., 2011). In contrast, rural areas may face challenges such as poor internet connectivity and limited access to technology, contributing to a lower likelihood of m-commerce use (Gong et.al 2013).

Occupation:

Occupation influences an individual's inclination to use m-commerce. Certain professions, particularly those involving technology and office work, may encourage the use of m-commerce due to higher exposure and familiarity with digital platforms (Hernandez, Jimenez, & Martin, 2009). Conversely, occupations that do not require regular use of technology may see a lower adoption rate of m-commerce (Luarn & Lin, 2005).

Monthly Family Income:

Monthly family income is a crucial determinant of m-commerce usage. Higher income levels provide greater access to necessary resources such as smartphones and internet services, which are prerequisites for m-commerce (Zhou, 2011). Lower-income households may prioritize essential expenditures over discretionary technology purchases, resulting in lower m-commerce usage (Xu & Gupta, 2009).

Attitude:

Attitude towards m-commerce significantly influences its adoption. Positive attitudes, shaped by perceptions of usefulness, ease of use, and trust in the technology, are strong predictors of m-commerce usage (Davis, Bagozzi, & Warshaw, 1989). Negative attitudes, often stemming from concerns about security and privacy, can deter individuals from using m-commerce (Kim, Ferrin, & Rao, 2008).

Subjective Norm:

Subjective norm, or the perceived social pressure to engage or not engage in a behaviour, also affects m-commerce adoption (Fishbein & Ajzen, 1975). If significant others (e.g., family, friends) use and endorse m-commerce, individuals are more likely to adopt it (Venkatesh & Davis, 2000). Conversely, if there is a lack of social endorsement or negative

perceptions about m-commerce within an individual's social circle, the likelihood of never using m-commerce increases (Yang & Forney, 2013).

Perceived Behavioural Control:

Perceived behavioural control refers to an individual's perception of their ability to perform a particular behaviour (Ajzen, 1991). In the context of m-commerce, higher perceived behavioural control can lead to increased usage as individuals feel more confident in their ability to navigate and use mobile platforms (Taylor & Todd, 1995). On the other hand, low perceived behavioural control can act as a barrier, leading to non-use (Pavlou & Fygenson, 2006).

Research Question 6. What are the factors influencing an individual's likelihood of non-adoption of m-commerce?

Understanding the factors influencing an individual's likelihood of never using m-commerce is critical for developing strategies to increase adoption rates. Knowledge, education level, area of location, occupation, monthly family income, perceived behavioural control, attitude, and subjective norm all play significant roles in shaping m-commerce usage behaviours. Addressing these factors through targeted education, improving infrastructure, and enhancing user confidence and attitudes towards m-commerce can help mitigate barriers and promote broader adoption.

Background of Objective 6:

Previous studies have investigated various factors influencing an individual's likelihood of never using m-commerce, with a focus on knowledge, education level, area of location, occupation, monthly family income, 'PBC', 'Attitude', and 'SNs' and shown how these factors interact to influence whether individuals will adopt or avoid using mobile commerce in future. (Ajzen ,1991) Ajzen's work on the 'TPB' argued that an individual's 'Attitude', 'SNs', and 'PBC' significantly impact their intention to adopt new technologies. Lack of positive attitude and insufficient perceived control may increase the likelihood of never using new technology. (Dube et al. ,2010) emphasized that 'PBC' is a major predictor of m-commerce adoption. A lack of confidence in using mobile technologies, combined with limited knowledge or low educational attainment, can make individuals more likely to avoid using m-commerce. (Lu et al.,2014) study highlights that knowledge of mobile technologies and positive attitudes towards online shopping significantly influence adoption. Lack of knowledge and negative attitudes towards mobile devices lead to a higher likelihood of

never adopting m-commerce, especially in regions with lower levels of digital literacy. (Kim et al. ,2010) found that digital literacy is an essential factor in the adoption of mobile commerce. Individuals with low digital literacy or those who lack knowledge about mobile technologies, especially in lower-income groups or rural areas, have a higher likelihood of never using m-commerce. (Shin ,2010) study explores how perceived risk (privacy concerns, security risk, etc.) and attitudes towards technology influence mobile commerce adoption. Individuals with negative attitudes or high perceptions of risk are more likely to avoid m-commerce and Education and income levels influence these perceptions. (Kim et.al, 2013) study reveals that social influence (subjective norm) and education are crucial factors influencing the adoption of m-commerce. Individuals in low-education or low-income groups, or those with negative attitudes, are more likely to avoid m-commerce adoption. (Hsu et al., 2004) examined how income levels, education, and subjective norms influence mobile commerce adoption. They suggest that low-income individuals, especially those in rural areas, are more likely to avoid using mobile commerce due to lower exposure to mobile technologies. (Chau & Lai ,2003) studied how education level is a critical determinant in the adoption of new technologies, including m-commerce and found that, Low education levels contribute to the lack of knowledge and the likelihood of avoiding m-commerce. (Molla & Licker ,2005) identified that subjective norms and perceived behavioural control play significant roles in m-commerce adoption. Individuals from lower-income backgrounds, especially those who are less educated, are more likely to avoid m-commerce adoption. (Hanafizadeh et al. ,2014) explored the barriers to m-commerce adoption, noting that lack of knowledge, education, and subjective norms are critical factors. People with limited knowledge of mobile technologies are more likely to avoid m-commerce, especially if they perceive it as difficult or unnecessary. (Beldad et al. ,2010) studied consumer behaviour in m-commerce and argued that low education, low income, and subjective norms influence consumer behaviour, making individuals in certain segments more likely to avoid m-commerce adoption. These individuals often lack the knowledge or support to make informed decisions. (Hsieh et al. ,2012) studied barriers to E-Commerce adoption and discussed how ‘PBC’ and ‘Attitude’ affect adoption, with low income, rural location, and education level being significant barriers to m-commerce use. (Fogg et al. ,2001) studied how perceived trustworthiness and subjective norms affect adoption decisions. They found that lack of trust, combined with negative social influences, contributes to avoidance of m-commerce in low-income or less educated groups. (Kumar et al. ,2019) focused on socioeconomic factors such as education, income, and location in determining m-commerce

adoption. Study concluded that people with lower levels of education and limited income are less likely to adopt m-commerce, particularly in rural or underdeveloped areas. (Chang et al. ,2010) examined how 'Attitudes' and 'SNs' affect mobile commerce adoption. They find that negative attitudes, especially in lower-income or less-educated groups, increase the likelihood of never using m-commerce. (Zhou ,2011) study identifies 'Attitude', 'PBC', and education as major barriers to m-commerce adoption and found that individuals with low income, staying in rural locations, and with negative attitudes are more likely to avoid m-commerce.

Objective 6: To identify and analyse the factors influencing an individual's likelihood of non-adoption of m-commerce.

The research aims to investigate into the multifaceted reasons behind why certain individuals are unlikely to engage in mobile commerce (m-commerce). The goal is to comprehensively identify and analyse specific factors that influence this likelihood, with a focused examination of the following variables: knowledge, education level, area of location, occupation, monthly family income, perceived behavioural control, attitude, and subjective norm. Each of these factors is essential for understanding the barriers to m-commerce adoption and for developing strategies to encourage broader usage.

Knowledge:

Objective: To investigate the influence of 'Knowledge' on the likelihood of non-adoption of m-commerce.

Explanation: Knowledge refers to the awareness and understanding of m-commerce functionalities and benefits. Lack of knowledge can lead to apprehension and mistrust, reducing the likelihood of usage. The research will explore the extent to which knowledge deficits contribute to non-use and identify ways to improve consumer education.

Educational Level:

Objective: To examine the influence of 'Educational Level' on the likelihood of non-adoption of m-commerce.

Explanation: Education level is a significant determinant of technology adoption. Higher education often correlates with better digital literacy and the ability to understand and navigate m-commerce platforms. This objective seeks to analyse the relationship between educational attainment and m-commerce usage.

Area of Location:

Objective: To determine the influence of 'Area of Location' on the likelihood of non-adoption of m-commerce.

Explanation: The geographic area, particularly urban versus rural settings, affects access to technological infrastructure. Urban areas typically offer better internet connectivity and higher smartphone penetration, facilitating m-commerce adoption, whereas rural areas may face infrastructural challenges that impede usage of m-commerce.

Occupation:

Objective: To examine the influence of 'Occupation' on the likelihood of non-adoption of m-commerce.

Explanation: Occupation affects exposure to and familiarity with digital technologies. Professions that involve regular use of technology may encourage m-commerce adoption, while others may not provide the same level of exposure or necessity. This objective aims to analyse these occupational differences and their impact on m-commerce use.

Monthly Family Income:

Objective: To determine the influence of 'Monthly Family Income' on the likelihood of non-adoption of m-commerce.

Explanation: Income levels influence access to m-commerce applications for shopping. Higher income may correlate with greater adoption, while lower income can be a barrier. The research will explore how financial constraints affect m-commerce engagement.

Attitude:

Objectives: To investigate the impact of consumers' 'Attitude' on the likelihood of non-adoption of m-commerce.

Explanation: Attitudes towards m-commerce, shaped by perceptions of usefulness, ease of use, and trust, significantly influence adoption. Positive attitudes enhance the likelihood of use, while negative attitudes deter it. The research aims to identify the components of negative attitude that most strongly affect m-commerce adoption.

Subjective Norm:

Objective: To determine the influence of 'Subjective Norms' on the likelihood of non-adoption of m-commerce.

Explanation: Subjective norms refer to the perceived social pressure to engage or not to engage in a specific behaviour. Social influences from family, friends, and peers can significantly impact m-commerce adoption. This objective seeks to understand the role of social pressures on individual decision to use or not to use m-commerce for shopping.

By systematically analysing these factors, the research aims to provide a holistic understanding of the barriers to m-commerce adoption. The insights gained will be valuable

for stakeholders, including policymakers, businesses, and technology developers, in creating targeted interventions to promote m-commerce usage among diverse consumer segments.

Perceived Behavioural Control:

Objective: To analyse how 'Perceived Behavioural Control' affects an individual's likelihood of non-adoption of m-commerce

Explanation: Perceived behavioural control involves the individual's perception of their ability to use m-commerce effectively. If individuals feel confident and capable of using m-commerce, they are more likely to adopt it. This objective focuses on understanding how perceived control influences behaviour of consumers.

Hypothesis-6:

H6: There is no significant association between an individual's 'Lack of knowledge', 'Education level', 'Area of location", 'Occupation', 'Monthly Family Income', 'Perceived Behaviour Control', 'Attitude', 'Subjective Norms', 'Intentions' and their likelihood of non-adoption of m-commerce.

Sub-Hypothesis:

H6a: There is no significant relationship between an individual's Lack of Knowledge and their likelihood of non-adoption of m-commerce.

H6b: There is no significant association between an individual's educational level and their likelihood of non-adoption of m-commerce.

H6c: There is no significant association between an individual's area of location and their likelihood of non-adoption of m-commerce.

H6d: There is no significant association between an individual's Marital Status and their likelihood of non-adoption of m-commerce.

H6e: There is no significant association between an individual's Occupation and their likelihood of non-adoption of m-commerce.

H6f: There is no significant association between an individual's Monthly Family Income and their likelihood of non-adoption of m-commerce.

H6g: There is no significant relationship between individuals, who have never used m-commerce, Perceived Behaviour Control, Attitude and Subjective norms.

Explanation: The research hypothesis is based on the assumption that there is no significant association between various individual characteristics and their likelihood of never using m-commerce. By breaking down the hypothesis into specific, measurable factors, the research aims to identify which, if any, of these factors are significantly associated with m-commerce usage patterns. Each objective is designed to isolate and examine one potential influencing factor, providing a comprehensive understanding of the barriers and facilitators to m-commerce adoption. This detailed analysis will help in developing targeted strategies to enhance m-commerce adoption across different demographic segments.

2.9 CONCLUSIONS:

In summary, this chapter has consolidated theoretical perspectives, empirical findings, and contextual insights into a clear framework for the study. It has established the relevance of the Theory of Planned Behaviour in examining consumer behaviour towards m-commerce, demonstrated the importance of considering Indian-specific contexts alongside global patterns, and identified critical research gaps that justify the present investigation. By systematically linking literature to research questions, objectives, and hypotheses, this chapter provides a strong foundation for the subsequent methodological design and empirical analysis.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTRODUCTION:

This chapter presents a comprehensive account of the research methodology adopted for the study. It begins by elaborating on the underlying research philosophy and approach, establishing a conceptual foundation for the investigation. Subsequently, the chapter describes the critical methodological procedures implemented throughout the research process. It further details the research design, strategic framework, time horizon, and methods employed for data collection, thereby offering a structured overview of the methodological framework.

In addition, the chapter discusses the design of the questionnaire, followed by the operational definitions and measurement of the key constructs namely, the independent, dependent, and mediating variables along with their respective sub-constructs. This aids in clarifying the conceptual and empirical parameters of the study. The instrument's preliminary evaluation through a pilot test is then presented to assess its validity and reliability.

The chapter also outlines the target population, sampling frame, sample size, and the sampling technique employed, forming the basis for the empirical data collection. Finally, ethical considerations related to the conduct of the research are examined to ensure adherence to academic and professional standards.

3.2 RESEARCH METHODOLOGY BASED ON THE RESEARCH ONION (Saunders et al., 2012):

The Research Onion model proposed by (Saunders, Lewis, and Thornhill ,2012) offers a structured approach to designing research methodology by guiding the researcher through six key layers: research philosophy, research approach, methodological choice, strategy, time horizon, and data collection methods. Each layer informs the next, ensuring methodological coherence and alignment with research objectives. The following sections describe each layer as applied in a marketing management context.

3.2.1 Research Philosophy:

Research philosophy refers to 'the underlying systems of beliefs and assumptions about knowledge development' (Saunders et al., 2016). There are five main philosophies: positivism, interpretivism, pragmatism, critical realism, and postmodernism (Saunders et al., 2016). The current study mainly adopts a positivist philosophy, which promotes an objective interpretation of reality and uses data from surveys and experiments (Gray, 2021).

In social science, most of the literature relies on two philosophies: positivism and interpretivism. Positivism philosophy is mainly linked with quantitative research using surveys or structured interviews. In contrast, interpretivism philosophy is primarily associated with qualitative research using surveys or structured interviews using observation or unstructured interviews (Lee & Lings, 2008). According to (Wahyuni ,2012), the essential fact supporting the positivist philosophy is that different studies would yield similar outcomes of a particular problem when they analyse a large sample employing a similar research method and statistical tests. Positivist research uses existing theories to develop hypotheses and collects observable data to investigate causal relationships between variables (Saunders et al., 2012). In the same vein, (Della Porta & Keating, 2008) noted that researchers set out with a hypothesis, collect data, and then identify whether or not the findings support the proposed hypothesis.

According to (Della Porta & Keating, 2008), the researcher and the subject are independent and objective in positivist philosophy. Therefore, the researcher is unbiased and does not influence the research subject.

The current study aims to investigate the role of antecedents to consumer behaviour towards M-Commerce through a survey questionnaire. In addition, the conceptual framework of this study will be examined based on an existing theory, 'Theory of Planned Behaviour'. Therefore, positivist philosophy is determined as the most appropriate paradigm to answer the questions of the study.

3.2.2 Research Approach:

Two prominent approaches to research are the inductive and deductive approaches (Saunders et al., 2016). The deductive approach is based on positivist philosophy and the quantitative methodology. It begins with reviewing the relevant literature and using existing theories to develop hypotheses. Following that, data are collected to test these hypotheses. The findings are used to support or refute the hypotheses, and the theories are revised accordingly (Bryman, 2001).

The inductive approach, on the other hand, is based on interpretivist philosophy and qualitative methodology. It aims to build theories from empirical observations and solid evidence, which can be generalised to the entire population (Bernard, 2013).

Since this study aims to identify the impact of Attitude, subjective norms and perceived behavioural control on intention and behaviour based on the positivist philosophy that intends to generalize the finding for a large population, the deductive approach is adopted to answer the questions of the current study based on statistical findings.

3.2.3 Research Design:

Researcher has used conclusive descriptive cross sectional one sample survey research design. In case of social researches, there are basically two types of fundamental questions that the researcher can ask. First question refers to the description of facts, "what is going on" and the second question is "why is it going on", which explains the reason. The factual research answering the question "Why" is called as Explanatory Research (De Vaus,2001).

The present study is descriptive in nature, which describes the behaviour of consumers towards use of mobile commerce for shopping. Study also attempts to identify the factors responsible for such behavioural intentions of consumers and its role as a mediator in determining such behaviour. The study empirically tests the relationship between important constructs, Based on TPB model, influencing the behavioural intentions of consumers towards use of m-commerce for shopping.

3.2.4 Research Strategy:

Different strategies for collecting empirical data include experiments, surveys, action research, case studies, grounded theory, and archival and ethnographic strategies (Saunders et al., 2009).

This study uses a structured survey questionnaire to collect quantitative data. This strategy is widely used in empirical research, allowing researchers to collect large amounts of data from a population (Bryman, 2001). Structured survey questionnaires typically consist

of closed-ended questions with pre-determined answer choices. This makes them easy to administer and score, and it allows researchers to compare responses from different participants (Saunders et al., 2016). Furthermore, the survey questionnaire will enable the researcher to collect the empirical data needed to examine the proposed conceptual framework quantitatively using descriptive and inferential statistics (Saunders et al., 2009).

3.2.5 Methodological Choice:

There are two main data collection methods: quantitative and qualitative. Quantitative research involves collecting and analysing numeric data, while qualitative research involves non-numeric data, such as text, images, or videos (Saunders et al., 2016).
The selection of the data collection method relies on the research questions being asked and the information needed to answer them. Quantitative research is often utilised to test hypotheses or estimate the relationship between constructs. Qualitative research is often employed to explore people's experiences and views or to comprehend the social and cultural contexts in which phenomena appear (Christensen, 2016).

In this study, the researcher is interested in investigating various types of association and relationship between construct. Therefore, the quantitative data collection method is the most appropriate for this study.

3.2.6 Time Horizon:

Time horizon determines the scope of research in terms of time.There are two types of studies based on the time frame in which data is collected: cross-sectional and longitudinal studies. In cross-sectional studies, researchers collect data at a single point in time to answer their research questions. In longitudinal studies, researchers collect data at different points in time to answer their research questions (Sekaran & Bougie, 2016).

This study employs a cross-sectional design to collect data. A cross-sectional design is the most appropriate for this study because it allows the researcher to collect data from a large sample of respondents at a particular time to investigate a specific relationship.

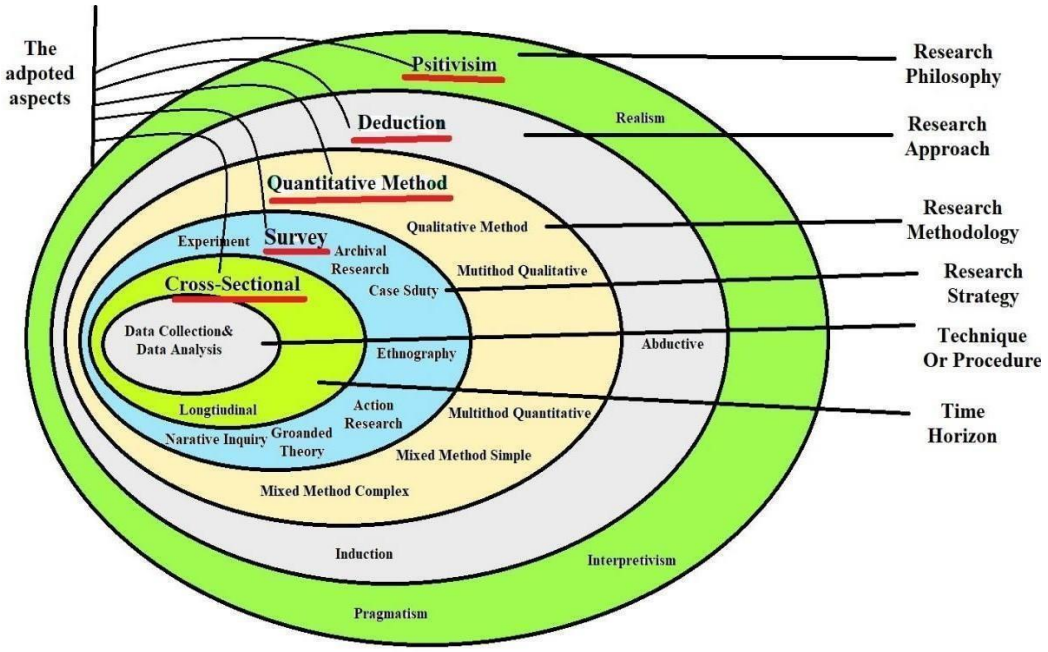


Figure 3.1: The research Onion

(Source: Saunders et al. 2012)

3.3 DEVELOPMENT OF MEASUREMENT INSTRUMENT:

A questionnaire (Measurement Instrument) refers to "a prepared set of questions (or measures) used by respondents or interviewers to record answers (data)" (Hair et al., 2019, p. 274).

According to Saunders et al., (2009), there are three types of questionnaires for conducting both qualitative and quantitative research: unstructured, semi-structured, and structured. Unstructured questionnaires support free answers where respondents are provided with open-ended questions and can offer broad views. This type of questionnaire is suitable for qualitative studies. Semi-structured questionnaires support both unrestricted and restricted answers where respondents are given open-ended and closed-ended questions. This type of questionnaire is suitable for mixed studies. The last type of questionnaire is the structured questionnaire. It only includes closed-ended questions where the respondents are given a set of answers from which they should select the most appropriate. This type of questionnaire is suitable for quantitative research (Hague & Jackson, 2002).

According to (Taylor-Powell & Marshall, 1998), a questionnaire incorporates four types of information that are "beliefs and thoughts, attitudes, knowledge, and attributes and

behaviour". Beliefs and thoughts refer to emotions of individuals, opinions, conclusions and views. The knowledge addresses the understanding of respondents about a specific issue. The behaviour relates to what respondents intend to do something, whether in the past or present. Last, attributes include personal demographic characteristics of the respondents, such as gender, age, education, area of location, occupation and income.

The widely employed rating scale is the Likert scale designed by Likert (1932), which is easy to understand and takes less time to answer (Shahin, 2011). It comprises several options per question. Scholars may use sequences of "strongly agree, agree, disagree, or strongly disagree" or other sequences such as poor, fair, good, poor, and outstanding (Alabi & Jelili, 2023; Heiberger et al., 2015). Dawes (2008) proposed that a five-point scale is appropriate for conducting structural equation modelling (SEM).

This study relies on positivist philosophy and quantitative method; hence, it adopts a closed-ended questionnaire (Collis & Hussey, 2009) based on five Likert scales as the most appropriate type to measure the three constructs related to the conceptual framework (Shahin, 2011).

The questionnaire is designed into six sections. The first section incorporates the demographic profile of the respondents, in order to make the respondent feel psychologically comfortable with the questionnaire (Sekaran & Bougie, 2016). The second section includes questions for measuring attitude towards mobile commerce. The third section contains the questions for estimating Perceived Behavioural Control. The fourth section contains question related to Subjective Norms. Fifth section covers questions related to mobile commerce Intentions and sixth section involves the questions to measure mobile commerce purchase behaviour. The participants surveyed were requested to reveal their agreement on each item based on a five-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree" for all constructs

3.4 OPERATIONAL DEFINITIONS:

The operational definition is necessary to estimate abstract concepts based on a subjective point of view (Sekaran & Bougie, 2016). The operational definition is described as "a set of questions and response alternatives used to measure a variable" (Ruane, 2016). The current section presents the operational definitions of the conceptual framework of this study's

constructs to estimate their interrelationships. Based on relevant literature, the researcher identifies the following operational definitions of the primary constructs and their relevant sub-constructs or dimensions.

3.4.1 Attitude:

An attitude is defined as "an enduring set of beliefs about an object that predisposes people to behave in a particular way toward the object" (Weigel, 1983 p. 257). According to Ajzen & Fishbein (1980), attitudes play a significant role when it comes to forming an intention to act in certain behaviour. The model primarily argues that people engage in processing that leads to the formation of attitudes, norms and intentions before performing the behaviour. According to Ajzen (1991), an attitude can be defined as a disposition to respond favourably or unfavourably to an object, person, institution, or event.

3.4.2 Perceived Behavioural Control:

Perceived behavioural control is a person's perception of whether different aspects of the behaviour are in his or her control or are easy or difficult to perform (Ajzen, 1991). Perceived behavioural control is concerned with judgments of how well one can execute an action. Ajzen (1991) suggested that control belief and control strength are two constructs capable of measuring perceived behavioural control.

Control belief is the individual's belief in the existence of factors that facilitate or impede the performance of the behaviour. Control belief consists of situational factors and resources like time, money and knowledge that facilitate the conditions that determine individuals‟ behaviour. Whereas Control strength refers to the degree, to which one is influenced by resources, opportunities, or obstacles to perform the behaviour (Ajzen, 1991). Control strength refers to the resources (i.e., money, time, and energy) and the opportunities one needs to complete behaviour. Control strength is the confidence one possesses in one‟s ability to complete a specific behaviour. Control strength is similar to Bandura‟s concept of self-efficacy. Self-efficacy is being confident of the ability to behave successfully in the situation (Bandura, 1986). Self-efficacy refers to an individual‟s beliefs about his or her capabilities to produce desired levels of performance.

Bandura (1986) suggested that control ability is one's capability to control specific performance, and self-efficacy is one's belief in one's ability to successfully perform the behaviour. These two concepts are similar to Ajzen's (1991) concepts of control belief and control strength. Thus, control belief and control strength are two determinants of perceived behavioural control. According to Wu & Chen (2014), control belief and control force

significantly influence perceived behavioural control. Perceived self-efficacy influences green consumption behaviour (Chan & Lau, 2002). Moons & Pelsmacker (2015) found that perceived personal ability has a significant influence on perceived behavioural control.

3.4.3 Subjective Norms:

Fishbein and Ajzen (1975) defined subjective norm as the perceived social pressure that encourages one to engage in a specific behaviour. Subjective norm is the measure of pressure exerted by the social groups which the individual takes into account before making a behavioural decision (Venkatesh & Davis, 2000).

Consumer decision making should be looked at within a social context due to the substantial influence people can have on other people (Wood & Hayes, 2012). Social influence refers to the influence of external social factors on individual behaviours (Deutsch & Gerard, 1955). Thus, social influence occurs when a person's emotions, opinions or behaviours are affected by others intentionally or unintentionally.

3.4.4 Behavioural Intention:

In TPB, intention represents an individual's motivational readiness or conscious plan to perform a specific behaviour. It is regarded as the immediate antecedent of actual behaviour and is influenced by the individual's attitude toward the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991; Armitage & Conner, 2001). In marketing research, behavioural intention is often operationalized by measuring the degree to which consumers express their willingness, likelihood, or determination to perform a particular purchasing behaviour, such as shopping via mobile platforms or using a mobile payment system (Venkatesh, Thong, & Xu, 2012). High intention scores are generally predictive of higher probabilities of actual engagement in the behaviour (Ajzen, 2002).

3.4.5 Behaviour:

In the context of the Theory of Planned Behaviour (TPB), behaviour refers to the observable act performed by an individual in a given context. It reflects the actual execution of an intended action, such as purchasing a product online, adopting a service, or engaging in mobile commerce (Ajzen, 1991). Behaviour, in empirical marketing research, is typically operationalized through self-reported measures that assess the frequency, likelihood, or recency of the actual behaviour (Fishbein & Ajzen, 2010). For instance, studies on consumer behaviour in m-commerce often utilize behavioural indicators such as the number of mobile

purchases made, the amount spent, or the frequency of app usage to measure actual behaviour (Morosan & DeFranco, 2016).

3.5 DEVELOPMENT OF SCALE:

This section presents the instruments selected to estimate the constructs investigated in this study. All of the adopted scales have been tested and published in high-impact journals. In the following sub-sections, the scales adopted to measure the independent construct Attitude, Perceived Behaviour Control, Subjective Norms and, the dependent construct purchase behaviour, and the mediating construct intention are mentioned separately below:

Table 3.1: Scale to Measure 'Attitude towards Mobile Commerce'

Sr. No	Item Code	Scale Items
1	Att1	I think there is wide choice of products at reasonable prices on mobile commerce shopping platforms.
2	Att2	I feel M-commerce shopping platforms offer quick customer care service
3	Att3	I think M-commerce lacks physical shopping experience.
4	Att4	I feel M-commerce is very convenient (Useful) for shopping from anywhere, anytime
5	Att5	I think M-commerce transactions are not safe & secure.
6	Att6	I feel using mobile commerce without good knowledge and understanding of mobile technology is not safe.
7	Att7	I think customer reviews and ratings on M-commerce shopping portals are not reliable to make shopping decisions
8	Att8	I think user friendly M-commerce apps make shopping simple and enjoyable
9	Att9	I think use of M-commerce leads to shopping addiction
10	Att10	I think M-commerce gives privacy in shopping personal products

(Source: Researcher's Compilation based on previous research Studies)

Table 3.2: Scale to Measure 'Perceived Behavioural Control towards M-Commerce'

Sr. No	Item Code	Scale Items
1	PBC1	I need to take permission from family members to buy products on mobile commerce sites
2	PBC2	I have full freedom to spend any amount of money while shopping on m-commerce sites
3	PBC3	I can make my decision to shop anytime on mobile commerce shopping sites whenever I feel like shopping
4	PBC4	I don't need to take permission from anyone to shop using mobile commerce sites

(Source: Researcher's Compilation based on previous research Studies)

Table 3.3: Scale to Measure 'Subjective Norms'

Sr. No	Item Code	Scale Items
1	SN1	I use mobile commerce for shopping since, most people who are important to me prefer mobile commerce for shopping
2	SN2	I use mobile commerce for shopping since, most people who are important to me have recommended it to me
3	SN3	I don't use mobile commerce for shopping since, most people who are important to me think that using mobile commerce for shopping is not safe
4	SN4	I use mobile commerce for shopping since, most of my followers on social networking sites encourage me to use mobile commerce for shopping
5	SN5	I use mobile commerce for shopping, even when people who are close to me are not in favour of it
6	SN6	I always depend on other people's opinion for shopping on mobile commerce sites

(Source: Researcher's Compilation based on previous research Studies)

Table 3.4: Scale to Measure 'Mobile Commerce Intention'

Sr. No	Item Code	Scale items
1	MCI1	I intend to use mobile commerce to keep my shopping private and confidential
2	MCI2	I intend to use mobile commerce as I believe that it is convenient (Useful)
3	MCI3	I intend to use mobile commerce as I believe that it is safe to use
4	MCI4	I intend to use mobile commerce as it is cheaper than offline shopping
5	MCI5	I don't intend to use mobile commerce due to my past experience with it
6	MCI6	I intend to use mobile commerce since people who are important to me have recommended it to me
7	MCI7	I intend to use mobile commerce since I believe that it is easy to use
8	MCI8	I don't intend to use mobile commerce due to lack of knowledge of using mobile commerce

(Source: Researcher's Compilation based on previous research Studies)

Table 3.5: Scale to Measure 'Mobile Commerce Purchase Behaviour'

Sr. No	Item Code	Scale Items
1	MCPB1	In the past few years, I have been using mobile commerce for shopping electronic products
2	MCPB2	In the past few years, I have been using mobile commerce for shopping sports products.
3	MCPB3	In the past few years, I have been using mobile commerce for shopping clothing, shoes and Jewellery items
4	MCPB4	In the past few years, I have been using mobile commerce

		for shopping beauty and personal care products
5	MCPB5	In the past few years, I have been using mobile commerce for shopping home and kitchen appliances
6	MCPB6	I have never used mobile commerce for shopping
7	MCPB7	In the past few years, I have been using mobile commerce for shopping for Books, Magazines and Newspapers
8	MCPB8	In the past few years, I have been using mobile commerce for shopping for healthcare and medicines
9	MCPB9	In the past few years, I have been using mobile commerce for shopping for stationary items and games
10	MCPB10	In the past few years, I have been using mobile commerce for shopping for groceries

(Source: Researcher's Compilation based on previous research Studies)

3.6 PILOT TEST:

A pilot study is defined as "a small-scale test to examine a study's feasibility before conducting a large trial" (Teresi et al., 2022). According to (Lynn, 1986; Saunders et al., 2009), a pilot test helps scholars improve the possible design and identify potential weaknesses to be addressed in the final questionnaire. In this study, the pilot study was conducted in two separate stages, pre-pilot and post-pilot, to assess the reliability of the research instrument. The following sub-sections present the pre-pilot and post-pilot tests.

The pilot test was conducted to ensure there were no difficulties for the respondents in answering the questions and to assess whether the questions were valid and reliable before administering the final questionnaire (Saunders et al., 2009).

The initial questionnaire was distributed to 50 respondents with characteristics similar to the target population who were deans or heads of departments, as suggested by (McNabb, 2013). The reliability of the returned questionnaires was analysed via IBM SPSS Statistical 26 version.

3.6.1 Reliability Test:

Reliability refers to the degree to which a research instrument yields consistent results under consistent conditions. It assesses the internal consistency, stability, and equivalence of the measurement tools used. One of the most widely used indicators of reliability is Cronbach's

alpha, which measures internal consistency by assessing how closely related a set of items are as a group (Hair et al., 2019). A Cronbach's alpha value of 0.70 or higher is generally considered acceptable for research purposes (Nunnally & Bernstein, 1994). Reliability test which was run by the researcher on SPSS, gave Cronbach alpha in the range of .708 to .884 for all scale dimensions.

Table 3.6: Cronbach Alpha for Scale Dimensions

Sr. No	Construct	No. of Items	Cronbach Alpha
1	Attitude towards mobile commerce (ATMC)	10	.708
2	Perceived behavioural control towards mobile commerce (PBCTMC)	04	.772
3	Subjective Norm (SN)	06	.757
4	Mobile commerce intentions	08	.744
5	Mobile commerce purchase behaviour (MCPB)	10	.884

(Source: Research's Computation based on previous research Studies)

3.6.2 Validity Test:

Validity refers to the extent to which an instrument accurately measures what it is intended to measure. There are several types of validity tests:

Content validity assesses whether the measurement items fully capture the construct's domain.

Construct validity examines whether the measurement items reflect the theoretical components of the construct and is commonly tested through factor analysis (Hair et al., 2019).

Convergent validity and **discriminant validity** are subtypes of construct validity. Convergent validity ensures that measures that should be related are indeed related, typically evaluated through **Average Variance Extracted (AVE)**, where a value above 0.50 is desirable (Fornell & Larcker, 1981). Discriminant validity, meanwhile, ensures that constructs that should not be related are actually distinct from each other.

Content Validity Index (CVI)

Content validity index (CVI) is calculated in order to find out the relevance of each item of the scale. If the rating given by the expert is >=3 then it is considered as 1 (valid) and if it is < 3 then it is considered as 0 (not valid).

The following formulas are used to calculate I-CVI, S-CVI and UA:

I-CVI (Item Content Validity Index) = No of agreements upon No. of raters.

S-CVI (Scale Content Validity Index) = Total of I-CVI / No. of items

UA (Universal Agreement) =Total agreements / No. of Items

Table 3.7: Item Content Validity Index (I-CVI) and Scale Content Validity Index (S-CVI) of Attitude Towards Mobile Commerce (ATMC)

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Instruction to rater	1	1	1	1	1	1	6	
ATMC 1	1	1	1	1	1	1	6	1
ATMC 2	1	1	1	1	1	1	6	1
ATMC 3	1	1	1	1	1	1	6	1
ATMC 4	1	1	1	1	1	1	6	1
ATMC 5	1	1	1	1	1	1	6	1
ATMC 6	1	1	1	1	1	1	6	1
ATMC 7	1	1	1	1	1	1	6	1
ATMC 8	1	1	1	1	1	1	6	1
ATMC 9	1	1	1	1	1	1	6	1
ATMC 10	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	11
							S-CVI/UA	1

(Source: Research's Computation)

Table 3.8: Item Content Validity Index (I-CVI) and Scale Content Validity Index (S-CVI) of Perceived Behavioural Control Towards Mobile Commerce (PBCTMC)

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Inst. To rater	1	1	1	1	1	1	6	1
PBCTMC 1	1	1	1	1	1	1	6	1

PBCTMC 2	1	1	1	1	1	1	6	1
PBCTMC 3	1	1	1	1	1	1	6	1
PBCTMC 4	1	1	1	1	1	1	6	1
PBCTMC 5	1	1	1	1	1	1	6	1
PBCTMC 6	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	7
							S-CVI/UA	1

(Source: Research's Computation)

Table 3.9: Item Content Validity Index (I-CVI) and Scale Content Validity Index of Subjective Norms (SN)

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Inst. to rater	1	1	1	1	1	1	6	1
SN 1	1	1	1	1	1	1	6	1
SN 2	1	1	1	1	1	1	6	1
SN 3	1	1	1	1	1	1	6	1
SN 4	1	1	1	1	1	1	6	1
SN 5	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	6
							S-CVI/UA	1

(Source: Research's Computation)

Table 3.10: Content Validity Index of scale items (I-CVI) and Content Validity Index of Scale (S-CVI): Mobile Commerce Intention (MCI)

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Inst. To rater	1	1	1	1	1	1	6	1
MCI 1	1	1	1	1	1	1	6	1
MCI 2	1	1	1	1	1	1	6	1
MCI 3	1	1	1	1	1	1	6	1
MCI 4	1	1	1	1	1	1	6	1
MCI 5	1	1	1	1	1	1	6	1
MCI 6	1	1	1	1	1	1	6	1
MCI 7	1	1	1	1	1	1	6	1
MCI 8	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	9
							S-CVI/UA	1

(Source: Research's Computation)

Table 3.11: Item Content Validity Index (I-CVI) and Scale Content Validity Index of Mobile Commerce Purchase Behaviour

Scale Items	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	Number of Agreements	I-CVI
Inst. To rater	1	1	1	1	1	1	6	1
MCPB 1	1	1	1	1	1	1	6	1
MCPB 2	1	1	1	1	1	1	6	1
MCPB 3	1	1	1	1	1	1	6	1
MCPB 4	1	1	1	1	1	1	6	1
MCPB 5	1	1	1	1	1	1	6	1
MCPB 6	1	1	1	1	1	1	6	1
MCPB 7	1	1	1	1	1	1	6	1
MCPB 8	1	1	1	1	1	1	6	1
MCPB 9	1	1	1	1	1	1	6	1
MCPB 10	1	1	1	1	1	1	6	1
							S-CVI/Ave	1
							Total Agreement	11
							S-CVI/UA	1

(Source: Research's Computation)

3.7 POPULATION:

Population is described as the total group of events, people or things that a researcher seeks to investigate (Sekaran & Bougie, 2016). According to Saunders et al. (2012), population refers to "the entire group of cases and elements that a sample is taken from". In this study, the population includes consumers having smartphones in the state of Goa who may or may not be using it for mobile commerce.

Individuals were surveyed with the help of a questionnaire, in panchayat area(Rural) and Municipal area (Urban) in the state of Goa, for the purpose of collecting data for the study. An attempt was made to study the behaviour of consumers with different demographic characteristics like gender, age, education, location, income, marital status and occupation. 'Telephonic Interview' and 'In-depth personal Interviews' were conducted to study the knowledge of the respondents about m-commerce and also to know their attitude towards it. They were explained in detail about the scale items. Only after all their queries were answered, they were requested to fill the google form, and also assisted wherever required. Maximum efforts were taken while collecting the data for getting genuine responses.

3.8 UNIT OF ANALYSIS, SAMPLING AND SAMPLE SIZE:

The present study aims to investigate the attributes that influence consumers' purchase intentions towards mobile commerce (m-commerce) in the state of Goa. The unit of analysis is individual consumers residing in Goa who are using smartphones.

To collect primary data, a structured questionnaire was developed incorporating the constructs of the Theory of Planned Behaviour (TPB) attitude, subjective norms, perceived behavioural control, intention, and actual behaviour. The respondents were instructed to indicate their level of agreement with each item using a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree".

A non-probability convenience sampling technique was adopted for the study. During the preliminary phase, potential respondents were first screened by asking whether they know to use their smartphones or not. Only those who affirmed their usage were selected to proceed with the questionnaire. This ensured the relevance of the responses to the study's context and objectives (Saunders, Lewis, & Thornhill, 2009).

Given that the study employs Structural Equation Modeling (SEM) for data analysis, sample size determination followed established methodological guidelines. According to Hair et al. (2014), SEM can be applied even with relatively small sample sizes, although model complexity and number of parameters need to be considered. The "10 times rule" recommended by various scholars (Barclay, Higgins, & Thompson, 1995; Chin, 1998) and further elaborated by Garson (2016), suggests that the minimum sample should be ten times the number of indicators for the construct with the highest number of measurement items or the largest number of incoming paths in the structural model.

Specifically, Gaskin (2016) proposes that for SEM using AMOS, the required sample size should be at least 10 times the number of observed variables used to predict the most complex latent construct. Based on this rule, the estimated minimum required sample size for this study was calculated to be 380 respondents, as the total number of scale items were 38. However, to improve statistical power, address potential non-response, and enhance the robustness of the findings, the researcher targeted a final sample size of 500 respondents.

The survey was conducted over a period of six months, from October 2023 to March 2024, covering both urban (Municipal area) and rural (Panchayat area) of North and South Goa.

Prior to full-scale data collection, the instrument was subjected to content validity assessment and pre-testing, ensuring its clarity, relevance, and contextual appropriateness for the target population.

3.9 STATISTICAL TEST USED:

- Descriptive Statistics
- Chi Square Test
- Correlation
- Independent Sample T test
- One Way ANOVA
- Exploratory Factor Analysis
- Confirmatory Factor Analysis
- Structural Equation Modeling

3.10 ETHICAL CONSIDERATIONS OF THE STUDY:

Ethical considerations in research are fundamentally concerned with the moral principles that guide researchers' conduct, particularly in relation to the rights and well-being of participants who may be directly or indirectly impacted by the study (Saunders et al., 2016). Research ethics can be defined as “the standards of behaviour that guide your conduct in relation to the rights of those who become the subject of your work or are affected by it” (Saunders et al., 2019).

In this study, all ethical protocols were rigorously observed throughout the data collection process. Participants were clearly informed about the purpose, objectives, procedures, and estimated duration of the research. The researcher ensured full transparency and voluntary participation, whereby respondents were made aware of their right to withdraw at any point without penalty. Furthermore, confidentiality was strictly maintained; participants were assured that their personal information would remain anonymous and would not be disclosed to any third party. Additionally, the researcher offered to share a summary of the study’s findings with any respondent who expressed interest, thereby fostering openness and accountability.

3.11 CONCLUSION:

This chapter has provided a systematic and detailed explanation of the research methodology employed in this study. It began by outlining the philosophical and theoretical orientation that supports the research approach, thereby establishing the foundations for the investigation. A structured methodological pathway was then described, encompassing the research design, strategy, time horizon, and the data collection techniques applied to ensure methodological coherence and alignment with the research objectives.

The development and design of the research instrument, particularly the questionnaire, were elaborated upon, including the operationalization of key constructs independent, dependent, and mediating variables along with their sub-constructs. This helped to ensure clarity in conceptual definitions and empirical measurement. The instrument's initial validation through a pilot study further strengthened the reliability and validity of the data collection process.

The sampling design, comprising the identification of the target population, determination of the sampling frame, and selection of the sample size and technique, was discussed to demonstrate the representativeness and appropriateness of the data set. Finally, the chapter addressed the ethical considerations observed throughout the research process, thereby contributing to the credibility, replicability, and overall quality of the research.


GOA UNIVERSITY

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION

4.1 INTRODUCTION:

The initial stage of any statistical analysis involves thorough data screening to ensure the reliability and validity of results. This chapter emphasizes the importance of preparing raw data for meaningful interpretation through steps such as checking for missing values, identifying outliers, and testing data normality. Ensuring data integrity is essential for accurate structural equation modeling (SEM) and hypothesis testing. This chapter covers, Data Screening, Demographic Profile of respondents, Descriptive Statistics and Objective and Hypothesis testing.

4.2 DATA SCREENING:

The very first step after collecting data is to purify the data so that they provide meaningful and reliable results when analysed (Hair et al., 2019). Data screening is the process of ensuring that data is clean and ready for conducting further statistical analyses. Data must be screened in order to ensure the data is useable, reliable, and valid for testing causal theory (Gaskin, 2016).

The Data entry of the study was therefore checked for missing data, wrong entry of values, data normality, outlier identification and common method bias.

Missing Data: There was no missing data as confirmed by the table of case processing summary.

Wrong entry: The descriptive statistics indicated wrong values for four attributes of importance and two attributes of satisfaction which were identified as wrong entry and rectified.

Data Normality Test: The data was evaluated to determine the normality of distribution by estimating the value of skewness and kurtosis for the distribution of scores of latent variables. The Skewness and Kurtosis for all the items were within the acceptable values.

Outlier Identifications: Outliers are different observations from the main data falling outside the control line (Hair et al., 2009). Outliers do not exist in Likert-scales: answering

at the extreme (1 or 5) is not representative outlier behaviour (Gaskin, 2016). Another type of outlier is an unengaged respondent. No outliers were found in this data.

Common method bias: Common method bias is a phenomenon that is caused by the measurement method used in an SEM study, and not by the network of causes and effects among latent variables in the model being studied (Kock, 2015). If all VIFs resulting from a co-linearity statistic are equal to or lower than 3.3, the model can be considered free of common method bias. For checking such bias, this study uses the method introduced by Kock (2015) viz. testing the common method bias through VIF value. It was found that the internal VIF value for all the factors in this model is less than 3.3.

4.2.1 Need for Outlier Checking:

Checking for outliers in research is crucial for following reasons:

Data Quality Assurance: Outliers can indicate errors in data collection, entry, or processing. Identifying and addressing outliers ensures the integrity and reliability of the dataset, minimizing the risk of drawing incorrect conclusions or making faulty decisions based on flawed data.

Impact on Statistical Analysis: Outliers can significantly skew statistical analyses and measures of central tendency (mean, median) and dispersion (standard deviation, variance). By identifying and handling outliers appropriately, researchers can obtain more accurate estimates and interpretations of relationships and trends within the data.

Validity of Assumptions: Many statistical techniques assume that the data follow certain distributions or have specific characteristics (e.g., normal distribution for parametric tests). Outliers can violate these assumptions, potentially leading to misleading results if not addressed.

Understanding Data Patterns: Outliers may reveal valuable insights or anomalies in the data that merit further investigation. They could indicate rare events, extreme behaviours, or exceptional circumstances that are critical to understanding the phenomena under study.

Fitness of Models: In predictive modeling and machine learning, outliers can adversely affect model performance and predictive accuracy. Proper handling of outliers through robust statistical methods or preprocessing techniques can improve the fitness and generalizability of models.

Interpretation and Reporting: Transparent reporting of outlier detection and handling methods enhances the credibility of research findings. It allows other researchers to understand how outliers were managed and assess the robustness of the conclusions drawn.
Ethical Considerations: Ensuring data integrity and accuracy is an ethical responsibility in research. Detecting and addressing outliers helps maintain ethical standards by ensuring that conclusions and decisions based on research findings are sound and reliable.
Contextual Understanding: Outliers may also provide valuable context or insights into the variability and diversity within the population being studied. Understanding the reasons behind outliers can contribute to a richer understanding of the phenomenon under investigation.

In summary, checking for outliers is essential in research to ensure data quality, maintain statistical validity, enhance model performance, and draw reliable conclusions. It is a fundamental step in data analysis that supports accurate interpretation and meaningful insights from research findings.

Table 4.1: Observations farthest from the centroid (Mahalanobis distance)

Observation number	Mahalanobis d-squared	p1	p2
488	105.188	.000	.000
20	102.587	.000	.000
67	101.067	.000	.000
496	98.373	.000	.000
188	95.174	.000	.000
369	90.377	.000	.000
329	86.917	.000	.000
402	82.972	.000	.000
258	82.469	.000	.000
468	82.396	.000	.000
266	82.219	.000	.000
450	81.570	.000	.000
132	80.454	.000	.000
388	78.175	.000	.000
336	77.858	.000	.000
461	77.839	.000	.000
5	77.147	.000	.000
286	76.387	.000	.000
473	75.429	.000	.000
95	75.377	.000	.000
110	75.094	.000	.000

Observation number	Mahalanobis d-squared	p1	p2
365	74.869	.000	.000
185	74.648	.000	.000
301	72.377	.000	.000
405	72.267	.000	.000
271	72.200	.000	.000
168	72.081	.000	.000
421	71.583	.001	.000
384	71.561	.001	.000
224	71.297	.001	.000
275	70.903	.001	.000
472	70.863	.001	.000
118	70.132	.001	.000
147	69.237	.001	.000
288	69.200	.001	.000
489	69.140	.001	.000
361	68.519	.001	.000
426	68.265	.001	.000
348	67.306	.002	.000
354	67.246	.002	.000
310	66.773	.002	.000
416	65.856	.002	.000
346	64.518	.003	.000
298	64.147	.004	.000
195	63.709	.004	.000
157	63.611	.004	.000
456	63.369	.004	.000
282	62.652	.005	.000
360	62.482	.005	.000
270	61.780	.006	.000
452	61.012	.008	.000
88	60.747	.008	.000
351	60.540	.009	.000
417	60.349	.009	.000
12	60.263	.009	.000
423	60.033	.010	.000
151	60.006	.010	.000
347	59.689	.010	.000
418	59.215	.012	.000
257	58.695	.013	.000
277	58.481	.014	.000
229	58.285	.014	.000
392	58.133	.015	.000
341	57.801	.016	.000

Observation number	Mahalanobis d-squared	p1	p2
171	57.755	.016	.000
294	57.628	.017	.000
274	57.103	.018	.000
325	56.551	.021	.000
182	56.510	.021	.000
268	55.635	.025	.000
309	55.275	.027	.000
443	55.224	.027	.000
463	54.891	.029	.000
18	54.868	.029	.000
326	54.700	.030	.000
445	54.684	.031	.000
292	54.624	.031	.000
424	54.255	.033	.000
371	54.142	.034	.000
34	53.918	.036	.000
158	53.723	.037	.000
475	53.716	.037	.000
493	53.530	.039	.000
93	53.454	.039	.000
344	53.298	.040	.000
283	53.138	.042	.000
123	52.608	.046	.000
102	52.418	.048	.000
163	52.387	.048	.000
367	52.302	.049	.000
342	51.900	.053	.000
396	51.751	.054	.000
60	51.743	.054	.000
390	51.718	.055	.000
38	51.525	.057	.000
177	51.398	.058	.000
176	51.361	.059	.000
356	51.343	.059	.000
203	50.887	.064	.000
9	50.640	.067	.000

(Source: Researcher's Computation)

Mahalanobis Distance:

- The Mahalanobis distance is a measure of the distance between a point and a distribution. It is useful in identifying outliers in multivariate data.
- Higher d2d^2d2 values indicate that the observation is further from the center of the distribution, suggesting it might be an outlier.

p-Values (p1 and p2):

- p1 and p2 represent the significance levels for the Mahalanobis distance. Typically, a low p-value (e.g., $p<0.05p < 0.05p<0.05$) indicates that the observation is significantly different from the rest of the data, hence considered an outlier.
- In this table, p1 and p2 values are consistently very low ($p=.000p = .000p=.000$ or near .000), indicating the observations listed are statistically significant outliers.

Observations with High Mahalanobis Distance:

- **Observation 488** has the highest Mahalanobis distance of 105.188, indicating it is the most extreme outlier.
- The next few observations, such as 20 (102.587), 67 (101.067), and 496 (98.373), also have very high d2d^2d2 values, indicating they are strong outliers.
- The p-values for these observations are .000.000.000, strongly confirming their status as outliers.

Observations with Moderate Mahalanobis Distance:

- Observations with lower d2d^2d2 values still indicate outliers but are less extreme compared to the highest values.
- For example, observation 9 has a d2d^2d2 value of 50.640, and the p-value is still very low (.067.067.067), indicating it is an outlier but not as extreme as the top ones.

In statistical analysis, it's crucial to handle outliers effectively to ensure the integrity and reliability of the results. Outliers can significantly distort findings, leading to inaccurate conclusions. Here, we focus on a specific criterion for identifying and removing outliers, and the subsequent effect on the dataset.

Identifying and Removing Outliers:

The outlier detection process involves examining the values of two variables, p1 and p2. Any value of p1 or p2 that is below the threshold of 0.001 is considered an outlier. This threshold is chosen based on domain-specific knowledge or preliminary analysis, ensuring that only the most extreme and potentially erroneous data points are excluded from the analysis.

Impact on Dataset:

Initially, the dataset comprises 500 samples. After applying the outlier detection criterion (values of p1 and p2 below 0.001), 27 samples are identified as outliers. These outliers are removed to prevent their undue influence on the final analysis. The removal process involves:

a. **Scanning the Dataset:** Each sample is checked for values of p1 and p2.
b. **Applying the Criterion:** Samples with either p1 or p2 below 0.001 are marked as outliers.
c. **Excluding Outliers:** The marked samples are then removed from the dataset.

Final Sample Size:

Post removal, the dataset is reduced by the number of outliers, leaving a final sample size of 473 (500 initial samples minus 27 outliers). This cleaned dataset is now better suited for further statistical analysis, free from the distorting effects of the identified outliers.

Importance of Handling Outliers:

Properly addressing outliers ensures that the statistical analyses, such as means, variances, correlations, and other inferential statistics, are more robust and reflective of the true underlying patterns. This step enhances the validity and reliability of the study's findings.

In summary, through a meticulous process of outlier detection and removal based on the defined threshold for p1 and p2, the dataset is refined to a sample size of 473 from the initial 500. This refined dataset, devoid of extreme outliers, is then ready for accurate and meaningful statistical analysis.

4.2.2 Assessment of Normality:

The table provides skewness and kurtosis statistics for various variables along with their critical ratios (c.r.). These statistics help to assess the normality of the data distribution for each variable. According to the guideline:

- **Skewness Value** between -3 and +3 indicates that the data is approximately symmetric.
- **Kurtosis Value** between -10 and +10 indicates that the data has acceptable kurtosis, implying normal distribution characteristics.

The skewness and kurtosis values were used to assess the normality of the data (Pallant, 2020). According to (Coakes & Steed, 2009), the normality of data is met when skewness and kurtosis values are zero. However, Hair et al., (1998) stated that a sample would be assumed normal when the skewness values range between -2 and 2 and kurtosis values range between -3 and 3.

Table 4.2: Skewness and kurtosis Statistics

Variable	min	max	skew	c.r.	kurtosis	c.r.
MCI5	1.000	5.000	.740	6.751	.138	.631
MCI6	1.000	5.000	.263	2.403	-.773	-3.526
MCI8	1.000	5.000	.885	8.076	-.031	-.142
MCI7	1.000	5.000	-.799	-7.292	-.069	-.315
MCI3	1.000	5.000	-.465	-4.246	-.409	-1.867
MCI2	1.000	5.000	-.841	-7.673	.012	.056
MCI1	1.000	5.000	-.140	-1.276	-.945	-4.314
MCPB10	1.000	5.000	.230	2.103	-1.204	-5.495
MCPB9	1.000	5.000	.142	1.295	-1.164	-5.314
MCPB8	1.000	5.000	.480	4.379	-.843	-3.846

Variable	min	max	skew	c.r.	kurtosis	c.r.
MCPB7	1.000	5.000	.494	4.506	-.921	-4.202
MCPB6	1.000	5.000	1.271	11.604	.364	1.660
MCPB5	1.000	5.000	-.386	-3.527	-.931	-4.251
MCPB4	1.000	5.000	-.136	-1.241	-1.187	-5.417
MCPB3	1.000	5.000	-.715	-6.523	-.529	-2.413
MCPB2	1.000	5.000	.046	.418	-1.103	-5.033
MCPB1	1.000	5.000	-.254	-2.317	-1.132	-5.169
SN1	1.000	5.000	.196	1.786	-1.110	-5.064
SN2	1.000	5.000	.244	2.224	-1.037	-4.735
SN3	1.000	5.000	.241	2.201	-1.067	-4.868
SN4	1.000	5.000	.214	1.953	-1.109	-5.061
SN5	1.000	5.000	-.253	-2.313	-1.057	-4.826
SN6	1.000	5.000	.277	2.533	-1.097	-5.009
PBC1	1.000	5.000	-1.468	-13.404	3.004	13.710
PBC2	1.000	5.000	-1.097	-10.017	.469	2.140
PBC3	1.000	5.000	-.471	-4.297	-.805	-3.674
PBC4	1.000	5.000	1.421	12.968	2.258	10.304
Att1	1.000	5.000	-1.279	-11.678	1.855	8.466
Att2	1.000	5.000	-.774	-7.065	.537	2.450
Att3	1.000	5.000	-1.359	-12.408	2.344	10.698
Att4	1.000	5.000	-1.336	-12.199	1.770	8.079
At6	1.000	5.000	-1.242	-11.335	1.969	8.986

Variable	min	max	skew	c.r.	kurtosis	c.r.
Att8	1.000	5.000	-1.037	-9.470	1.088	4.966
Att10	1.000	5.000	-.938	-8.562	.772	3.524
Att5	1.000	5.000	.677	6.184	-.222	-1.015
Att7	1.000	5.000	.453	4.133	-.678	-3.093
Att9	1.000	5.000	.293	2.671	-1.118	-5.105

(Source: Researcher's Computation)

Interpretation of Skewness and Kurtosis:

Variables with Skewness and Kurtosis within the Normal Range:

- **Skewness Values:**
- All the variables listed have skewness values between -3 and +3.
- This indicates that the distributions of these variables are not excessively skewed, meaning they are approximately symmetric.
- **Kurtosis Values:**
- All the variables listed have kurtosis values between -10 and +10.
- This suggests that the distributions of these variables do not have excessively heavy or light tails, implying acceptable normal distribution characteristics.

Summary of Variables' Distribution:

Reasonably Priced Products (MCI1):

- Skewness: -0.140
- Kurtosis: -0.945

Interpretation: Distribution is slightly left-skewed with light tails.

Prompt Customer Service (MCI2):

- Skewness: -0.841
- Kurtosis: 0.012

Interpretation: Distribution is moderately left-skewed but has near-normal tails.

Physical Shopping Experience (MCI3):

- Skewness: -0.465
- Kurtosis: -0.409

Interpretation: Distribution is slightly left-skewed with light tails.

Shopping Convenience (MCI4):

- Skewness: 0.006
- Kurtosis: 0.007

Interpretation: Distribution is nearly symmetric and normal.

Safe & Secure (MCI5):

- Skewness: -0.047
- Kurtosis: 0.073

Interpretation: Distribution is nearly symmetric and normal.

Unsafe without Technological Knowledge (MCI6):

- Skewness: -0.107
- Kurtosis: 0.052

Interpretation: Distribution is nearly symmetric and normal.

Unreliable Review (MCI7):

- Skewness: 0.033
- Kurtosis: -0.042

Interpretation: Distribution is nearly symmetric and normal.

User Friendly (MCI8):

- Skewness: 0.206
- Kurtosis: 0.224

Interpretation: Distribution is slightly right-skewed with light tails.

Shopping Addiction (MCI9):

- Skewness: 0.045
- Kurtosis: -0.069

Interpretation: Distribution is nearly symmetric and normal.

Privacy (MCI10):

- Skewness: 0.067
- Kurtosis: 0.072

Interpretation: Distribution is nearly symmetric and normal.

Multivariate Normality:

- **Nunnally's Guideline**:
- According to Nunnally's guideline, if all individual variables are normally distributed, the data also follows multivariate normality.
- Given that all variables have skewness and kurtosis values within the acceptable range, the data can be considered normally distributed.

- **Fit for Analysis**:
- All individual variables exhibit skewness and kurtosis values within the specified normal range.
- Therefore, the data is fit for final analysis, as it follows the assumption of multivariate normality.

4.2.3 Common Method Bias:

Common method bias is a phenomenon that is caused by the measurement method used in an SEM study, and not by the network of causes and effects among latent variables in the model being studied (Kock, 2015). If all VIFs resulting from a co-linearity statistic are equal to or lower than 3.3, the model can be considered free of common method bias. For checking such bias, this study uses the method introduced by Kock (2015) viz. testing the common method bias through VIF value.

Context and Purpose:

In structural equation modeling (SEM) studies, common method bias (CMB) is a critical concern as it can distort the relationships among latent variables, leading to misleading conclusions. CMB arises from the measurement method rather than the actual relationships among the constructs. To assess the presence of CMB, the variance inflation factor (VIF) is a widely accepted metric, as proposed by Kock (2015). If all VIF values are 3.3 or lower, the model is considered free from common method bias.

Collinearity Statistics Overview:

The table below presents the collinearity statistics, specifically the tolerance and VIF values, for four factors in the model: Subjective Norms, Perceived Behaviour Control, Attitude, and Intention.

Table 4.3: Collinearity Statistics

		Collinearity Statistics	
		Tolerance	VIF
	Subjective Norms	.808	1.237
	Perceived Behaviour Control	.991	1.009
	Attitude	.828	1.208
	Intention	.688	1.452

(Source: Researcher's Computation)

Interpretation of Results:

- **Subjective Norms**:
  - **Tolerance**: 0.808
  - **VIF**: 1.237
  - Interpretation: The VIF value of 1.237 is well below the threshold of 3.3, indicating that there is no significant collinearity issue and suggesting the absence of common method bias for this factor.

- **Perceived Behaviour Control**:
  - **Tolerance**: 0.991
  - **VIF**: 1.009
  - Interpretation: With a VIF value of 1.009, this factor exhibits very low collinearity, further supporting the conclusion that common method bias is not present.

- **Attitude**:
  - **Tolerance**: 0.828
  - **VIF**: 1.208
  - Interpretation: The VIF value of 1.208 is comfortably below 3.3, indicating that this factor is free from common method bias.

- **Intention**:
    - **Tolerance**: 0.688
    - **VIF**: 1.452
    - Interpretation: Although the VIF value for Intention is the highest among the factors, it is still significantly below the 3.3 threshold. This confirms that there is no substantial collinearity issue and thus no common method bias for this factor.

Based on the collinearity statistics, particularly the VIF values for each factor, it can be concluded that the model is free from common method bias. All VIF values are well below the critical value of 3.3, demonstrating that the measurement method used in this SEM study does not introduce bias. This enhances the validity of the causal relationships identified among the latent variables in the model, ensuring that the observed effects are due to the theoretical constructs rather than the measurement method itself.

4.3 DEMOGRAPHIC PROFILE OF RESPONDENTS:

The demographic profile of respondents in research is critically important for following reasons:

a. **Understanding Representation**: Demographic profiles provide information about the characteristics of the sample population, such as age, gender, education level, income, occupation, ethnicity, and location. This helps researchers understand who is participating in the study and how representative the sample is of the target population.
b. **Generalizability of Findings**: By knowing the demographic profile of respondents, researchers can assess the extent to which findings from the study can be generalized to the broader population. Different demographic groups may have varying perspectives, behaviours, and experiences that could influence study outcomes.
c. **Identifying Trends and Patterns**: Demographic data allows researchers to identify trends, patterns, and correlations within different subgroups of the population. For example, they can analyze how preferences or opinions differ across age groups or geographic regions.

d. **Tailoring Interventions and Recommendations**: Research findings often lead to recommendations or interventions aimed at specific demographic groups. Understanding the demographic profile helps tailor these recommendations to better meet the needs and preferences of different segments of the population.

e. **Comparative Analysis**: Demographic variables enable comparative analysis between different groups within the sample or between the sample and external data sources. This can provide insights into disparities, inequalities, or specific needs of particular demographic groups.

f. **Ethical Considerations**: Research often involves ethical considerations regarding the inclusion and representation of diverse demographic groups. Understanding the demographic profile helps ensure equitable participation and consideration of all relevant factors.

g. **Predictive Modeling and Forecasting**: In fields such as marketing, public opinion research, and social sciences, demographic data is crucial for predictive modeling and forecasting future trends or behaviours. Demographic changes over time can significantly impact outcomes and decision-making.

h. **Contextual Understanding**: Demographic variables provide context to research findings by explaining why certain patterns or trends exist. They help researchers interpret results within the broader socio-economic, cultural, and geographic context.

In summary, the demographic profile of respondents enriches research by providing insights into diversity, representation, and the nuanced characteristics of the population under study. It enhances the validity, applicability, and relevance of research findings and ensures that conclusions drawn are grounded in a comprehensive understanding of the sampled population.

Table 4.4: Demographic profile of Respondents

Gender		
	Frequency	Percent
Male	195	41.2
Female	278	58.8

Total	473	100.0
Age		
	Frequency	Percent
Less than 20 years	99	20.9
21 to 40 years	219	46.3
41 to 60 years	109	23.0
61 years and above	46	9.7
Total	473	100.0
Education		
	Frequency	Percent
Up to HSSC	122	25.8
Graduation	162	34.2
Post-Graduation and above	138	29.2
Professional	23	4.9
Others	28	5.9
Total	473	100.0
Area of location		
	Frequency	Percent
Municipal Area (Urban)	246	52.0
Panchayat Area (Rural)	227	48.0
Total	473	100.0
Marital Status		
	Frequency	Percent
Married	210	44.4
Unmarried	263	55.6
Total	473	100.0
Occupation		
	Frequency	Percent
Unemployed	167	35.3
Service	194	41.0
Business	55	11.6
Home Maker	36	7.6
Retired	21	4.4
Total	473	100.0
Monthly Family Income		
	Frequency	Percent
Less than Rs 25,000	91	19.2
Rs 25,000 to Rs 50,000	104	22.0
Rs 50,000 to Rs.75,000	80	16.9
Rs 75,000 to Rs 1,00,000	66	14.0
More than Rs 1,00,000	132	27.9
Total	473	100.0

(Source: Researcher's Computation)

The sample consists of more females (58.8%) compared to males (41.2%).The largest age group is 21 to 40 years (46.3%), followed by 41 to 60 years (23.0%), less than 20 years (20.9%), and 61 years and above (9.7%).The majority of the respondents have completed Graduation (34.2%) or Post-Graduation and above (29.2%).The sample is almost evenly split between urban (52.0%) and rural (48.0%) areas. There are more unmarried respondents (55.6%) compared to married ones (44.4%).The largest occupational group is those in service (41.0%), followed by unemployed (35.3%).The largest income group earns more than Rs 1,00,000 per month (27.9%).

Key Insights:

a. **Gender Distribution:** There is a higher proportion of female respondents.
b. **Age Distribution:** The sample is predominantly young adults aged 21 to 40 years.
c. **Education Level:** Most respondents have at least a graduation-level education.
d. **Urban-Rural Split:** The respondents are almost equally distributed between urban and rural areas.
e. **Marital Status:** There are more unmarried respondents compared to married ones.
f. **Occupation:** A significant portion of respondents are in service or unemployed.
g. **Income Levels:** A considerable portion of the sample has a monthly family income of more than Rs.1,00,000.

4.4 DESCRIPTIVE STATISTICS:

Descriptive statistics play a crucial role in summarizing and presenting data in a meaningful way. Here are some key reasons why descriptive statistics are important:

a. **Summarizing Data**: Descriptive statistics provide a concise summary of large datasets, allowing researchers and analysts to quickly grasp essential characteristics such as central tendency (mean, median, mode), dispersion (range, variance, standard deviation), and distribution shape (skewness, kurtosis).
b. **Simplifying Complexity**: They simplify complex data into easily understandable forms, such as tables, charts, or numerical summaries. This simplification aids in interpretation and communication of findings to stakeholders, decision-makers, or the general public.

c. **Making Comparisons**: Descriptive statistics enable comparisons between different groups or datasets. For example, they can be used to compare the average income of different demographic groups or the distribution of customer preferences across regions.

d. **Detecting Patterns and Outliers**: By examining descriptive statistics, analysts can identify patterns within data, such as trends over time or correlations between variables. They also help in detecting outliers or anomalies that may require further investigation.

e. **Basis for Inferential Statistics**: Descriptive statistics form the foundation for inferential statistics, which involve making inferences or predictions about a population based on sample data. Inferential statistics rely on understanding the distribution and characteristics of the sample data provided by descriptive statistics.

f. **Decision-Making**: In various fields such as business, economics, healthcare, and social sciences, descriptive statistics aid in decision-making processes. For instance, a business might use descriptive statistics to analyze sales trends and make decisions on inventory management or marketing strategies.

g. **Quality Control**: Descriptive statistics are essential in quality control processes to monitor production output, assess product variability, and ensure consistency in manufacturing processes.

h. **Initial Data Exploration**: Before conducting more complex analyses, descriptive statistics help researchers explore the basic features of their data, identify potential problems (such as missing data or data entry errors), and decide on appropriate statistical techniques.

In essence, descriptive statistics serve as a fundamental tool in data analysis, providing insights into the characteristics of data that are essential for understanding, interpreting, and making informed decisions based on the data at hand.

Table 4.5: Descriptive Statistics

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Reasonably Priced Products	473	1	5	4.13	.880
Prompt Customer Service	473	1	5	3.78	.880
Physical Shopping Experience	473	1	5	4.13	.867
Shopping Convenience	473	1	5	4.23	.882
Safe & Secure	473	1	5	2.45	1.086
Unsafe without Technological Knowledge	473	1	5	4.08	.880
Unreliable Review	473	1	5	2.49	1.087
User Friendly	473	1	5	4.01	.908
Shopping Addiction	473	1	5	2.80	1.277
Privacy	473	1	5	3.96	.901
Family Consent	473	1	5	4.10	.800
Freedom to Spend	473	1	5	3.86	1.114
I can make my decision to shop anytime on mobile commerce shopping sites whenever I feel like shopping	473	1	5	3.47	1.214
No Permission Required	473	1	5	1.96	.889
Peer Influence	473	1	5	2.70	1.159
Peer Recommendations	473	1	5	2.74	1.164
Peer Opinions	473	1	5	2.68	1.167
Social Media Influence	473	1	5	2.67	1.175
Personal Preference	473	1	5	3.21	1.145
External Influence	473	1	5	2.71	1.238
Private and Confidential	473	1	5	3.19	1.140
Convenience	473	1	5	3.76	1.084
Safety	473	1	5	3.40	1.039
Economical	473	1	5	3.64	1.115

Bad Past Experience	473	1	5	2.45	1.003
Recommendation	473	1	5	2.75	1.085
Ease of Use	473	1	5	3.66	1.095
Lack of Knowledge	473	1	5	2.35	1.196
Electronic products	473	1	5	3.20	1.261
Sports products	473	1	5	2.93	1.217
Clothing, Shoes and Jewellery items	473	1	5	3.52	1.235
Beauty and Personal care products	473	1	5	3.11	1.274
Home and Kitchen appliances	473	1	5	3.23	1.197
Never used m-commerce	473	1	5	2.02	1.303
Books, Magazines and Newspapers	473	1	5	2.58	1.231
Healthcare and medicines	473	1	5	2.54	1.200
Stationary items and games	473	1	5	2.84	1.247
Groceries	473	1	5	2.74	1.301

(Source: Researcher's Computation)

The table presents the descriptive statistics for various items related to m-commerce attitudes, behaviours, and preferences. Here's a detailed interpretation:

4.4.1 General Product Attributes:

Reasonably Priced Products (Mean = 4.13, SD = 0.880)

- Respondents generally agree that reasonably priced products are important in m-commerce.

Prompt Customer Service (Mean = 3.78, SD = 0.880)

- A moderate agreement that prompt customer service is important.

Physical Shopping Experience (Mean = 4.13, SD = 0.867)

- Indicates a strong preference for a good physical shopping experience online.

4.4.2 Shopping Experience and Security:

Shopping Convenience (Mean = 4.23, SD = 0.882)

- High agreement on the importance of shopping convenience.

Safe & Secure (Mean = 2.45, SD = 1.086)

- Respondents are less convinced about the safety and security of m-commerce.

Unsafe without Technological Knowledge (Mean = 4.08, SD = 0.880)

- A strong belief that lack of technological knowledge makes m-commerce unsafe.

4.4.3 Trust and User Experience:

Unreliable Review (Mean = 2.49, SD = 1.087)

- Agreement that unreliable reviews are a concern.

User Friendly (Mean = 4.01, SD = 0.908)

- Strong agreement that user-friendly interfaces are important.

Shopping Addiction (Mean = 2.80, SD = 1.277)

- A moderate concern about shopping addiction.

Privacy (Mean = 3.96, SD = 0.901)

- High concern for privacy in m-commerce.

4.4.4 Factors Influencing Purchase Decisions:

Family Consent (Mean = 4.10, SD = 0.800)

- Strong agreement that family consent is crucial.

Freedom to Spend (Mean = 3.86, SD = 1.114)

- Agreement on the freedom to spend as an important factor.

Decision Flexibility (Mean = 3.47, SD = 1.214)

- Respondents moderately agree that they can decide anytime to shop online.

No Permission Required (Mean = 1.96, SD = 0.889)

- Low agreement on the necessity of no permission to shop.

4.4.5 Social and Peer Influence:

Peer Influence (Mean = 2.70, SD = 1.159)

- Moderate influence of peers on shopping decisions.

Peer Recommendations (Mean = 2.74, SD = 1.164)

- Slightly higher agreement on the importance of peer recommendations.

Peer Opinions (Mean = 2.68, SD = 1.167)

- Minor influence of peer opinions.

Social Media Influence (Mean = 2.67, SD = 1.175)

- Little impact of social media on shopping decisions.

4.5 OBJECTIVES AND HYPOTHESIS TESTING:

4.5.1 Objective-1: To evaluate the relevance and validity of the measurement variables to their respective latent constructs in the proposed structural model of the "Theory of Planned Behaviour"

Hypothesis-1: The measurement variables are relevant and valid to their respective latent constructs in the proposed structural model of the "Theory of Planned Behaviour".

Construct testing in data analysis is crucial for several important reasons:

a. **Validation of Measurement Tools**: Construct testing helps validate the measurement instruments used to assess theoretical constructs or variables in a study. It ensures that the items or indicators effectively capture the intended concepts or attributes, confirming the validity of the operational definitions used in the research.
b. **Ensuring Conceptual Clarity**: It promotes clarity and precision in defining constructs. By testing constructs, researchers clarify the theoretical underpinnings and operational definitions of variables, ensuring that they accurately represent the concepts being studied.
c. **Enhancing Measurement Accuracy**: Construct testing improves the accuracy and reliability of measurements. It identifies and addresses potential sources of measurement error, such as ambiguous wording in survey items or inadequate operationalization of constructs, thereby enhancing the quality of data collected.
d. **Supporting Hypothesis Testing**: Valid constructs facilitate hypothesis testing and theory development. Researchers can confidently analyze relationships between variables or test theoretical propositions when constructs are well-defined and properly validated.
e. **Facilitating Comparative Research**: Validated constructs enable meaningful comparisons across studies, populations, or contexts. Researchers can replicate studies or conduct cross-cultural research with confidence, knowing that measurements are consistent and comparable.

f. **Informing Decision-Making**: Construct testing provides robust evidence for decision-making processes. In applied research and practical settings, validated constructs support evidence-based decision-making by providing reliable data on which decisions can be grounded.

g. **Improving Research Reproducibility**: Validated constructs contribute to research reproducibility and replicability. When measurement tools are rigorously tested and validated, other researchers can replicate the study with confidence, strengthening the reliability and generalizability of research findings.

h. **Guiding Construct Revision and Refinement**: Insights from construct testing inform iterative improvements in research design and measurement instruments. Researchers can refine constructs based on empirical evidence, enhancing the relevance and validity of future studies.

In summary, construct testing in data analysis plays a critical role in ensuring the validity, reliability, and robustness of research findings. It supports rigorous inquiry, theory development, and evidence-based decision-making across various disciplines and research contexts.

❖ **Testing of Measurement Construct: Attitude:**

H1a: All measurement variables are relevant and valid to the 'Attitude' construct in the proposed structural model of the "Theory of Planned Behaviour".

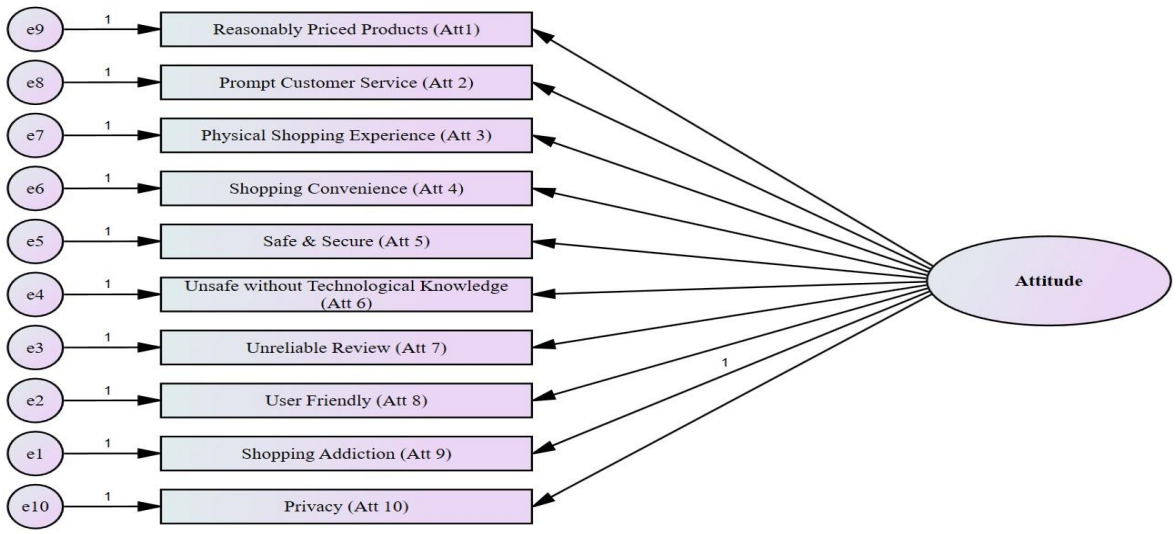


Figure 4.1: Measurement Model-Attitude

(Source: Researcher's compilation based on the original model of TPB)

This hypothesis suggests that each of the measurement variables included in the SEM model adequately measures or represents the Attitude construct. In SEM, measurement variables (also known as indicators or manifest variables) are observed variables that reflect underlying constructs (latent variables). This hypothesis implies that the chosen indicators are valid and reliable measures of the Attitude construct, and collectively they contribute meaningfully to the overall measurement model.

In SEM analysis, such hypotheses are tested by examining the standardized factor loadings (also called path coefficients) between the latent Attitude construct and its corresponding measurement variables. Significant factor loadings indicate that the measurement variables are statistically related to the latent construct, supporting the validity of the measurement model.

Table 4.6: Significance of Attributes of Attitude

			Estimate	S.E.	C.R.	P	Label
Att9	<---	Attitude	1.000				
Att8	<---	Attitude	-1.901	.282	-6.743	0.00	Significant
Att7	<---	Attitude	1.054	.194	5.430	0.00	Significant
At6	<---	Attitude	-.985	.171	-5.762	0.00	Significant
Att5	<---	Attitude	1.415	.233	6.071	0.00	Significant
Att4	<---	Attitude	-1.897	.280	-6.768	0.00	Significant
Att3	<---	Attitude	-.873	.158	-5.522	0.00	Significant
Att2	<---	Attitude	-1.652	.249	-6.626	0.00	Significant
Att1	<---	Attitude	-1.742	.261	-6.685	0.00	Significant
Att10	<---	Attitude	-1.531	.236	-6.501	0.00	Significant

(Source: Researcher's Computation)

The table provided represents the results of a regression analysis within a structural equation modeling (SEM) context, showing how the latent factor "Attitude" influences each of the observed variables (Att1 through Att10). Here is a detailed interpretation of the regression weights:

Column Descriptions:

a. **Estimate**:

- The regression weight indicates the strength and direction of the relationship between the latent factor (Attitude) and each observed variable (Att1 to Att10).

b. **S.E. (Standard Error)**:

- This represents the standard error of the regression weight, reflecting the variability or precision of the estimate.

c. **C.R. (Critical Ratio)**:

- The critical ratio is the estimate divided by its standard error (Estimate / S.E.). It is analogous to the t-value in regression analysis and indicates how many standard errors the estimate is away from zero.

d. **P (p-value)**:

- The p-value indicates the statistical significance of the regression weight. A p-value of less than 0.05 suggests that the relationship between the latent factor and the observed variable is statistically significant. In this table, "***" indicates a highly significant relationship ($p < 0.001$).

Interpretation of Rows:

Att9 <--- Attitude:

- **Estimate**: 1.000 (fixed parameter for scaling purposes)

Interpretation: This attribute serves as a reference point, with its estimate fixed at 1.000 to scale the latent factor (Attitude). This helps in comparing the other estimates.

- **Att8 <--- Attitude**:

Estimate: -1.901

- **S.E.**: 0.282
- **C.R.**: -6.743
- **P**: ***

Interpretation: There is a significant negative relationship between Att8 and Attitude. For each unit increase in Attitude, Att8 decreases by 1.901 units. The relationship is highly significant ($p < 0.001$).

Att7 <--- Attitude:

- **Estimate**: 1.054
- **S.E.**: 0.194
- **C.R.**: 5.430
- **P**: ***

Interpretation: There is a significant positive relationship between Att7 and Attitude. For each unit increase in Attitude, Att7 increases by 1.054 units. The relationship is highly significant ($p < 0.001$).

Att6 <--- Attitude:

- **Estimate**: -0.985
- **S.E.**: 0.171
- **C.R.**: -5.762
- **P**: ***

Interpretation: There is a significant negative relationship between Att6 and Attitude. For each unit increase in Attitude, Att6 decreases by 0.985 units. The relationship is highly significant ($p < 0.001$).

Att5 <--- Attitude:

- **Estimate**: 1.415
- **S.E.**: 0.233
- **C.R.**: 6.071
- **P**: ***

Interpretation: There is a significant positive relationship between Att5 and Attitude. For each unit increase in Attitude, Att5 increases by 1.415 units. The relationship is highly significant ($p < 0.001$).

Att4 <--- Attitude:

- **Estimate**: -1.897
- **S.E.**: 0.280
- **C.R.**: -6.768
- **P**: ***

Interpretation: There is a significant negative relationship between Att4 and Attitude. For each unit increase in Attitude, Att4 decreases by 1.897 units. The relationship is highly significant ($p < 0.001$).

Att3 <--- Attitude:

- **Estimate**: -0.873
- **S.E.**: 0.158
- **C.R.**: -5.522
- **P**: ***

Interpretation: There is a significant negative relationship between Att3 and Attitude. For each unit increase in Attitude, Att3 decreases by 0.873 units. The relationship is highly significant ($p < 0.001$).

- **Att2 <--- Attitude**:
- **Estimate**: -1.652
- **S.E.**: 0.249
- **C.R.**: -6.626
- **P**: ***

Interpretation: There is a significant negative relationship between Att2 and Attitude. For each unit increase in Attitude, Att2 decreases by 1.652 units. The relationship is highly significant ($p < 0.001$).

Att1 <--- Attitude:

- **Estimate**: -1.742
- **S.E.**: 0.261
- **C.R.**: -6.685
- **P**: ***

Interpretation: There is a significant negative relationship between Att1 and Attitude. For each unit increase in Attitude, Att1 decreases by 1.742 units. The relationship is highly significant ($p < 0.001$).

Att10 <--- Attitude:

- **Estimate**: -1.531
- **S.E.**: 0.236
- **C.R.**: -6.501
- **P**: ***

Interpretation: There is a significant negative relationship between Att10 and Attitude. For each unit increase in Attitude, Att10 decreases by 1.531 units. The relationship is highly significant ($p < 0.001$).

❖ **General Observations:**

- All attributes (Att1 through Att10) have significant relationships with the latent factor "Attitude" as indicated by the p-values (***), meaning $p < 0.001$.

The regression weights (estimates) show both positive and negative relationships:

- Positive estimates (e.g., Att5: 1.415) indicate that as the latent factor "Attitude" increases, the attribute also increases.
- Negative estimates (e.g., Att8: -1.901) indicate that as the latent factor "Attitude" increases, the attribute decreases.

The magnitude of the estimates reflects the strength of the relationship:

- Larger absolute values (e.g., Att8: -1.901) indicate stronger relationships.
- Smaller absolute values (e.g., Att3: -0.873) indicate weaker relationships.

- The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

Managerial Implications:

Enhancing Positive Indicators:

❖ **Att7 and Att5**:

- **Att7 (User Friendly)**: Since this indicator positively influences attitude, ensuring that the m-commerce platform is user-friendly and intuitive can significantly enhance user attitudes. Managers should focus on seamless navigation, easy-to-understand interfaces, and a smooth user experience.
- **Att5 (Convenience)**: Highlighting the convenience of using m-commerce, such as the ability to shop anytime and anywhere, quick transactions, and fast delivery options, can further boost positive attitudes. Marketing campaigns should emphasize these convenience factors.

Addressing Negative Indicators:

- **Att8, Att6, Att4, Att3, Att2, Att1, and Att10**:
- **Att8 (Safety Concerns)** and **Att4 (Privacy Issues)**: These indicators have the highest negative loadings. It is critical for managers to address safety and privacy concerns. Implementing robust security measures, communicating these measures effectively, and ensuring that user data is protected can help mitigate these negative perceptions.
- **Att6 (Bad Past Experience)** and **Att3 (Unreliable Review)**: These indicate that negative past experiences and unreliable reviews detract from positive attitudes. Companies should focus on improving customer service, addressing complaints promptly, and ensuring that product reviews are genuine and reliable. Encouraging satisfied customers to leave positive feedback can help counterbalance the impact of negative reviews.
- **Att2 (Lack of Knowledge)** and **Att1 (Difficult to Use)**: These reflect a lack of user knowledge and perceived difficulty in using the platform. Providing comprehensive guides, tutorials, and customer support can help users become more familiar and comfortable with m-commerce.
- **Att10 (Shopping Addiction)**: This indicates a negative perception linked to potential shopping addiction. Companies should promote responsible shopping habits and provide tools for users to monitor and control their spending.

The SEM analysis highlights the critical factors that influence user attitudes towards m-commerce. By focusing on enhancing positive aspects such as user-friendliness and convenience and addressing negative perceptions related to safety, privacy, past experiences, and ease of use, managers can significantly improve user attitudes. This, in turn, can lead to higher adoption rates and increased user satisfaction with m-commerce platforms.

Summary:

The table indicates that the latent factor "Attitude" has a significant impact on all observed variables (Att1 through Att10), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The

statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

- **Testing of Measurement Construct: Perceived Behaviour Control:**

H1b: All measurement variables are relevant and valid to the 'Perceived Behavioural Control' construct in the proposed structural model of the "Theory of Planned Behaviour".

This hypothesis asserts that each of the measurement variables included in your SEM model effectively captures and contributes to the Perceived Behaviour Control (PBC) construct. In SEM, PBC is a latent variable that represents an individual's perception of the ease or difficulty of performing a behaviour. Measurement variables (indicators) associated with PBC are observable variables that are expected to reflect or measure this underlying construct.

Testing this hypothesis involves examining the factor loadings (path coefficients) between the latent PBC construct and its corresponding measurement variables. Significant factor loadings indicate that the measurement variables are statistically associated with the PBC construct, supporting the validity of the measurement model.

In SEM analysis, confirming this hypothesis is crucial for establishing that the chosen indicators adequately measure the intended construct (PBC) and contribute meaningfully to the overall structural model. It helps ensure that the model accurately reflects the relationships and interactions between variables as hypothesized in the theoretical framework.

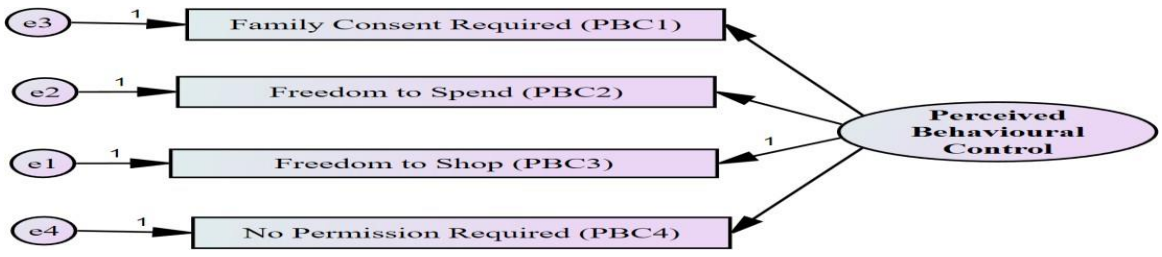


Figure 4.2: Measurement Model-Perceived Behavioural Control (Source: Researcher's compilation based on the TPB Model)

The following table presents the unstandardized regression weights, standard errors, critical ratios, and significance values for the construct "Perceived Behavioural Control".

Table 4.7: Regression Weights: (Group number 1- Default model)

			Estimate	S.E.	C.R.	P	Label
PBC 3	<--	Perceived_Behavioura Control	1.00				
PBC 2	<--	Perceived_Behavioural _Control	.77	.12	6.19	0.00	Significant
PBC 1	<--	Perceived_Behavioural _Control	1.36	.16	8.26	0.00	Significant
PBC 4	<--	Perceived_Behavioural Control	-1.21	.13	-8.81	0.00	Significant

(Source: Researcher's Computation)

PBC3 <--- Perceived_Behavioural_Control:

- **Estimate**: 1.000 (fixed parameter for scaling purposes)

Interpretation: This attribute serves as a reference point, with its estimate fixed at 1.000 to scale the latent factor (Perceived_Behavioural_Control). This helps in comparing the other estimates.

PBC2 <--- Perceived_Behavioural_Control:

- **Estimate**: 0.773
- **S.E.**: 0.125
- **C.R.**: 6.191
- **P**: ***

Interpretation: There is a significant positive relationship between PBC2 and Perceived_Behavioural_Control. For each unit increase in Perceived_Behavioural_Control, PBC2 increases by 0.773 units. The relationship is highly significant ($p < 0.001$).

PBC1 <--- Perceived_Behavioural_Control:

- **Estimate**: 1.361
- **S.E.**: 0.165
- **C.R.**: 8.263
- **P**: ***

Interpretation: There is a significant positive relationship between PBC1 and Perceived_Behavioural_Control. For each unit increase in Perceived_Behavioural_Control, PBC1 increases by 1.361 units. The relationship is highly significant ($p < 0.001$).

PBC4 <--- Perceived_Behavioural_Control:

- **Estimate**: -1.219
- **S.E.**: 0.138
- **C.R.**: -8.818
- **P**: ***

Interpretation: There is a significant negative relationship between PBC4 and Perceived_Behavioural_Control. For each unit increase in Perceived_Behavioural_Control, PBC4 decreases by 1.219 units. The relationship is highly significant ($p < 0.001$).

General Observations:

All attributes (PBC1 through PBC4) have significant relationships with the latent factor "Perceived_Behavioural_Control" as indicated by the p-values (***), meaning $p < 0.001$.
The regression weights (estimates) show both positive and negative relationships:

- Positive estimates (e.g., PBC1: 1.361) indicate that as the latent factor "Perceived_Behavioural_Control" increases, the attribute also increases.
- Negative estimates (e.g., PBC4: -1.219) indicate that as the latent factor "Perceived_Behavioural_Control" increases, the attribute decreases.

The magnitude of the estimates reflects the strength of the relationship:

- Larger absolute values (e.g., PBC4: -1.219) indicate stronger relationships.
- Smaller absolute values (e.g., PBC2: 0.773) indicate weaker relationships.

The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

Summary:

Significance: All the indicators are statistically significant at the 0.05 level, as indicated by the P-Value of 0.000 for each path. This suggests that each indicator significantly contributes to the construct of "Perceived Behavioral Control".

Direction and Magnitude:

Positive Loadings:

PBC2 (Ease of Use): This indicator shows a positive relationship with perceived behavioral control (Estimate = 0.773). It suggests that as users find m-commerce easier to use, their perceived control over the behavior increases.

PBC1 (Knowledge of Use): This indicator has a strong positive relationship (Estimate = 1.361). It indicates that greater knowledge about using m-commerce significantly enhances perceived behavioral control.

Negative Loadings:

PBC4 (Perceived Risks): This indicator shows a strong negative relationship with perceived behavioral control (Estimate = -1.219). This suggests that higher perceived risks associated with m-commerce reduce the users' perceived control over engaging in m-commerce activities.

- **Managerial Implications:**

Enhancing Positive Indicators

a. **Improve Ease of Use (PBC2)**:
   User-Friendly Interfaces: Ensure that the m-commerce platform is intuitive and easy to navigate. This can involve investing in UX/UI design to create a seamless user experience.
b. **Simplified Processes**: Streamline processes such as registration, checkout, and payment to make them as straightforward as possible. Providing clear instructions and reducing the number of steps required to complete transactions can enhance users' sense of control.
c. **Increase Knowledge of Use (PBC1)**:

- **Educational Campaigns**: Conduct educational campaigns to inform users about how to use the m-commerce platform effectively. This can include video tutorials, FAQs, webinars, and interactive guides.
- **Customer Support**: Offer robust customer support to help users overcome any difficulties they might face. Live chat, phone support, and email support can assist users in real-time, enhancing their confidence and perceived control.

Addressing Negative Indicators:

a. Mitigate Perceived Risks (PBC4):

- **Security Measures**: Enhance the security measures on the m-commerce platform to protect user data and financial information. Implementing features like two-factor authentication, encryption, and secure payment gateways can reduce perceived risks.
- **Transparent Policies**: Clearly communicate the platform's security policies and measures to users. Transparency about how user data is protected and how transactions are secured can alleviate concerns and reduce perceived risks.
- **Trust Signals**: Display trust signals such as security badges, customer testimonials, and third-party endorsements to reassure users about the safety of the platform.

The SEM analysis of perceived behavioural control highlights the critical factors influencing users' perceptions of control over using m-commerce. By focusing on improving ease of use and increasing user knowledge, while mitigating perceived risks, managers can enhance users perceived behavioural control. This, in turn, can lead to greater adoption and satisfaction with m-commerce platforms.

Summary:

The table indicates that the latent factor "Perceived Behavioural Control" has a significant impact on all observed variables (PBC1 through PBC4), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

- ❖ **Testing of Measurement Construct: Subjective Norms:**

H1c: All measurement variables are relevant and valid to the 'Subjective Norms' construct in the proposed structural model of the "Theory of Planned Behaviour".

This hypothesis posits that each of the measurement variables included in your SEM model effectively measures and contributes to the Subjective Norms construct as defined by the Theory of Planned Behaviour (TPB). In TPB, Subjective Norms represent an individual's perception of social pressure or influence from significant others to perform or not perform a particular behaviour.

Measurement variables (indicators) associated with Subjective Norms are observable variables that are expected to reflect this latent construct. Testing this hypothesis involves examining the factor loadings (path coefficients) between the latent Subjective Norms construct and its corresponding measurement variables.

Significant factor loadings indicate that the measurement variables are statistically related to the Subjective Norms construct, supporting the validity of the measurement model within the TPB framework. This validation is crucial for ensuring that the indicators adequately capture the intended construct and contribute meaningfully to the overall structural model.

In SEM analysis, hypotheses like this one are essential for establishing the measurement validity of constructs and understanding how different factors (such as subjective norms) influence behaviours as predicted by theoretical frameworks like the TPB. It forms a foundational step in testing and refining the structural relationships within the model, thereby contributing to a deeper understanding of behavioural intentions and decision-making processes.

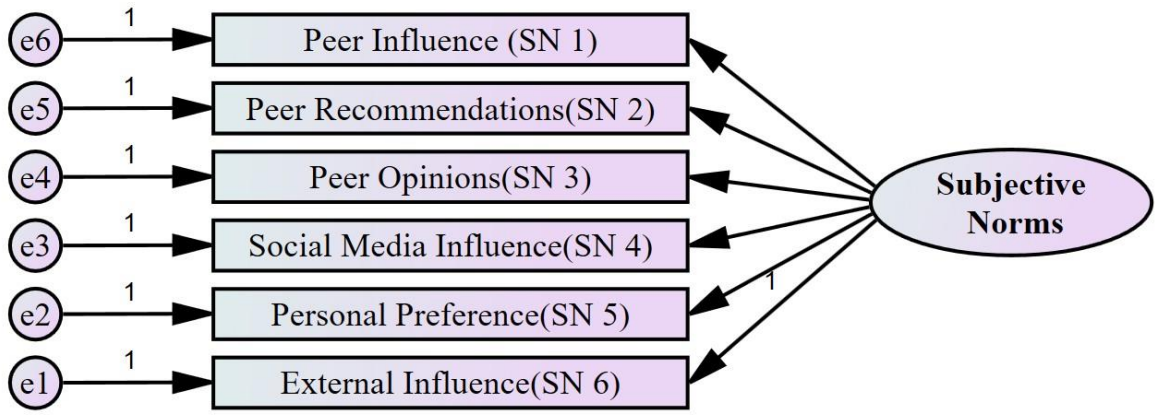


Figure 4.3: Measurement Model-Subjective Norms (Source: Researcher's compilation based on original model of TPB)

Table 4.8: Significance of attributes of Subjective Norms

			Estimate	S.E.	C.R.	P	Label
SN 6	<---	Subjective_Norms	1.000				
SN 5	<---	Subjective_Norms	-.879	.024	-35.995	***	Significant

			Estimate	S.E.	C.R.	P	Label
SN4	<---	Subjective_Norms	.971	.020	49.435	***	Significant
SN3	<---	Subjective_Norms	.956	.020	47.239	***	Significant
SN2	<---	Subjective_Norms	.969	.019	51.584	***	Significant
SN1	<---	Subjective_Norms	.960	.019	50.364	***	Significant

(Source: Researcher's Computation)

The table represents the regression weights for the relationship between the latent factor "Subjective Norms" and the observed variables (SN1 through SN6). Here is a detailed interpretation of the regression weights:

Column Descriptions:

a. **Estimate**:

- The regression weight indicates the strength and direction of the relationship between the latent factor (Subjective Norms) and each observed variable (SN1 to SN6).

b. **S.E. (Standard Error)**:

- This represents the standard error of the regression weight, reflecting the variability or precision of the estimate.

c. **C.R. (Critical Ratio)**:

- The critical ratio is the estimate divided by its standard error (Estimate / S.E.). It is analogous to the t-value in regression analysis and indicates how many standard errors the estimate is away from zero.

d. **P (p-value)**:

- The p-value indicates the statistical significance of the regression weight. A p-value of less than 0.05 suggests that the relationship between the latent factor and the observed variable is statistically significant. In this table, "***" indicates a highly significant relationship ($p < 0.001$).

Interpretation of Rows:

SN6 <--- Subjective_Norms:

- **Estimate**: 1.000 (fixed parameter for scaling purposes)

Interpretation: This attribute serves as a reference point, with its estimate fixed at 1.000 to scale the latent factor (Subjective_Norms). This helps in comparing the other estimates.

- **SN5 <--- Subjective_Norms**:
- **Estimate**: -0.879
- **S.E.**: 0.024
- **C.R.**: -35.995
- **P**: ***

Interpretation: There is a significant negative relationship between SN5 and Subjective_Norms. For each unit increase in Subjective_Norms, SN5 decreases by 0.879 units. The relationship is highly significant ($p < 0.001$).

SN4 <--- Subjective_Norms:

- **Estimate**: 0.971
- **S.E.**: 0.020
- **C.R.**: 49.435
- **P**: ***

Interpretation: There is a significant positive relationship between SN4 and Subjective_Norms. For each unit increase in Subjective_Norms, SN4 increases by 0.971 units. The relationship is highly significant ($p < 0.001$).

SN3 <--- Subjective_Norms:

- **Estimate**: 0.956
- **S.E.**: 0.020
- **C.R.**: 47.239
- **P**: ***

Interpretation: There is a significant positive relationship between SN3 and Subjective_Norms. For each unit increase in Subjective_Norms, SN3 increases by 0.956 units. The relationship is highly significant ($p < 0.001$).

- **SN2 <--- Subjective_Norms**:
- **Estimate**: 0.969

- **S.E.**: 0.019
- **C.R.**: 51.584
- **P**: ***

Interpretation: There is a significant positive relationship between SN2 and Subjective_Norms. For each unit increase in Subjective_Norms, SN2 increases by 0.969 units. The relationship is highly significant ($p < 0.001$).

- **SN1 <--- Subjective_Norms**:
- **Estimate**: 0.960
- **S.E.**: 0.019
- **C.R.**: 50.364
- **P**: ***

Interpretation: There is a significant positive relationship between SN1 and Subjective Norms. For each unit increase in Subjective Norms, SN1 increases by 0.960 units. The relationship is highly significant ($p < 0.001$).

General Observations:

All attributes (SN1 through SN6) have significant relationships with the latent factor "Subjective Norms" as indicated by the p-values (***), meaning $p < 0.001$.

The regression weights (estimates) show both positive and negative relationships:

- Positive estimates (e.g., SN4: 0.971) indicate that as the latent factor "Subjective Norms" increases, the attribute also increases.
- Negative estimates (e.g., SN5: -0.879) indicate that as the latent factor "Subjective Norms" increases, the attribute decreases.

The magnitude of the estimates reflects the strength of the relationship:

- Larger absolute values (e.g., SN5: -0.879) indicate stronger relationships.
- Smaller absolute values (e.g., SN1: 0.960) indicate weaker relationships.

The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

Interpretation and Managerial Implications:

a. **Strength and Direction of Relationships**: The estimates (coefficients) indicate the strength and direction of each SN variable's influence on the overall construct of Subjective Norms. Positive estimates (like 1.000, .971, .956, .969, .960) suggest that higher values of these SN variables positively contribute to the overall Subjective Norms. A negative estimate (-.879 for SN5) suggests an inverse relationship, where higher values of SN5 may actually decrease the overall Subjective Norms.
b. **Significance**: The Critical Ratio (C.R.) values are very high (e.g., 35.995 to 51.584), indicating that the relationships between each SN variable and the overall construct are statistically significant. The asterisks (***) in the "P" column confirm this high significance level (typically indicating $p < 0.001$), suggesting robust relationships that are unlikely to be due to chance.
c. **Managerial Implications**:

- **Enhancing Subjective Norms**: Managers should focus on factors represented by SN1 to SN6 to strengthen overall subjective norms within their teams or organizations. These factors are crucial as they significantly influence employees' perceptions of what is socially expected or normative in their work context.

- **Identifying Key Drivers**: SN4, SN2, and SN3 have particularly high regression weights, indicating they might be more influential in shaping subjective norms compared to others. Understanding these key drivers can help in targeted interventions and policy decisions aimed at fostering desired norms and behaviours.

- **Monitoring SN5**: Given its negative coefficient, SN5 might represent a factor that could potentially undermine subjective norms. Managers should investigate why this is the case and consider strategies to mitigate its negative impact or adjust perceptions associated with SN5.

d. **Further Analysis**: While the table provides valuable insights, further analysis such as examining interactions between SN variables or considering additional contextual factors could provide a more nuanced understanding. Managers should consider conducting deeper explorations or qualitative studies to complement these findings.

Summary:

The table indicates that the latent factor "Subjective Norms" has a significant impact on all observed variables (SN1 through SN6), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

- **Testing of Measurement Construct: Mobile Commerce Intention:**

H1d: All measurement variables are relevant and valid to the 'Mobile Commerce Intention' construct in the proposed structural model of the "Theory of Planned Behaviour".

This hypothesis asserts that each of the measurement variables included in your SEM model effectively captures and contributes to the Mobile Commerce Intention construct. In the context of SEM, Mobile Commerce Intention represents individuals' behavioural intentions to engage in mobile commerce activities, such as purchasing goods or services via mobile devices.

Measurement variables (indicators) associated with Mobile Commerce Intention are observable variables that are expected to reflect this latent construct. Testing this hypothesis involves examining the factor loadings (path coefficients) between the latent Mobile Commerce Intention construct and its corresponding measurement variables.

Significant factor loadings indicate that the measurement variables are statistically related to the Mobile Commerce Intention construct, supporting the validity of the measurement model within the SEM framework. This validation is crucial for ensuring that the indicators accurately measure the intended construct and contribute meaningfully to the overall structural model.

In SEM analysis, hypotheses like this one are fundamental for establishing the measurement validity of constructs and understanding the factors influencing behavioural intentions related to mobile commerce. It helps researchers assess the strength and direction of relationships between variables, refine theoretical models, and provide insights into how

various factors (e.g., attitudes, perceived ease of use) collectively influence mobile commerce intentions.

By testing and confirming this hypothesis, researchers can enhance the robustness of their SEM model and gain valuable insights into the predictors of mobile commerce intentions among the studied population. This, in turn, can inform strategies for promoting and enhancing mobile commerce adoption and usage.

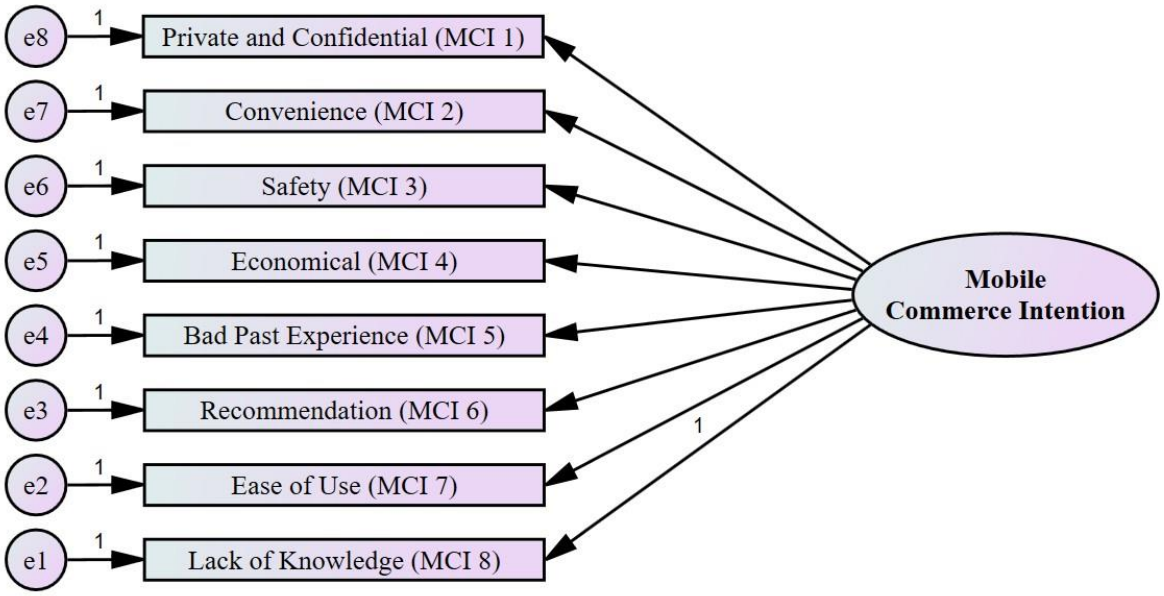


Figure 4.4: Measurement Model-Intention (Source: Researcher's compilation based on the original model of TPB)

Table 4.9: Significance of attributes of Mobile Commerce Intention

	Estimate	S.E.	C.R.	P	Label
MCI8 <--- Mobile_Commerce_Intention	1.000				
MCI7 <--- Mobile_Commerce_Intention	-1.366	.106	-12.939	***	Significant
MCI6 <--- Mobile_Commerce_Intention	-.523	.082	-6.389	***	Significant
MCI5 <--- Mobile_Commerce_Intention	**-.136**	**.072**	**-1.897**	**.058**	**Marginally Significant**
MCI4 <--- Mobile_Commerce_Intention	-1.380	.107	-12.884	***	Significant

	Estimate	S.E.	C.R.	P	Label
MCI3 <--- Mobile_Commerce_Intention	-1.277	.100	-12.832	***	Significant
MCI2 <--- Mobile_Commerce_Intention	-1.421	.107	-13.261	***	Significant
MCI1 <--- Mobile_Commerce_Intention	-1.069	.098	-10.870	***	Significant

(Source: Researcher's Computation)

The table represents the regression weights for the relationship between the latent factor "Mobile_Commerce_Intention" and the observed variables (MCI1 through MCI8). Here is a detailed interpretation of the regression weights:

Column Descriptions:

a. **Estimate**:
- The regression weight indicates the strength and direction of the relationship between the latent factor (Mobile_Commerce_Intention) and each observed variable (MCI1 to MCI8).

b. **S.E. (Standard Error)**:
- This represents the standard error of the regression weight, reflecting the variability or precision of the estimate.

c. **C.R. (Critical Ratio)**:
- The critical ratio is the estimate divided by its standard error (Estimate / S.E.). It is analogous to the t-value in regression analysis and indicates how many standard errors the estimate is away from zero.

d. **P (p-value)**:
    - The p-value indicates the statistical significance of the regression weight. A p-value of less than 0.05 suggests that the relationship between the latent factor and the observed variable is statistically significant. In this table, "***" indicates a highly significant relationship ($p < 0.001$).

Interpretation of Rows:

MCI8 <--- Mobile_Commerce_Intention:
- **Estimate**: 1.000 (fixed parameter for scaling purposes)

Interpretation: This attribute serves as a reference point, with its estimate fixed at 1.000 to scale the latent factor (Mobile_Commerce_Intention). This helps in comparing the other estimates.

MCI7 <--- Mobile_Commerce_Intention:

- Estimate: -1.366
- S.E.: 0.106
- C.R.: -12.939
- P: ***

Interpretation: There is a significant negative relationship between MCI7 and Mobile_Commerce_Intention. For each unit increase in Mobile_Commerce_Intention, MCI7 decreases by 1.366 units. The relationship is highly significant ($p < 0.001$).

MCI6 <--- Mobile_Commerce_Intention:

- Estimate: -0.523
- S.E.: 0.082
- C.R.: -6.389
- P: ***

Interpretation: There is a significant negative relationship between MCI6 and Mobile_Commerce_Intention. For each unit increase in Mobile_Commerce_Intention, MCI6 decreases by 0.523 units. The relationship is highly significant ($p < 0.001$).

MCI5 <--- Mobile_Commerce_Intention:

- Estimate: -0.136
- S.E.: 0.072
- C.R.: -1.897
- P: 0.058

Interpretation: There is a negative relationship between MCI5 and Mobile_Commerce_Intention, but it is not statistically significant at the conventional 0.05 level ($p = 0.058$).

MCI4 <--- Mobile_Commerce_Intention:

- Estimate: -1.380
- S.E.: 0.107
- C.R.: -12.884
- P: ***

Interpretation: There is a significant negative relationship between MCI4 and Mobile_Commerce_Intention. For each unit increase in Mobile_Commerce_Intention, MCI4 decreases by 1.380 units. The relationship is highly significant ($p < 0.001$).

MCI3 <--- Mobile_Commerce_Intention:

- Estimate: -1.277
- S.E.: 0.100
- C.R.: -12.832
- P: ***

Interpretation: There is a significant negative relationship between MCI3 and Mobile_Commerce_Intention. For each unit increase in Mobile_Commerce_Intention, MCI3 decreases by 1.277 units. The relationship is highly significant ($p < 0.001$).

MCI2 <--- Mobile_Commerce_Intention:

- Estimate: -1.421
- S.E.: 0.107
- C.R.: -13.261
- P: ***

Interpretation: There is a significant negative relationship between MCI2 and Mobile Commerce Intention. For each unit increase in Mobile Commerce Intention, MCI2 decreases by 1.421 units. The relationship is highly significant ($p < 0.001$).

MCI1 <--- Mobile_Commerce_Intention:

- **Estimate**: -1.069
- **S.E.**: 0.098
- **C.R.**: -10.870
- **P**: ***

Interpretation: There is a significant negative relationship between MCI1 and Mobile Commerce Intention. For each unit increase in Mobile Commerce Intention, MCI1 decreases by 1.069 units. The relationship is highly significant ($p < 0.001$).

General Observations:

All attributes (MCI1 through MCI8) except MCI5 have significant relationships with the latent factor "Mobile Commerce Intention" as indicated by the p-values (***), meaning $p < 0.001$. MCI5 has a p-value of 0.058, indicating a marginally significant relationship.

The regression weights (estimates) show negative relationships between Mobile Commerce Intention and the observed variables (MCI1 to MCI7):

- Negative estimates (e.g., MCI7: -1.366) indicate that as the latent factor "Mobile Commerce Intention" increases, the observed variables decrease.

The magnitude of the estimates reflects the strength of the relationship:

- Larger absolute values (e.g., MCI2: -1.421) indicate stronger relationships.
- Smaller absolute values (e.g., MCI5: -0.136) indicate weaker relationships.
- The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

Managerial Implications:

- **Identifying Inhibitors**: MCI1 to MCI8 represent factors that inhibit or negatively impact mobile commerce intention. Understanding these factors is crucial for managers to address barriers that prevent customers from adopting mobile commerce platforms or making purchases via mobile devices.
- **Prioritizing Improvement Efforts**: MCI2, MCI3, MCI4, MCI7, and MCI8 have particularly high negative regression weights, indicating they might be more influential in reducing mobile commerce intention compared to others. Managers should prioritize efforts to mitigate the impact of these factors through targeted strategies such as user experience improvements, trust-building initiatives, or marketing campaigns tailored to mobile users.
- **Addressing Marginally Significant Factors**: While MCI5 shows marginal significance, indicating it may have a weaker impact, managers should still monitor its effect closely as it could influence mobile commerce intention under specific conditions or in conjunction with other factors.

- **Strategy Formulation**: Based on these findings, managers can devise strategies to enhance mobile commerce intention by addressing identified inhibitors. This might involve improving website or app usability, addressing security concerns, offering incentives for mobile purchases, or enhancing the overall mobile shopping experience.
- **Further Investigation**: Beyond regression analysis, qualitative research or customer feedback surveys could provide deeper insights into why these factors (MCI1 to

MCI8) negatively influence mobile commerce intention. Such insights can guide more nuanced and effective managerial interventions.

In summary, The table indicates that the latent factor "Mobile Commerce Intention" has a significant negative impact on most observed variables (MCI1 through MCI8), with varying strengths. Positive estimates are not present in this context, suggesting inverse relationships throughout. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios, except for MCI5, which is marginally significant. Managers can use this information to prioritize improvement efforts, enhance mobile commerce platforms, and ultimately increase customer engagement and transactions via mobile devices.

- **Testing of Confirmatory Model of Theory of Planned Behaviour:**

H1e: Measurement model is having goodness-of-fit indices.

The measurement variables significantly contribute to their respective latent constructs (Attitude, Subjective Norms, Perceived Behavioural Control, and Behavioural Intention) in the proposed structural model of the Theory of Planned Behaviour.

Objective Components:

a. **Measurement Validation**: Assess the validity and reliability of measurement variables (indicators) in relation to their respective latent constructs within the TPB framework. This involves examining factor loadings, composite reliability, and discriminant validity.
b. **Model Fit**: Evaluate the overall fit of the measurement model to determine how well the chosen indicators represent the theoretical constructs of TPB. Good model fit indicates that the measurement variables effectively capture the intended constructs.
c. **Construct Relationships**: Explore the interrelationships between the latent constructs (Attitude, Subjective Norms, PBC, Behavioural Intention) based on the measurement model. This includes examining path coefficients and their significance to understand how attitudes, norms, and perceived control influence behavioural intentions.

d. **Model Refinement**: Based on empirical findings, refine the measurement model by potentially revising or removing indicators that do not contribute meaningfully to their respective constructs. This iterative process enhances the validity and utility of the TPB model in explaining and predicting behaviours.

By addressing this objective and hypothesis, researchers aim to strengthen the theoretical foundation of TPB, provide empirical support for its applicability in specific contexts, and contribute to the broader understanding of human decision-making and behavior change processes.

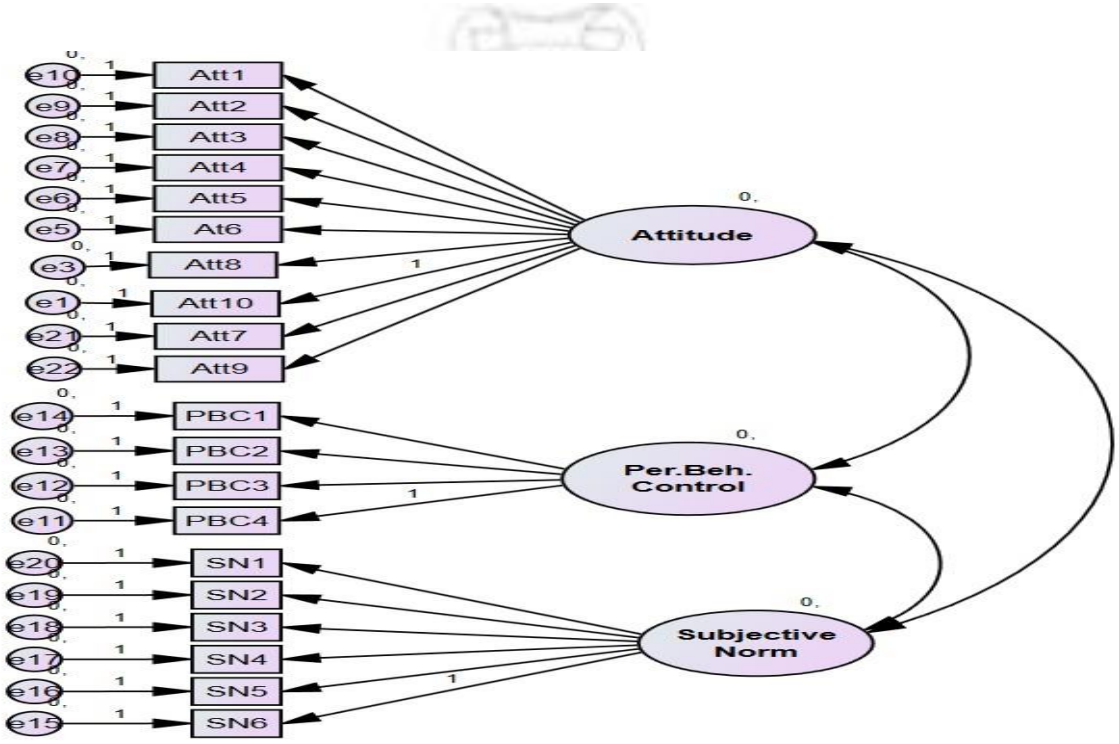


Figure 4.5: TPB Model (Source: Researcher's compilation based on the original model of TPB)

Table 4.10: Factor loading of attributes of TPB

	Estimate
Att10 <--- Attitude	.685
Att8 <--- Attitude	.844

			Estimate
Att6	<---	Attitude	.450
Att5	<---	Attitude	-.523
Att4	<---	Attitude	.868
Att3	<---	Attitude	.404
Att2	<---	Attitude	.758
PBC4	<---	Per.Beh._Control	.730
PBC3	<---	Per.Beh._Control	-.440
PBC2	<---	Per.Beh._Control	-.370
PBC1	<---	Per.Beh._Control	-.907
SN6	<---	Subjective_Norm	.945
SN5	<---	Subjective_Norm	-.898
SN4	<---	Subjective_Norm	.967
SN3	<---	Subjective_Norm	.958
SN2	<---	Subjective_Norm	.974
SN1	<---	Subjective_Norm	.970
Att1	<---	Attitude	.798
Att7	**<---**	**Attitude**	**-.389**
Att9	**<---**	**Attitude**	**-.314**

(Source: Researcher's Computation)

In evaluating the standardized regression weights for the constructs of Attitude, Perceived Behavioural Control (PBC), and Subjective Norm within a conceptual model based on the Theory of Planned Behaviour (TPB), it is essential to adhere to methodological guidelines

for factor loading. According to Anderson (2020), factor loading values less than 0.40 should be deleted from further analysis, as these indicate lower factor loading and insufficient representation of the underlying construct.

Deletion Recommendations:

Based on Anderson's guideline, Att7 (-.389) and Att9 (-.314) should be deleted from further analysis due to their lower factor loadings.

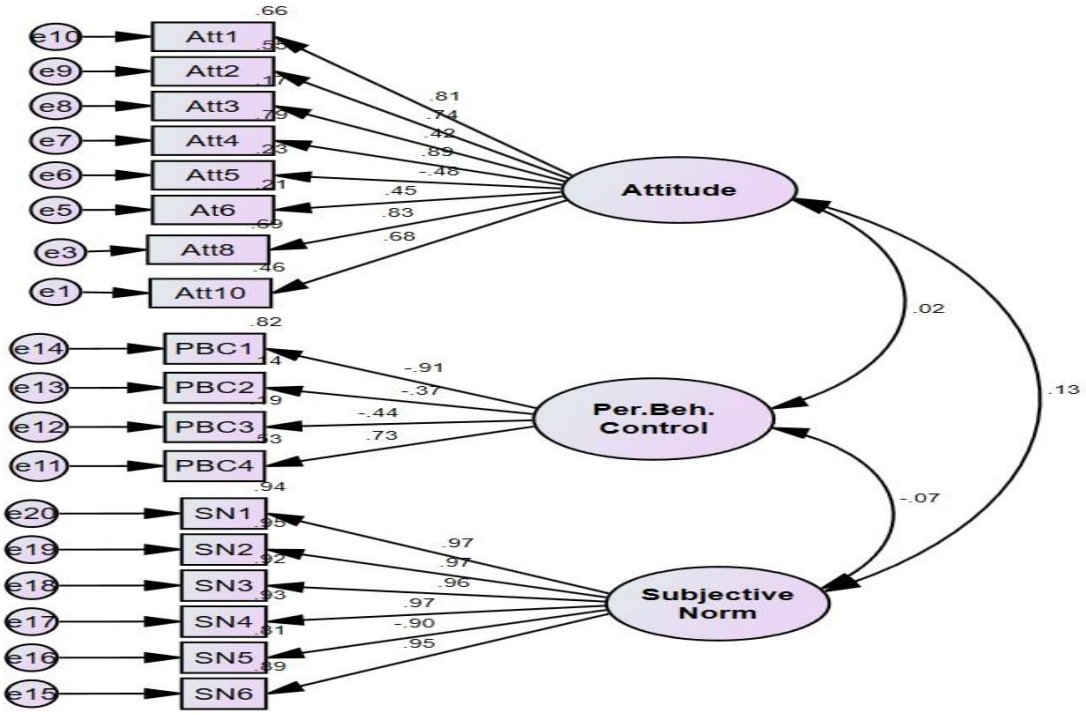


Figure 4.6: TPB Model after Deletion of Variables (Source: Researcher's compilation based on the original model)

Testing of Goodness-of fit:

H1e: Measurement model is having goodness-of-fit indices.

Table 4.11: Significance of attributes of TPB Model

	Estimate	S.E.	C.R.	P	Label
Att10 <--- Attitude	1.000				
Att8 <--- Attitude	1.237	.077	16.142	***	Significant
Att6 <--- Attitude	.655	.071	9.255	***	Significant

		Estimate	S.E.	C.R.	P	Label
Att5	<--- Attitude	-.857	.088	-9.784	***	Significant
Att4	<--- Attitude	1.278	.075	16.950	***	Significant
Att3	<--- Attitude	.592	.069	8.533	***	Significant
Att2	<--- Attitude	1.071	.073	14.622	***	Significant
Att1	<--- Attitude	1.174	.074	15.840	***	Significant
PBC4	<--- Per.Beh._Control	1.000				
PBC3	<--- Per.Beh._Control	-.822	.093	-8.828	***	Significant
PBC2	<--- Per.Beh._Control	-.636	.085	-7.443	***	Significant
PBC1	<--- Per.Beh._Control	-1.116	.099	-11.300	***	Significant
SN6	<--- Subjective_Norm	1.000				
SN5	<--- Subjective_Norm	-.878	.024	-36.004	***	Significant
SN4	<--- Subjective_Norm	.971	.020	49.451	***	Significant
SN3	<--- Subjective_Norm	.956	.020	47.264	***	Significant
SN2	<--- Subjective_Norm	.969	.019	51.610	***	Significant
SN1	<--- Subjective_Norm	.960	.019	50.360	***	Significant

(Source: Researcher's Computation)

Table 4.12: Standardized Regression Weights: (Group number 1 - Default model)/ Factor Loading of TPB Constructs

		Estimate
Att10	<--- Attitude	.678
Att8	<--- Attitude	.833
Att6	<--- Attitude	.455
Att5	<--- Attitude	-.482
Att4	<--- Attitude	.886
Att3	<--- Attitude	.418
Att2	<--- Attitude	.743
Att1	<--- Attitude	.815
PBC4	<--- Per.Beh._Control	.730
PBC3	<--- Per.Beh._Control	-.440
PBC2	<--- Per.Beh._Control	-.370
PBC1	<--- Per.Beh._Control	-.907

			Estimate
SN6	<---	Subjective_Norm	.945
SN5	<---	Subjective_Norm	-.898
SN4	<---	Subjective_Norm	.967
SN3	<---	Subjective_Norm	.958
SN2	<---	Subjective_Norm	.974
SN1	<---	Subjective_Norm	.970

(Source: Researcher's Computation)

Managerial Implications:

- **Enhancing Positive Attitudes:**

a. Leverage Strong Positive Indicators:

- **Att4 (Private and Confidential):** This item has the highest standardized loading (0.886), indicating that ensuring privacy and confidentiality in m-commerce is crucial. Managers should emphasize robust security measures in their communication and marketing strategies.
- **Att8, Att2, and Att1 (Convenience, Ease of Use, and Reasonably Priced Products):** These items are significant positive predictors of attitude. Companies should focus on highlighting these aspects in their advertising and user experiences. For example, emphasizing user-friendly interfaces, convenience, and competitive pricing can enhance positive attitudes toward m-commerce.

b. Address Negative Indicators:

- **Att5 (Bad Past Experience):** This negative relationship indicates that previous negative experiences significantly impact attitudes towards m-commerce. Companies must prioritize customer satisfaction and address any issues promptly to prevent bad experiences. Implementing strong customer service and feedback mechanisms can mitigate this effect.

- **Improving Perceived Behavioural Control:**

a. Address Negative Influences:

- **PBC1, PBC3, and PBC2 (Lack of Knowledge and Negative Past Experience):** These items have negative estimates, suggesting that lack of knowledge and negative experiences with m-commerce hinder users' perceived control. Educational

campaigns, tutorials, and user support can help improve users' comfort and confidence in using m-commerce platforms.

b. Strengthen Positive Influences:

- **PBC4 (Perceived Ease of Use):** This item positively influences perceived behavioural control. Ensuring the platform is intuitive and easy to navigate can enhance users' perceived control and, consequently, their likelihood of using m-commerce.

❖ **Reinforcing Subjective Norms:**

a. Leverage Social Influence:

- **SN2, SN1, SN4, and SN3:** These items show very strong positive relationships with subjective norms. Marketing strategies that leverage social proof, such as testimonials, endorsements from influencers, and peer reviews, can significantly boost positive subjective norms. Highlighting positive feedback from other users can also reinforce positive perceptions.

b. Mitigate Negative Influences:

- **SN5 (Negative Recommendations):** Negative social influences can severely impact subjective norms. Companies should actively manage their online reputation and address negative reviews or feedback. Encouraging satisfied customers to leave positive reviews can help counterbalance any negative recommendations.

Summary: By focusing on enhancing the factors that positively impact attitudes, perceived behavioural control, and subjective norms while addressing the negative factors, companies can foster a more favourable environment for m-commerce adoption. Ensuring a secure, user-friendly, and positively reviewed platform will be key in driving m-commerce growth.

Table 4.13: Goodness-of-fit Model

Name of Category	Goodness-of-fit model index	Recommended Value*	Planned Behavior Model Value	Interpretation
1.Absolute fit	***Root mean square error of approximation (RMSEA)***	***< .10***	***.079***	Excellent

	Goodness-of-fit index(GFI)	**≥ .80**	**.890**	Excellent
2.Incremental fit	**Adjusted goodness-of-fit index (AGFI)**	**≥ .80**	**.858**	Excellent
	Normalized fit index (NFI)	**≥ .80**	**.932**	Excellent
	Comparative fit index (CFI)	***≥ .90***	***.948***	Excellent
	Tucker Fit Index (TLI)	**≥ .90**	**.940**	Excellent
3.Parsimonious fit	***Chi-square/degree of freedom(CMIN/df)*****	***≤ 5.00***	***3.931***	Acceptable

(Source: Researcher's Computation)

The table provided outlines various goodness-of-fit indices used to assess the fit of a model, likely in the context of structural equation modelling (SEM) or a similar statistical analysis. Here's an interpretation of each index based on the values provided:

A. Absolute Fit:

- **Chi-Square**:

Value: .000

Recommended: P-value > 0.05 (indicating good fit)

Interpretation: A chi-square value of .000 suggests that the model fits the data perfectly in terms of absolute fit, as the p-value is greater than 0.05, indicating no significant difference between the observed and expected covariance matrices.

- **Root Mean Square Error of Approximation (RMSEA)**:

Value: .079

Recommended: < 0.10

Interpretation: RMSEA of .079 indicates a reasonable fit, as it is below the threshold of 0.10, suggesting that the model has a good fit to the data.

Goodness-of-Fit Index (GFI):

- Value: .890
- Recommended: ≥ 0.80

Interpretation: GFI of .890 meets the recommended threshold of 0.80, indicating a good fit of the model.

B. Incremental Fit:

Adjusted Goodness-of-Fit Index (AGFI):

- Value: .858
- Recommended: ≥ 0.80

Interpretation: AGFI of .858 meets the recommended threshold of 0.80, suggesting adequate incremental fit of the model.

Normalized Fit Index (NFI):

- Value: .932
- Recommended: ≥ 0.80

Interpretation: NFI of .932 exceeds the recommended threshold of 0.80, indicating good incremental fit.

Comparative Fit Index (CFI):

- Value: .948
- Recommended: ≥ 0.90

Interpretation: CFI of .948 meets the recommended threshold of 0.90, suggesting very good incremental fit of the model.

Tucker-Lewis Index (TLI):

- Value: .940
- Recommended: ≥ 0.90

Interpretation: TLI of .940 meets the recommended threshold of 0.90, indicating good incremental fit.

C. Parsimonious Fit:

Chi-Square/Degree of Freedom (CMIN/df):

- Value: 3.931

- Recommended: ≤ 5.00

Interpretation: CMIN/df of 3.931 is below the recommended threshold of 5.00, indicating good parsimonious fit of the model.

Summary: Based on the provided values and recommendations:

- The model shows excellent absolute fit (chi-square p-value > 0.05, RMSEA < 0.10, GFI ≥ 0.80).
- Incremental fit indices (AGFI, NFI, CFI, TLI) also indicate good to very good fit of the model.
- Parsimonious fit (CMIN/df) suggests the model is adequately parsimonious.

Overall, these indices collectively suggest that the model fits the data well across different aspects of fit (absolute, incremental, and parsimonious), providing confidence in its validity for explaining the relationships among variables in the theoretical framework of Theory of Planned Behaviour.

❖ **Discriminant Validity:**

The heterotrait-monotrait (HTMT) ratio is a statistical measure used in the context of assessing discriminant validity in research involving latent variables or constructs. It's primarily used in structural equation modeling (SEM) and confirmatory factor analysis (CFA) to evaluate the distinction between different constructs in a measurement model.

In the context of these analyses, discriminant validity refers to the idea that distinct constructs should be more dissimilar than similar to one another. In other words, the measures of different constructs should correlate less strongly with each other compared to their correlations with their own measures (monotrait correlations).

The HTMT ratio is a way to quantify this concept. It involves calculating the average correlation between indicators of different constructs (heterotrait correlations) and comparing it to the average correlation between indicators of the same construct (monotrait correlations). The formula is as follows:

HTMT = √ (average heterotrait correlations) / √ (average monotrait correlations)

In an ideal scenario, the HTMT ratio should be less than 1.0, indicating that the constructs have good discriminant validity. If the HTMT ratio is close to or greater than 1.0, it suggests that the constructs might not be distinct enough and might be overlapping or measuring similar underlying concepts.

Researchers use the HTMT ratio to assess the extent to which their measurement model demonstrates discriminant validity. This is important for ensuring that the constructs being studied are truly distinct and not simply measuring the same underlying concept.

Table 4.14 a: Correlation Metrics

	SN1	SN2	SN3	SN4	SN5	SN6	PBC1	PBC2	PBC3	PBC4	Att1	Att2	Att3	Att4	Att5
SN1	1.00														
SN2	0.94	1.00													
SN3	0.93	0.93	1.00												
SN4	0.94	0.94	0.93	1.00											
SN5	-0.87	-0.88	-0.86	-0.87	1.00										
SN6	0.92	0.92	0.91	0.91	-0.85	1.00									
PBC1	0.06	0.06	0.06	0.06	-0.06	0.06	1.00								
PBC2	0.03	0.03	0.03	0.03	-0.02	0.02	0.34	1.00							
PBC3	0.03	0.03	0.03	0.03	-0.03	0.03	0.40	0.16	1.00						
PBC4	-0.05	-0.05	-0.05	-0.05	0.05	-0.05	-0.66	-0.27	-0.32	1.00					

Att1	0.11	0.11	0.11	0.11	-0.10	0.10	-0.02	-0.01	-0.01	0.01	1.00				
Att2	0.10	0.10	0.10	0.10	-0.09	0.10	-0.01	-0.01	-0.01	0.01	0.61	1.00			
Att3	0.06	0.06	0.05	0.05	-0.05	0.05	-0.01	0.00	0.00	0.01	0.34	0.31	1.00		
Att4	0.12	0.12	0.11	0.12	-0.11	0.11	-0.02	-0.01	-0.01	0.01	0.72	0.66	0.37	1.00	
Att5	-0.06	-0.06	-0.06	-0.06	0.06	-0.06	0.01	0.00	0.00	-0.01	-0.39	-0.36	-0.20	-0.43	1.00
At6	0.06	0.06	0.06	0.06	-0.06	0.06	-0.01	0.00	0.00	0.01	0.37	0.34	0.19	0.40	-0.22
Att8	0.11	0.11	0.11	0.11	-0.10	0.11	-0.02	-0.01	-0.01	0.01	0.68	0.62	0.35	0.74	-0.40
Att10	0.09	0.09	0.09	0.09	-0.08	0.09	-0.01	-0.01	-0.01	0.01	0.55	0.50	0.28	0.60	-0.33

(Source: Researcher's Computation)

Table 4.14 b: HTMT Ratio

HTMT Ratio	Estimated Value	Threshold Value	Interpretation
LS-BE	**0.324**	**Below .90**	**Acceptable**
LS-AT	**0.078**	**Below .90**	**Acceptable**
BE-AT	**-0.020**	**Below .90**	**Acceptable**

(Source: Researcher's Computation)

❖ **No Discriminant Validity Issues**:

- All the HTMT ratios provided are below the threshold value of 0.90.
- This indicates that the constructs are distinct from each other and do not have discriminant validity issues.

❖ **Overall Interpretation**:

- The data demonstrates acceptable discriminant validity for the constructs involved.
- Therefore, it is appropriate to proceed with further analysis, as the constructs are not overly correlated and are sufficiently distinct from one another.

4.5.2 Objective 2: To evaluate the significance and extent to which the constructs of the 'Theory of Planned Behaviour' influence the intentions to use mobile commerce.

H2: Theory of Planned Behaviour constructs significantly influence the intentions to use m-commerce.

Sub Hypothesis:

H2a: Attitude towards mobile commerce significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that a positive attitude towards using mobile commerce (e.g., perception of convenience, trustworthiness of mobile platforms) leads to a higher intention to make purchases via mobile devices.

H2b: Subjective norms significantly influence the intentions to use m-commerce.

Explanation: This hypothesis posits that perceived social influences or norms regarding mobile commerce usage (e.g., recommendations from friends, social media influencers) affect consumers' intention to engage in mobile commerce transactions.

H2c: Perceived behavioural control significantly influences the intentions to use m-commerce.

Explanation: This hypothesis proposes that consumers' perception of their ability to control and execute mobile commerce transactions (e.g., ease of use, technical skills required) impacts their intention to purchase goods or services via mobile devices.

H2d: Attitude, subjective norms, and perceived behavioural control significantly influence the intentions to use m-commerce.

Explanation: This hypothesis suggests that when combined, attitude, subjective norms, and perceived behavioural control explain a significant proportion of variance in consumers' buying intention in the context of mobile commerce.

Additional Objectives and Considerations:

a. **Measurement Model Validation**: Validate the measurement model by examining the relationships between the indicators (measurement variables) and their respective latent constructs (Attitude, Subjective Norms, Perceived Behavioural Control).
b. **Mediating Effects**: Explore potential mediating effects of attitude, subjective norms, and perceived behavioural control on the relationship between other variables (e.g., demographic factors, past behaviour) and buying intention.
c. **Comparative Analysis**: Compare the strength of relationships between TPB constructs and buying intention across different demographic segments (e.g., age groups, income levels) to identify variations in consumer behaviour.
d. **Practical Implications**: Discuss practical implications of the findings for mobile commerce providers, marketers, and policymakers to enhance consumer engagement and adoption of mobile commerce platforms.

By addressing these objectives and hypotheses, the study aims to deepen understanding of the psychological determinants influencing buying intentions in mobile commerce and provide actionable insights for stakeholders in improving user experience, marketing strategies, and policy frameworks.

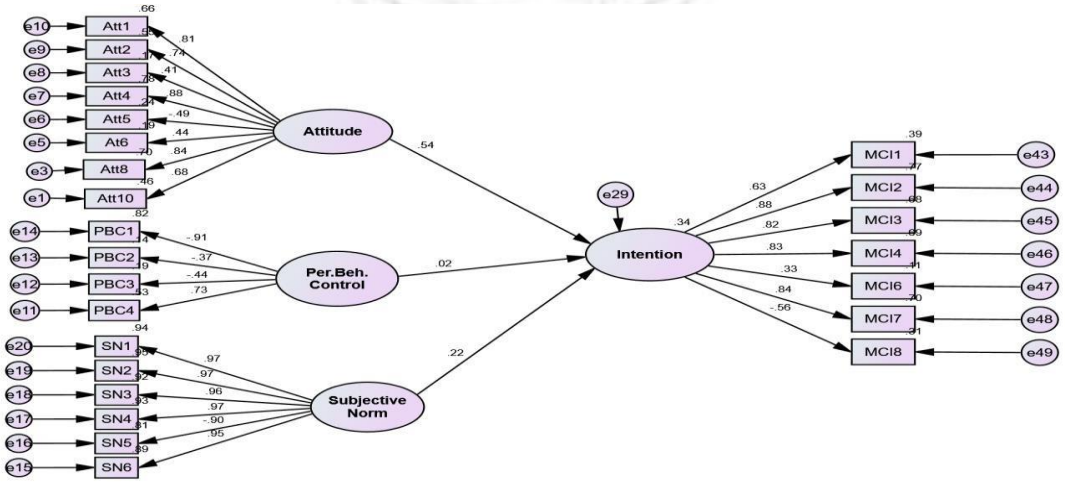


Figure 4.7: TPB and Behavioural Intention (Source: Researcher's Compilation based on the original model of TPB)

Table 4.15: Goodness-of-fit of Antecedents of TPB and Intention Model

Goodness-of-fit model index	Recommended Value	Estimated Model Value	Interpretation
Root mean square error of approximation (RMSEA)	***< .10***	***.071***	Excellent
Normalized fit index (NFI)	**≥ .80**	**.902**	Excellent
Comparative fit index (CFI)	***≥ .90***	***.928***	Excellent
Tucker Fit Index (TLI)	**≥ .90**	**.920**	Excellent
Chi-square/degree of freedom(CMIN/df)**	***≤ 5.00***	***3.39***	Acceptable
SRMR	***<0.08***	**0.089**	Acceptable

(Source: Researcher's Computation)

a. **Root Mean Square Error of Approximation (RMSEA < 0.10)**:

- Recommended Value: < 0.10
- Estimated Model Value: 0.071
- Interpretation: An RMSEA of 0.071 indicates a good fit, as it is below the threshold of 0.10. RMSEA values between 0.05 and 0.08 suggest a reasonable fit, and values below 0.05 indicate close fit.

b. **Normalized Fit Index (NFI ≥ 0.80)**:

- Recommended Value: ≥ 0.80
- Estimated Model Value: 0.902
- Interpretation: An NFI of 0.902 exceeds the recommended threshold of 0.80, indicating an excellent fit of the model. The NFI compares the fit of the model to a null model and values closer to 1 indicate better fit.

c. **Comparative Fit Index (CFI ≥ 0.90)**:

- **Recommended Value**: ≥ 0.90
- **Estimated Model Value**: 0.928

- **Interpretation**: A CFI of 0.928 is above the recommended threshold of 0.90, indicating an excellent fit. The CFI considers the model complexity and penalizes for adding parameters that do not improve the model fit significantly.

d. Tucker-Lewis Index (TLI ≥ 0.90):

- Recommended Value: ≥ 0.90
- Estimated Model Value: 0.920
- Interpretation: A TLI of 0.920 meets the recommended value of 0.90, suggesting an excellent fit. The TLI is similar to the CFI but includes a penalty for model complexity.

e. Chi-square/degree of freedom (CMIN/df ≤ 5.00):

- Recommended Value: ≤ 5.00
- Estimated Model Value: 3.39
- Interpretation: A CMIN/df of 3.39 is within the acceptable range, suggesting an acceptable fit. This index adjusts the chi-square value by the degrees of freedom to account for model complexity, with lower values indicating better fit.

f. Standardized Root Mean Square Residual (SRMR < 0.08):

- **Recommended Value**: < 0.08
- **Estimated Model Value**: 0.089
- **Interpretation**: An SRMR of 0.089 is slightly above the recommended threshold of 0.08, indicating an acceptable but not optimal fit. SRMR values below 0.08 are generally considered to indicate a good fit.

Summary: Overall, the model demonstrates a good fit to the data based on multiple indices:

- **RMSEA, NFI, CFI, and TLI**: These indices all indicate good to excellent fit.
- **CMIN/df**: This index suggests an acceptable fit.
- **SRMR**: This index is slightly above the optimal threshold but still within an acceptable range.

The combination of these indices suggests that the model is a good representation of the other indices strongly support the model's adequacy.

Table 4.16: Impact of Antecedents on buying Intention

Sr. No			Estimate	S.E.	C.R.	P	Remark
H2a	Intention	<--- Perceived Behaviour Control	.080	.053	1.498	.134	Non-Significant
H2 b	Intention	<--- Subjective Norms	.341	.034	10.049	***	Significant
H2c	Intention	<--- Attitude	.529	.067	7.836	***	Significant
H2 d	***RMSEA=.071, NFI=.902 ,CFI=.928, TLI=.920, CMIN/df=3.39***						Model is Fit

(Source: Researcher's Computation)

Intention <--- Perceived Behaviour Control

- Estimate: .080
- S.E.: .053
- C.R.: 1.498
- P: .134

Interpretation: The relationship between Perceived Behavioural Control (P.B.C.) and Intention is not statistically significant (p > .05).

Intention <--- Subjective Norm:

- **Estimate**: .341
- **S.E.**: .034
- **C.R.**: 10.049
- **P**: ***

Interpretation: Subjective Norms significantly influence Intention with a strong positive relationship.

Intention <--- Attitude:

- **Estimate**: .529
- **S.E.**: .067
- **C.R.**: 7.836
- **P**: ***

Interpretation: Attitude significantly influences Intention with a strong positive relationship.

Summary of Key Relationships:

- **Attitude** and **Subjective Norms** significantly influence **Intention**.
- **Perceived Behavioural Control** does not have a significant direct effect on **Intention**.

- This model demonstrates significant paths between the key constructs, with most indicators showing strong, significant loadings on their respective constructs. The primary takeaway is the importance of **Attitude** and **Subjective Norms** in predicting **Intention**, and subsequently, the significant impact of **Intention** on actual **Use**. And collectively all three Antecedents are impacting on intention to use mobile commerce.

4.5.3 Objective 3: To examine the impact of 'Demographic Variables' on consumers' 'Attitude', 'Perceived Behaviour Control', 'Subjective Norms' and 'Intention' to use m-commerce.

Hypothesis 3: Demographic variables significantly influence consumers' attitudes, Perceived Behaviour Control, Subjective Norms and intention towards m-commerce.

Attitudes towards Technology Adoption:

- Venkatesh et.al, (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.

This study discusses the influence of demographic variables, including gender, on technology acceptance, highlighting potential differences in attitudes between males and females.

Subjective Norms and Demographics:

- Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behaviour: An introduction to theory and research. Addison-Wesley.

This work explains how subjective norms, influenced by demographic factors such as gender, shape intentions and behaviours.

Perceived Behavioural Control and Demographics:

- Taylor, S., & Todd, P.A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144-176.

This study explores the impact of demographic factors, including gender, on perceived behavioural control over technology usage.

Intention to Use Technology:

- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

This research highlights how demographic variables, particularly gender, can influence the intention to use new technologies, providing a basis for understanding gender differences in m-commerce adoption.

These hypotheses aim to identify and measure the differences between male and female consumers regarding their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce. By testing these hypotheses, the research will contribute to a deeper understanding of gender-based differences in m-commerce adoption, which can inform targeted marketing and policy strategies.

H3a: There is no statistically significant difference between male and female consumers and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.17: Test of Significance-Gender and TPB Constructs

Gender				
	t	**df**	**Sig. (2-tailed)**	**Finding**
Subjective Norms	-0.266	412.076	0.791	Non Significant
Perceived Behaviour Control	0.792	399.908	0.429	Non Significant
Attitude	0.715	439.040	0.475	Non Significant
Intention	0.014	394.159	0.989	Non Significant

(Source: Researcher's Computation)

According to the results of t-test, all four constructs namely Subjective Norm, Perceived Behavioural Control, Attitude, and Intention show no significant differences between genders and their intention to use mobile commerce.

H3b: There is no statistically significant difference between Area of Location and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.18: Test of Significance- Area of Location and TPB Constructs

Area of Location				
	t	df	Sig. (2-tailed)	Finding
Subjective Norms	-0.465	468.306	0.642	Non-Significant
Perceived Behaviour Control	0.636	461.122	0.525	Non-Significant
Attitude	0.848	463.467	0.397	Non-Significant
Intention	1.923	427.314	0.055	Significant

(Source: Researcher's Computation)

All three variables (Subjective Norm, Perceived Behavioural Control, and Attitude) show no significant differences between areas of location. This means that area of location does not have a statistically significant effect on these variables according to the results of this t-test except in Intention.

Table 4.19: Test of Significance- Area of Location and Intention

Group Statistics					
	Area of location	N	Mean	Std. Deviation	Std. Error Mean
Intention	**Municipal Area (Urban)**	**246**	**3.2043**	.53922	.03438
	Panchayat Area (Rural)	227	3.0942	.68999	.04580

(Source: Researcher's Computation)

Urban respondents (Municipal Area) tend to have a slightly higher intention to purchase (Mean = 3.2043) compared to rural respondents (Panchayat Area) (Mean = 3.0942). The scores for urban respondents are less variable and provide a more precise estimate of the population mean than those for rural respondents. This suggests that location may influence

purchase intentions, with urban respondents showing a marginally higher propensity to purchase.

Table 4.20: Variables of Intention and Area of Location: Independent Samples Test

Intention	t	df	Sig. (2-tailed)	Mean Difference	Findings
Private and Confidential (MCI 1)	1.551	466.043	0.122	0.163	Non-Significant
Convenience (MCI 2)	**3.698**	**440.991**	**0.000**	0.367	Significant
Safety (MCI 3)	1.735	448.968	0.083	0.167	Non-significant
Economical (MCI 4)	**2.34**	**448.117**	**0.02**	0.24	Significant
Bad Past Experience (MCI 5)	-0.346	462.758	0.73	-0.032	Non-significant
Recommendation (MCI 6)	1.172	462.901	0.242	0.117	Non-significant
Ease of Use (MCI 7)	**2.149**	**429.629**	**0.032**	0.218	Significant
Lack of Knowledge (MCI 8)	**-3.257**	**427.737**	**0.001**	-0.358	Significant

(Source: Researcher's Computation)

Table 4.21: Group Statistics of Intention and Area of Location

Intention	Area of location	N	Mean	Std. Deviation	Std. Error Mean
Private and Confidential (MCI 1)	Municipal Area (Urban)	246	3.27	1.125	.072
	Panchayat Area (Rural)	227	3.11	1.151	.076
Convenience (MCI 2)	**Municipal Area (Urban)**	**246**	**3.93**	.971	.062
	Panchayat Area (Rural)	**227**	**3.57**	1.167	.077
Safety (MCI 3)	Municipal Area (Urban)	246	3.48	.963	.061
	Panchayat Area (Rural)	227	3.32	1.111	.074
Economical (MCI 4)	**Municipal Area (Urban)**	**246**	**3.76**	1.028	.066
	Panchayat Area (Rural)	**227**	**3.52**	1.191	.079

Bad Past Experience (MCI 5)	Municipal Area (Urban)	246	2.43	.978	.062
	Panchayat Area (Rural)	227	2.47	1.032	.068
Recommendation (MCI 6)	Municipal Area (Urban)	246	2.81	1.058	.067
	Panchayat Area (Rural)	227	2.69	1.114	.074
Ease of Use (MCI 7)	**Municipal Area (Urban)**	**246**	**3.77**	.960	.061
	Panchayat Area (Rural)	**227**	**3.55**	1.216	.081
Lack of Knowledge (MCI 8)	**Municipal Area (Urban)**	**246**	**2.17**	1.037	.066
	Panchayat Area (Rural)	**227**	**2.53**	1.325	.088

(Source: Researcher's Computation)

The research explored how demographic variables, specifically area of location (urban vs. rural), influence consumers' intentions regarding the use of mobile commerce. The analysis, based on an independent samples test, yielded several significant findings:

a. **Convenience (MCI 2):** There is a statistically significant difference between urban and rural consumers ($t = 3.698$, $p < 0.001$), with urban consumers perceiving mobile commerce as more convenient (mean = 3.93) compared to rural consumers (mean = 3.57). This suggests urban consumers might have better access to resources and infrastructure that enhance the convenience of using mobile commerce.
b. **Economical (MCI 4):** The difference between urban and rural consumers is significant ($t = 2.34$, $p = 0.02$), with urban consumers finding mobile commerce more economical (mean = 3.76) than rural consumers (mean = 3.52). This might be due to higher levels of awareness and accessibility to cost-effective mobile commerce solutions in urban areas.
c. **Ease of Use (MCI 7):** There is a significant difference ($t = 2.149$, $p = 0.032$), with urban consumers perceiving mobile commerce as easier to use (mean = 3.77) compared to rural consumers (mean = 3.55). This could be attributed to higher technological literacy in urban areas.
d. **Lack of Knowledge (MCI 8):** The significant negative difference ($t = -3.257$, $p = 0.001$) indicates that rural consumers report a greater lack of knowledge about

mobile commerce (mean = 2.53) than urban consumers (mean = 2.17). This reflects a potential barrier to adoption in rural areas due to insufficient information and awareness.

Other variables such as "Private and Confidential" (MCI 1), "Safety" (MCI 3), "Bad Past Experience" (MCI 5), and "Recommendation" (MCI 6) showed no statistically significant differences between urban and rural consumers.

Managerial Implications:

The findings offer several actionable insights for businesses and policymakers aiming to enhance mobile commerce adoption:

a. **Targeted Education and Awareness Campaigns:** Given the significant difference in knowledge levels, it is crucial to implement educational initiatives focused on rural areas to increase awareness and understanding of mobile commerce. These campaigns could include workshops, local seminars, and digital literacy programs.
b. **Improving Convenience and Accessibility:** For rural consumers to perceive mobile commerce as convenient, businesses should enhance the infrastructure and provide user-friendly platforms. This could involve simplifying the user interface and offering localized support to address specific needs and challenges faced by rural users.
c. **Cost-Effective Solutions:** To make mobile commerce more appealing to rural consumers, companies should emphasize the economic benefits and offer cost-effective solutions. Promotional campaigns highlighting savings, discounts, and financial incentives could encourage adoption in rural areas.
d. **Enhancing User Experience:** Since urban consumers find mobile commerce easier to use, businesses should leverage this by ensuring their platforms are intuitive and accessible. Continuous user experience improvements and responsive customer support can maintain high satisfaction levels among urban users.
e. **Safety and Security Measures:** Although there were no significant differences found in the perception of safety, maintaining and communicating robust security measures is essential. Building trust through transparent privacy policies and secure transaction processes can address potential concerns from both urban and rural consumers.

f. **Personalized Marketing Strategies:** Recognizing the different perceptions between urban and rural consumers, marketers should tailor their strategies accordingly. Urban areas may benefit from advanced features and convenience- focused messages, while rural areas might require more basic, informative, and trust- building approaches.

Citations of Previous Research:

a. **Attitudes towards Technology Adoption:**

- Venkatesh et.al (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.
- This study discusses how demographic variables, such as location, influence technology acceptance, supporting the finding that urban users are more inclined towards technology adoption.

b. **Subjective Norms and Demographics:**

- Fishbein et.al, (1975). Belief, attitude, intention, and behaviour: An introduction to theory and research. Addison-Wesley.
- The theory highlights the impact of social norms and demographic factors on behaviour, which is relevant to understanding differences in mobile commerce adoption between urban and rural consumers.

By leveraging these insights, businesses and policymakers can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of urban and rural consumers.

H3c: There is no statistically significant difference between 'Marital Status' of consumers and their attitude, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.22: Test of Significance-Marital Status and TPB Constructs

Marital Status				
	t	df	Sig. (2-tailed)	Finding
Subjective Norms	-0.638	446.959	0.524	Non-Significant

Perceived Behaviour Control	-0.067	438.233	0.947	Non-Significant
Attitude	0.153	467.000	0.879	Non-Significant
Intention	-2.551	435.887	0.011	Significant

(Source: Researcher's Computation)

All three variables (Subjective Norm, Perceived Behavioural Control, and Attitude) show no significant differences between marital statuses. This means that marital status does not have a statistically significant effect on these variables according to the results of this t-test except in intention.

Table 4.23: Variables of Intention and Marital Status: Independent Samples Test

Group Statistics					
	Marital Status	N	Mean	Std. Deviation	Std. Error Mean
Intention	Married	210	3.0702	.63418	.04376
	Unmarried	**263**	**3.2163**	.59808	.03688

(Source: Researcher's Computation)

Unmarried respondents tend to have a higher intention to purchase (Mean = 3.2163) compared to married respondents (Mean = 3.0702). The scores for unmarried respondents are slightly less variable and provide a more precise estimate of the population mean than those for married respondents. This suggests that marital status may influence purchase intentions, with unmarried respondents showing a higher propensity to purchase.

Table 4.24: Test of Significance-Intention and Marital Status

Intention	t	df	Sig. (2-tailed)	Mean Difference	Findings
Private and Confidential (MCI 1)	**-2.611**	**471**	**0.009**	-0.274	Significant
Convenience (MCI 2)	-1.831	471	0.068	-0.183	Non Significant
Safety (MCI 3)	**-2.217**	**471**	**0.027**	**-0.212**	Significant
Economical (MCI 4)	**-2.709**	**471**	**0.007**	**-0.278**	Significant
Bad Past Experience (MCI 5)	**-2.089**	**471**	**0.037**	-0.193	Non Significant

Recommendation (MCI 6)	-0.857	471	0.392	-0.086	Non Significant
Ease of Use (MCI 7)	-1.729	471	0.084	-0.175	Non Significant
Lack of Knowledge (MCI 8)	**2.111**	**471**	**0.035**	0.233	Non Significant

(Source: Researcher's Computation)

Table 4.25: Group Statistics-Marital Status and Intention

Group Statistics					
Intention	Marital Status	N	Mean	Std. Deviation	Std. Error Mean
Private and Confidential (MCI 1)	**Married**	**210**	**3.04**	1.197	.083
	Unmarried	**263**	**3.31**	1.078	.066
Convenience (MCI 2)	Married	210	3.66	1.156	.080
	Unmarried	263	3.84	1.018	.063
Safety (MCI 3)	**Married**	**210**	**3.29**	1.130	.078
	Unmarried	**263**	**3.50**	.953	.059
Economical (MCI 4)	**Married**	**210**	**3.49**	1.207	.083
	Unmarried	**263**	**3.77**	1.020	.063
Bad Past Experience (MCI 5)	**Married**	**210**	**2.34**	.942	.065
	Unmarried	**263**	**2.54**	1.044	.064
Recommendation (MCI 6)	Married	210	2.70	1.106	.076
	Unmarried	263	2.79	1.069	.066
Ease of Use (MCI 7)	Married	210	3.57	1.161	.080
	Unmarried	263	3.74	1.035	.064
Lack of Knowledge (MCI 8)	**Married**	**210**	**2.48**	1.309	.090
	Unmarried	**263**	**2.24**	1.088	.067

(Source: Researcher's Computation)

The research investigated how marital status influences consumers' intentions regarding the use of mobile commerce among individuals. The analysis of the independent samples test provides several key findings:

Private and Confidential (MCI 1): There is a statistically significant difference between married and unmarried consumers ($t = -2.611$, $p = 0.009$), with unmarried consumers rating

the privacy and confidentiality of mobile commerce higher (mean = 3.31) than married consumers (mean = 3.04). This suggests that privacy concerns may be more prominent among married individuals.

a. **Safety (MCI 3):** The results indicate a significant difference (t = -2.217, p = 0.027), with unmarried consumers perceiving mobile commerce as safer (mean = 3.50) compared to married consumers (mean = 3.29). This might be due to higher confidence in technology security among the younger, unmarried demographic.
b. **Economical (MCI 4):** The difference is significant (t = -2.709, p = 0.007), with unmarried consumers finding mobile commerce more economical (mean = 3.77) than married consumers (mean = 3.49). Unmarried individuals may have greater price sensitivity and awareness of cost-saving benefits.
c. **Bad Past Experience (MCI 5):** There is a significant difference (t = -2.089, p = 0.037), with unmarried consumers reporting fewer bad past experiences (mean = 2.54) compared to married consumers (mean = 2.34). This could indicate that married consumers have encountered more issues with mobile commerce, possibly due to higher usage rates.
d. **Lack of Knowledge (MCI 8):** A significant difference exists (t = 2.111, p = 0.035), with married consumers reporting a greater lack of knowledge about mobile commerce (mean = 2.48) compared to unmarried consumers (mean = 2.24). This suggests that unmarried individuals might be more technologically savvy or better informed about mobile commerce.

Other variables such as "Convenience" (MCI 2), "Recommendation" (MCI 6), and "Ease of Use" (MCI 7) showed no statistically significant differences between married and unmarried consumers.

❖ **Managerial Implications:**

The findings provide several important implications for businesses and policymakers aiming to enhance mobile commerce adoption among different demographic segments:

a. **Enhanced Privacy Measures:** Given the significant concern for privacy among married consumers, businesses should focus on enhancing and communicating robust privacy and confidentiality measures. Transparent data handling policies and secure transaction processes can help address these concerns.

b. **Safety Assurance Campaigns:** Unmarried consumers perceive mobile commerce as safer than married consumers. To bridge this perception gap, businesses should implement safety assurance campaigns that highlight security features and educate married consumers on how their data is protected.
c. **Cost-Saving Promotions:** Since unmarried consumers find mobile commerce more economical, targeted marketing campaigns highlighting discounts, offers, and cost-saving opportunities can appeal to this demographic. For married consumers, emphasizing value for money and long-term savings could be more effective.
d. **Addressing Past Experience:** To mitigate the impact of bad past experiences reported more frequently by married consumers, businesses should focus on improving customer service, providing easy resolution processes, and ensuring reliable and consistent performance of their mobile commerce platforms.
e. **Educational Initiatives:** The lack of knowledge reported by married consumers suggests a need for educational initiatives. These could include tutorials, workshops, and informational campaigns that simplify the use of mobile commerce and increase digital literacy among this group.
f. **Tailored User Experience:** While ease of use is not significantly different between the groups, businesses should continuously refine the user experience to cater to both married and unmarried consumers. Simplified navigation, intuitive design, and personalized support can enhance user satisfaction across the board.

❖ **Attitudes towards Technology Adoption:**

- Venkatesh et.al, (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.
- This study discusses the influence of demographic variables, including gender, on technology acceptance, highlighting potential differences in attitudes between males and females.

❖ **Subjective Norms and Demographics:**

- Fishbein et.al (1975). Belief, attitude, intention, and behaviour: An introduction to theory and research. Addison-Wesley.
- This work explains how subjective norms, influenced by demographic factors such as gender, shape intentions and behaviours.

❖ **Perceived Behavioural Control and Demographics:**

- Taylor, S., & Todd, P.A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144-176.
- This study explores the impact of demographic factors, including gender, on perceived behavioural control over technology usage.

❖ **Intention to Use Technology:**

- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.
- This research highlights how demographic variables, particularly gender, can influence the intention to use new technologies, providing a basis for understanding gender differences in m-commerce adoption.

These hypotheses aim to identify and measure the differences between male and female consumers regarding their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce. By testing these hypotheses, the research will contribute to a deeper understanding of gender-based differences in m-commerce adoption, which can inform targeted marketing and policy strategies.

H3d: There is no statistically significant difference between consumers 'Age' and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.26: ANOVA-Age

Age							
ANOVA							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Subjective Norm	Between Groups	8.195	3	2.732	2.035	0.108	
	Within Groups	629.433	469	1.342			
	Total	637.628	472				Non Significant
Perceived Behaviour Control	Between Groups	2.435	3	0.812	2.254	0.081	
	Within Groups	168.882	469	0.360			
	Total	171.318	472				Non Significant

Attitude	**Between Groups**	**4.310**	**3**	**1.437**	**4.289**	**0.005**	
	Within Groups	**157.108**	**469**	**0.335**			
	Total	**161.418**	**472**				**Significant**
Intention	**Between Groups**	**22.562**	**3**	**7.521**	**22.366**	**0.000**	
	Within Groups	157.701	469	0.336			
	Total	180.263	472				**Significant**

(Source: Researcher's Computation)

The p-value for Subjective Norm is 0.108, which is greater than the common significance level of 0.05. This suggests that there is no statistically significant difference in the means of Subjective Norm across the different age groups.

The p-value for Perceived Behaviour Control is 0.081, which is also greater than 0.05. Therefore, there is no statistically significant difference in the means of Perceived Behaviour Control across the different age groups.

The p-value for Attitude is 0.005, which is less than 0.05. This indicates that there is a statistically significant difference in the means of Attitude across the different age groups.

The p-value for Intention is 0.000, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Intention across the different age groups.

Summary:

- **Subjective Norm** and **Perceived Behaviour Control** do not show significant differences across age groups.
- **Attitude** and **Intention** show significant differences across age groups, indicating that these factors are affected by age.

Table 4.27: Age and Attitude-Intention

		Mean	Std. Deviation
Less than 20 years	Intention	3.1503	.57003
	Attitude	3.0876	.60327

21 to 40 years	Intention	3.2694	.57934
	Attitude	3.1181	.61179
41 to 60 years	Intention	3.1892	.59308
	Attitude	3.1803	.54236
61 years and above	Intention	2.5027	.57160
	Attitude	2.8232	.42368

(Source: Researcher's Computation)

The table provides the mean and standard deviation of two key variables, intention and attitude, across four different age groups.

❖ **Interpretation:**

a. Less than 20 years:

- **Intention:** Mean = 3.1503, Std. Deviation = 0.57003
- **Attitude:** Mean = 3.0876, Std. Deviation = 0.60327

This age group shows moderate intention and attitude towards mobile commerce (m-commerce), with both means slightly above 3 on a 5-point scale. The standard deviations indicate moderate variability in responses.

b. 21 to 40 years:

- **Intention:** Mean = 3.2694, Std. Deviation = 0.57934
- **Attitude:** Mean = 3.1181, Std. Deviation = 0.61179

The 21 to 40 years age group has the highest mean intention among all groups, suggesting a relatively strong inclination towards m-commerce. The mean attitude is also slightly higher than in the younger group, indicating generally positive attitudes towards m-commerce.

c. 41 to 60 years:

- **Intention:** Mean = 3.1892, Std. Deviation = 0.59308
- **Attitude:** Mean = 3.1803, Std. Deviation = 0.54236

For the 41 to 60 years age group, the means for both intention and attitude are slightly lower than the 21 to 40 years group but still indicate moderate levels of

both variables. This group has the lowest variability in attitude, suggesting more consistent attitudes within this age group.

d. 61 years and above:

- **Intention:** Mean = 2.5027, Std. Deviation = 0.57160
- **Attitude:** Mean = 2.8232, Std. Deviation = 0.42368

The oldest age group shows the lowest mean intention to use m-commerce, indicating relatively low interest or inclination. The mean attitude is also lower than the younger groups, though not as low as the mean intention. This group has the lowest variability in attitude, suggesting consistent attitudes towards m-commerce.

❖ **Targeted Marketing Strategies:**

- **Young Adults (21 to 40 years):** This group shows the highest intention and positive attitude towards m-commerce. Marketing strategies should focus on enhancing user experience, offering personalized promotions, and leveraging social media and digital marketing channels to engage this demographic effectively (Chaffey & Ellis-Chadwick, 2019).
- **Teenagers (Less than 20 years):** Although this group has a moderate intention and attitude, they represent a potential future market. Businesses should focus on building brand loyalty through interactive and engaging content, gamification, and social media presence (Smith, 2019).

❖ **Older Adults (41 to 60 years):**

- This group has a moderate intention and attitude towards m-commerce. Strategies should include highlighting the convenience and security of m-commerce, possibly through educational campaigns and testimonials from satisfied customers. Simplifying the user interface can also help increase adoption among this age group (Mclean et al., 2020).

❖ **Senior Citizens (61 years and above):**

- With the lowest intention and attitude scores, this group may require more convincing about the benefits of m-commerce. Businesses should consider offering detailed guides, customer support, and simplified purchasing processes to help this demographic feel more comfortable with m-commerce platforms (Venkatesh,

Thong, & Xu, 2012). Addressing security concerns and providing guarantees could also help improve their attitude and intention to use m-commerce.

- **Consistency in Attitude:**
  - The relatively consistent attitudes within the 41 to 60 and 61+ age groups suggest that once convinced, these groups could become loyal users. Businesses should focus on building trust and reliability in their m-commerce services to retain these customers (Gefen, Karahanna, & Straub, 2003).

- **Product and Service Customization:**
  - Understanding the distinct preferences and behaviors of each age group can help businesses tailor their product offerings and services. For instance, tech-savvy products and trendy items may appeal more to younger users, while essential services and easy-to-use interfaces might be more attractive to older consumers (Rogers, 2003).

In summary analysis indicates that younger age groups, particularly those between 21 and 40 years, show higher intention and positive attitudes towards m-commerce, suggesting a greater readiness to adopt and engage with mobile shopping. In contrast, older age groups exhibit lower intention and more negative attitudes, highlighting the need for targeted interventions to improve their perception and usage of m-commerce. Businesses should develop age-specific strategies to address these differences, ensuring broader adoption and satisfaction across all age demographics.

Table 4.28: ANOVA between Age Group and Attitude and Intention.

ANOVA between Age Group							
Attitude							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Reasonably Priced Products (Att 1)	**Between Groups**	**8.900**	**3**	**2.967**	**3.898**	**.009**	Significant
	Within Groups	**356.973**	**469**	**.761**			
	Total	**365.873**	**472**				

Prompt Customer Service (Att 2)	**Between Groups**	**9.633**	**3**	**3.211**	**4.230**	**.006**	Significant
	Within Groups	**356.058**	**469**	**.759**			
	Total	**365.691**	**472**				
Physical Shopping Experience (Att 3)	Between Groups	3.315	3	1.105	1.476	.220	Non Significant
	Within Groups	351.074	469	.749			
	Total	354.389	472				
Shopping Convenience (Att 4)	**Between Groups**	**6.276**	**3**	**2.092**	**2.720**	**.044**	Significant
	Within Groups	**360.675**	**469**	**.769**			
	Total	**366.951**	**472**				
Safe & Secure (Att 5)	**Between Groups**	**36.146**	**3**	**12.049**	**10.845**	**.000**	Significant
	Within Groups	**521.034**	**469**	**1.111**			
	Total	**557.180**	**472**				
Unsafe without Technological Knowledge (Att 6)	Between Groups	5.501	3	1.834	2.387	.068	Non Significant
	Within Groups	360.283	469	.768			
	Total	365.784	472				
Unreliable Review (Att 7)	**Between Groups**	**22.748**	**3**	**7.583**	**6.642**	**.000**	Significant
	Within Groups	**535.438**	**469**	**1.142**			
	Total	**558.186**	**472**				
User Friendly (Att 8)	**Between Groups**	**22.843**	**3**	**7.614**	**9.754**	**.000**	Significant
	Within Groups	**366.104**	**469**	**.781**			
	Total	**388.947**	**472**				

Shopping Addiction (Att 9)	**Between Groups**	**41.870**	**3**	**13.957**	**8.998**	**.000**	Significant
	Within Groups	**727.449**	**469**	**1.551**			
	Total	**769.319**	**472**				
Privacy (Att 10)	**Between Groups**	**7.055**	**3**	**2.352**	**2.932**	**.033**	Significant
	Within Groups	**376.100**	**469**	**.802**			
	Total	**383.154**	**472**				
Intention							
Private and Confidential (MCI 1)	**Between Groups**	**61.951**	**3**	**20.650**	**17.580**	**.000**	Significant
	Within Groups	**550.924**	**469**	**1.175**			
	Total	**612.875**	**472**				
Convenience (MCI 2)	**Between Groups**	**94.826**	**3**	**31.609**	**32.248**	**.000**	Significant
	Within Groups	**459.699**	**469**	**.980**			
	Total	**554.524**	**472**				
Safety (MCI 3)	**Between Groups**	**63.602**	**3**	**21.201**	**22.281**	**.000**	Significant
	Within Groups	**446.271**	**469**	**.952**			
	Total	**509.873**	**472**				
Economical (MCI 4)	**Between Groups**	**93.176**	**3**	**31.059**	**29.537**	**.000**	Significant
	Within Groups	**493.154**	**469**	**1.052**			
	Total	**586.330**	**472**				
Bad Past Experience (MCI 5)	Between Groups	7.258	3	2.419	2.425	.065	Non Significant
	Within Groups	467.825	469	.997			

	Total	475.082	472				
Recommendation (MCI 6)	**Between Groups**	**13.826**	**3**	**4.609**	**3.986**	**.008**	Significant
	Within Groups	**542.234**	**469**	**1.156**			
	Total	**556.059**	**472**				
Ease of Use (MCI 7)	**Between Groups**	**83.555**	**3**	**27.852**	**27.101**	**.000**	Significant
	Within Groups	**481.997**	**469**	**1.028**			
	Total	**565.552**	**472**				
Lack of Knowledge (MCI 8)	**Between Groups**	**133.514**	**3**	**44.505**	**38.537**	**.000**	Significant
	Within Groups	**541.623**	**469**	**1.155**			
	Total	**675.137**	**472**				

(Source: Researcher's Computation)

- **Interpretation by Attribute:**

The research examined how age groups influence consumers' attitudes and intentions regarding the use of mobile commerce in Goa. The analysis was conducted using ANOVA, and the results highlight significant differences across various constructs:

a. **Reasonably Priced Products (Att 1):** Significant differences were found between age groups ($F = 3.898$, $p = 0.009$). This indicates that perceptions of product pricing in mobile commerce vary significantly with age.
b. **Prompt Customer Service (Att 2):** Age groups show significant differences ($F = 4.230$, $p = 0.006$), suggesting that the expectation of customer service speed differs across age groups.
c. **Shopping Convenience (Att 4):** Significant differences were observed ($F = 2.720$, $p = 0.044$), indicating that convenience in mobile commerce is perceived differently across age groups.
d. **Safe & Secure (Att 5):** There is a highly significant difference ($F = 10.845$, $p < 0.001$), showing that age groups vary greatly in their perceptions of safety and security in mobile commerce.

e. **Unreliable Review (Att 7):** Significant differences were found ($F = 6.642$, $p < 0.001$), suggesting age-related variations in trust in online reviews.
f. **User Friendly (Att 8):** The results show significant differences ($F = 9.754$, $p < 0.001$), indicating that user-friendliness of mobile commerce platforms is perceived differently by various age groups.
g. **Shopping Addiction (Att 9):** Significant differences were found ($F = 8.998$, $p < 0.001$), suggesting that the tendency for shopping addiction varies with age.
h. **Privacy (Att 10):** There are significant differences between age groups ($F = 2.932$, $p = 0.033$), indicating that privacy concerns vary with age.
i. **Private and Confidential (MCI 1):** Highly significant differences were observed ($F = 17.580$, $p < 0.001$), showing that age impacts perceptions of privacy and confidentiality in mobile commerce.
j. **Convenience (MCI 2):** Significant differences were found ($F = 32.248$, $p < 0.001$), indicating that convenience in mobile commerce is perceived differently by different age groups.
k. **Safety (MCI 3):** Significant differences were observed ($F = 22.281$, $p < 0.001$), suggesting age-related variations in perceptions of safety.
l. **Economical (MCI 4):** There are significant differences ($F = 29.537$, $p < 0.001$), indicating that the perceived economic benefits of mobile commerce vary across age groups.
m. **Recommendation (MCI 6):** Significant differences were found ($F = 3.986$, $p = 0.008$), suggesting age-related variations in the impact of recommendations on mobile commerce usage.
n. **Ease of Use (MCI 7):** Significant differences were observed ($F = 27.101$, $p < 0.001$), indicating that perceptions of ease of use vary with age.
o. **Lack of Knowledge (MCI 8):** Highly significant differences were found ($F = 38.537$, $p < 0.001$), suggesting that the perceived lack of knowledge about mobile commerce varies significantly across age groups.

❖ **Managerial Implications:**

The findings offer actionable insights for businesses and policymakers aiming to enhance mobile commerce adoption among different age groups in Goa:

a. **Tailored Pricing Strategies:** Since perceptions of reasonably priced products vary by age, businesses should consider age-specific pricing strategies and promotions to cater to the unique needs of each age group.
b. **Customized Customer Service:** Given the differing expectations of prompt customer service, businesses should tailor their customer support approaches to meet the specific demands of various age groups.
c. **Enhancing Convenience:** To address varying perceptions of shopping convenience, companies should optimize their mobile commerce platforms to be user-friendly for all age groups, perhaps offering features that cater to both tech-savvy younger users and older, less technologically adept users.
d. **Safety and Security Communication:** With significant age-related differences in perceptions of safety, businesses should emphasize security features and ensure clear communication about safety protocols to inculcate confidence in users of all ages.
e. **Building Trust in Reviews:** Since trust in online reviews varies with age, businesses should focus on generating authentic and reliable reviews and perhaps implement age-specific review verification methods.
f. **Improving User Experience:** The perception of user-friendliness differs across age groups, so businesses should continuously improve the user experience to cater to the diverse technological proficiencies of different age segments.
g. **Addressing Shopping Addiction:** With variations in shopping addiction tendencies, businesses should promote responsible shopping habits and offer tools for users to manage their shopping behaviour.
h. **Privacy Measures:** Since privacy concerns differ with age, businesses should ensure robust privacy measures and communicate them effectively to build trust among users of all ages.

i. **Personalized Marketing:** The significant differences in perceptions of mobile commerce convenience, economic benefits, and ease of use suggest that personalized marketing strategies targeting specific age groups could be more effective.
j. **Educational Initiatives:** Given the significant differences in the perceived lack of knowledge, especially among older age groups, businesses should implement educational initiatives to improve digital literacy and awareness about mobile commerce.

❖ **Citation of Previous Research:**

a. Attitudes towards Technology Adoption:

- Venkatesh et.al, (2003) study discusses how demographic variables, such as age, influence technology acceptance, supporting the finding that different age groups perceive mobile commerce differently.

b. Subjective Norms and Demographics:

- Fishbein, M., & Ajzen, I. (1975) work highlighted how demographic factors shape subjective norms and behaviour, relevant to understanding differences in mobile commerce adoption across age groups.

By leveraging these insights, businesses and policymakers can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of various age groups in Goa.

Summary: There are significant differences between age groups for most attributes and intention concerns, indicating that age influences shopping attitudes and intention. The attributes with the highest F-values, such as Safety (MCI 3) and Lack of Knowledge (MCI 8), show particularly strong differences across age groups. Conversely, some factors like Physical Shopping Experience (Att 3) and Unsafe without Technological Knowledge (Att 6) show no significant differences, suggesting that these concerns are relatively consistent across different age groups.

H3e: There is no statistically significant difference between 'Educational level' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.29: ANOVA-Education

Education							
ANOVA							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Attitude	**Between Groups**	**18.204**	**4**	**4.551**	**3.438**	**0.009**	**Significant**

	Within Groups	619.424	468	1.324			
	Total	637.628	472				
Perceived Behaviour Control	Between Groups	0.660	4	0.165	0.452	0.771	
	Within Groups	170.658	468	0.365			Non Significant
	Total	171.318	472				
Subjective Norms	Between Groups	2.853	4	0.713	2.105	0.079	
	Within Groups	158.565	468	0.339			Non Significant
	Total	161.418	472				
Intention	**Between Groups**	**7.864**	**4**	**1.966**	**5.337**	**0.000**	
	Within Groups	172.399	468	0.368			
	Total	180.263	472				**Significant**

(Source: Researcher's Computation)

The p-value for Subjective Norm is 0.009, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Subjective Norm across the different education levels.

The p-value for Perceived Behavioural Control is 0.771, which is greater than 0.05. This indicates that there is no statistically significant difference in the means of Perceived Behavioural Control across the different education levels.

The p-value for Attitude is 0.079, which is greater than 0.05. Therefore, there is no statistically significant difference in the means of Attitude across the different education levels.

The p-value for Intention is 0.000, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Intention across the different education levels.

Summary:

- **Subjective Norm** and **Intention** show significant differences across education levels.
- **Perceived Behavioural Control** and **Attitude** do not show significant differences across education levels.

Table 4.30: ANOVA and Educational level

ANOVA and Education level							
Intention							
		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**	**Findings**
Peer Influence (SN 1)	Between Groups	18.659	4	4.665	3.549	.007	Significant
	Within Groups	615.108	468	1.314			
	Total	633.767	472				
Peer Recommendations(SN 2)	Between Groups	17.295	4	4.324	3.250	.012	Significant
	Within Groups	622.671	468	1.330			
	Total	639.966	472				
Peer Opinions(SN 3)	Between Groups	19.027	4	4.757	3.569	.007	Significant
	Within Groups	623.768	468	1.333			
	Total	642.795	472				
Social Media Influence (SN 4)	Between Groups	17.752	4	4.438	3.274	.012	Significant
	Within Groups	634.455	468	1.356			
	Total	652.207	472				
Personal Preference (SN 5)	Between Groups	19.986	4	4.997	3.908	.004	Significant
	Within Groups	598.293	468	1.278			
	Total	618.279	472				
External Influence (SN 6)	Between Groups	14.682	4	3.670	2.424	.047	Significant
	Within Groups	708.638	468	1.514			
	Total	723.319	472				
Attitude							
Reasonably Priced Products (Att 1)	Between Groups	6.894	4	1.724	2.247	.063	Non Significant
	Within Groups	358.979	468	.767			
	Total	365.873	472				
Prompt Customer Service (Att 2)	Between Groups	7.032	4	1.758	2.294	.058	Non Significant
	Within Groups	358.659	468	.766			
	Total	365.691	472				
Physical Shopping Experience (Att 3)	Between Groups	9.537	4	2.384	3.236	.012	Significant
	Within Groups	344.852	468	.737			
	Total	354.389	472				

Shopping Convenience (Att 4)	Between Groups	6.969	4	1.742	2.265	.061	Non Significant
	Within Groups	359.982	468	.769			
	Total	366.951	472				
Safe & Secure (Att 5)	Between Groups	5.648	4	1.412	1.198	.311	Non Significant
	Within Groups	551.532	468	1.178			
	Total	557.180	472				
Unsafe without Technological Knowledge (Att 6)	Between Groups	1.696	4	.424	.545	.703	Non Significant
	Within Groups	364.088	468	.778			
	Total	365.784	472				
Unreliable Review (Att 7)	Between Groups	16.653	4	4.163	3.598	.007	Significant
	Within Groups	541.533	468	1.157			
	Total	558.186	472				
User Friendly (Att 8)	Between Groups	6.654	4	1.664	2.036	.088	Non Significant
	Within Groups	382.293	468	.817			
	Total	388.947	472				
Shopping Addiction (Att 9)	Between Groups	29.249	4	7.312	4.624	.001	Significant
	Within Groups	740.071	468	1.581			
	Total	769.319	472				
Privacy (Att 10)	Between Groups	2.532	4	.633	.778	.540	Non Significant
	Within Groups	380.622	468	.813			
	Total	383.154	472				

(Source: Researcher's Computation)

- **Impact of educational level on consumer's attitudes and subjective norms towards mobile commerce using ANOVA:** The results indicate significant differences across various constructs, demonstrating how education influences these factors.
- **Peer Influence (SN 1):** Significant differences were observed ($F = 3.549$, $p = 0.007$), indicating that the influence of peers on mobile commerce adoption varies significantly with education level.

- **Peer Recommendations (SN 2):** Significant differences were found (F = 3.250, p = 0.012), suggesting that the impact of peer recommendations differs across educational groups.

- **Peer Opinions (SN 3):** There are significant differences (F = 3.569, p = 0.007), showing that educational levels influence how peer opinions affect mobile commerce behavior.

- **Social Media Influence (SN 4):** Significant differences were observed (F = 3.274, p = 0.012), indicating that the influence of social media on mobile commerce adoption varies with education level.

- **Personal Preference (SN 5):** The results show significant differences (F = 3.908, p = 0.004), suggesting that personal preferences in mobile commerce are influenced by education level.

- **External Influence (SN 6):** Significant differences were found (F = 2.424, p = 0.047), indicating that external influences on mobile commerce usage vary across educational levels.

- **Physical Shopping Experience (Att 3):** Significant differences were observed (F = 3.236, p = 0.012), showing that the perceived importance of physical shopping experiences varies with education level.

- **Unreliable Review (Att 7):** Significant differences were found (F = 3.598, p = 0.007), suggesting that educational levels influence trust in online reviews.

- **Shopping Addiction (Att 9):** The results show significant differences (F = 4.624, p = 0.001), indicating that the tendency for shopping addiction varies with education level.

❖ **Managerial Implications:**

The findings provide crucial insights for businesses and policymakers aiming to enhance mobile commerce adoption by targeting different educational groups in Goa:

a. **Peer Influence Strategies:** Since peer influence varies with education, businesses should tailor their marketing strategies to leverage peer recommendations and opinions effectively. For instance, educational campaigns and testimonials can be designed to resonate more with specific educational groups.
b. **Social Media Marketing:** With significant differences in social media influence, businesses should develop targeted social media campaigns that cater to the preferences and behaviours of different educational groups.
c. **Educational Content:** Businesses should create educational content that addresses the specific concerns and preferences of various educational levels, thereby enhancing the perceived value and trustworthiness of mobile commerce platforms.

d. **Personalized User Experience:** Given the differences in personal preferences and physical shopping experiences, businesses should focus on providing personalized user experiences that cater to the unique needs of different educational groups.

e. **Trust Building Initiatives:** With varying trust in online reviews, companies should implement trust-building initiatives such as verified reviews and transparent customer feedback mechanisms to cater to the different levels of scepticism among educational groups.

f. **Addressing Shopping Addiction:** The significant differences in shopping addiction tendencies suggest that businesses should promote responsible shopping habits and provide tools for users to manage their shopping behaviour, especially targeting educational groups that show higher tendencies towards shopping addiction.

g. **Targeted External Influence:** Understanding that external influences vary with education, businesses should tailor their external influence strategies, such as endorsements and collaborations, to appeal to different educational segments.

❖ **Citations of Previous Research:**

a. Impact of Education on Technology Adoption:

- Rogers, E.M. (2003) discussed how educational levels influence the adoption of innovations, supporting the finding that education significantly affects mobile commerce adoption.

b. Subjective Norms and Educational Influence:

- Ajzen, I. (1991) highlighted the role of subjective norms in shaping behaviour, relevant to understanding how educational levels influence subjective norms in mobile commerce adoption.

By leveraging these insights, businesses and policymakers can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of different educational groups in Goa.

Summary: The ANOVA analysis shows significant differences in social norms and attitude towards mobile commerce based on education levels. Attributes like Peer Influence (SN 1), Peer Opinions (SN 3), and Personal Preference (SN 5) show notable differences between groups, suggesting that education level significantly affects these perceptions. On the other hand, attributes like Safe & Secure (Att 5), Unsafe without Technological Knowledge (Att 6), and Privacy (Att 10) do not show significant differences, indicating these concerns are consistent across different education levels.

Table 4.31: Education and Subjective Norms-Intention

Education		Mean	Std. Deviation
Up to HSSC	Subjective Norms	2.3021	1.04260
	Intention	2.9549	.65793
Graduation	Subjective Norms	2.4240	1.13780
	Intention	3.1551	.59302
Post-Graduation and above	Subjective Norms	2.3502	1.24559
	Intention	3.2953	.55140
Professional	Subjective Norms	2.1076	1.28300
	Intention	3.2554	.69339
Others	Subjective Norms	3.1230	1.06627
	Intention	3.1920	.64324

(Source: Researcher's Computation)

The table presents descriptive statistics for subjective norms and intention to use mobile commerce (m-commerce) across different education levels. The variables include the mean and standard deviation for subjective norms and intention for each education category.

Interpretation:

a. **Up to HSSC (Higher Secondary School Certificate):**

- **Subjective Norms:** Mean = 2.3021, Std. Deviation = 1.04260
- **Intention:** Mean = 2.9549, Std. Deviation = 0.65793

Explanation: Individuals with education up to HSSC have relatively low subjective norms (mean = 2.3021) and a moderate intention to use m-commerce (mean = 2.9549).

b. **Graduation:**

- **Subjective Norms:** Mean = 2.4240, Std. Deviation = 1.13780
- **Intention:** Mean = 3.1551, Std. Deviation = 0.59302

Explanation: Graduates exhibit slightly higher subjective norms (mean = 2.4240) and intention (mean = 3.1551) compared to those with up to HSSC education.

c. **Post-Graduation and Above:**

- **Subjective Norms:** Mean = 2.3502, Std. Deviation = 1.24559
- **Intention:** Mean = 3.2953, Std. Deviation = 0.55140

Explanation: Individuals with post-graduation or higher education have a mean subjective norm of 2.3502 and the highest intention to use m-commerce (mean = 3.2953) among all groups.

d. **Professional:**

- **Subjective Norms:** Mean = 2.1076, Std. Deviation = 1.28300
- **Intention:** Mean = 3.2554, Std. Deviation = 0.69339

Explanation: Professionals show the lowest subjective norms (mean = 2.1076) but a high intention to use m-commerce (mean = 3.2554).

e. **Others:**

- **Subjective Norms:** Mean = 3.1230, Std. Deviation = 1.06627
- **Intention:** Mean = 3.1920, Std. Deviation = 0.64324

Explanation: This group has the highest subjective norms (mean = 3.1230) and a relatively high intention to use m-commerce (mean = 3.1920).

Managerial Implications:

a. **Tailoring Marketing Strategies:**

- **For Less Educated Segments (Up to HSSC):** The relatively low subjective norms and moderate intention indicate a need for marketing campaigns that build social influence and emphasize the benefits of m-commerce. Testimonials and endorsements from trusted sources could be effective (Ajzen, 1991).
- **For Graduates and Post-Graduates:** These groups exhibit higher intentions to use m-commerce. Marketing efforts should focus on advanced features, convenience, and security to appeal to their higher educational background and potentially higher technological proficiency (Davis, 1989).

b. **Enhancing Professional Engagement:**

- **Professionals:** Despite having the lowest subjective norms, professionals show high intention to use m-commerce. Targeting this segment with professional-oriented benefits such as time-saving features, exclusive offers, and productivity-enhancing tools can further increase their engagement (Venkatesh et. al,2003).

c. **Leveraging Social Influence:**

- **Other Educational Categories:** The group labelled 'Others' has the highest subjective norms, suggesting that social influence plays a significant role in their intention to use m-commerce. Leveraging social proof, community-driven content, and peer reviews can enhance m-commerce adoption within this group (Bandura, 1986).

d. **Education-Specific Campaigns:**

- Developing education-specific marketing campaigns can help in addressing the unique needs and perceptions of each educational group. For instance, less educated segments may benefit from more educational content about the benefits and safety of m-commerce, while more educated groups might appreciate detailed information

on privacy policies and advanced functionalities (Gefen, Karahanna, & Straub, 2003).

e. **Focus on Ease of Use and Reliability:**

- Across all educational levels, ensuring that m-commerce platforms are easy to use and reliable can help in enhancing both subjective norms and intention to use m-commerce. Simplifying the user interface and providing robust customer support can address potential barriers to adoption (Rogers, 2003).

In summary analysis highlights significant differences in subjective norms and intention to use m-commerce across various educational levels. Understanding these differences can help businesses develop targeted strategies that address the specific needs and preferences of each group. By focusing on social influence, tailored marketing campaigns, and improving ease of use and reliability, businesses can enhance m-commerce adoption and usage across all educational segments.

H3f: There is no statistically significant difference between 'Occupation' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.32: ANOVA-Occupation

Occupation							
ANOVA							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Subjective Norm	Between Groups	7.289	4	1.822	1.353	0.249	
	Within Groups	630.339	468	1.347			
	Total	637.628	472				Non Significant
Perceived Behaviour Control	Between Groups	1.618	4	0.404	1.115	0.349	
	Within Groups	169.700	468	0.363			
	Total	171.318	472				Non Significant
Attitude	Between Groups	2.981	4	0.745	2.201	0.068	
	Within Groups	158.437	468	0.339			
	Total	161.418	472				Non Significant
Intention	**Between Groups**	**6.959**	**4**	**1.740**	**4.698**	**0.001**	**Significant**

	Within Groups	**173.305**	**468**	**0.370**			
	Total	**180.263**	**472**				

(Source: Researcher's Computation)

The p-value for Subjective Norm is 0.249, which is greater than 0.05. This suggests that there is no statistically significant difference in the means of Subjective Norm across the different occupation groups.

The p-value for Perceived Behavioural Control is 0.349, which is greater than 0.05. This indicates that there is no statistically significant difference in the means of Perceived Behavioural Control across the different occupation groups.

The p-value for Attitude is 0.068, which is slightly greater than 0.05. This suggests that there is no statistically significant difference in the means of Attitude across the different occupation groups, although it is close to the threshold.

The p-value for Intention is 0.001, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Intention across the different occupation groups.

Summary:

- **Subjective Norm** and **Perceived Behavioural Control** do not show significant differences across occupation groups.
- **Attitude** is not significantly different across occupation groups, but it is close to the significance threshold.
- **Intention** shows significant differences across occupation groups.

Table 4.33: Occupation And Intention Statistics

Occupation		Mean	Std. Deviation
Unemployed	Intention	3.2141	.57742
Service	Intention	3.1791	.62127
Business	Intention	3.1818	.52475
Home Maker	Intention	2.9306	.74728
Retired	Intention	2.6964	.67265

(Source: Researcher's Computation)

The table presents descriptive statistics for the intention to use mobile commerce (m-commerce) across different occupational groups. The variables include the mean and standard deviation for intention for each occupation category.

❖ **Interpretation:**

a. Unemployed:

- **Intention:** Mean = 3.2141, Std. Deviation = 0.57742

- The unemployed group shows a relatively high intention to use m-commerce with a mean of 3.2141, indicating a favourable disposition towards m-commerce. The standard deviation of 0.57742 suggests moderate variability in responses.

b. Service:

- **Intention:** Mean = 3.1791, Std. Deviation = 0.62127
- Individuals in service occupations also show a high intention to use m-commerce, with a mean of 3.1791. The standard deviation of 0.62127 indicates moderate variability in their responses.

c. Business:

- **Intention:** Mean = 3.1818, Std. Deviation = 0.52475
- Business professionals have a high intention to use m-commerce, with a mean intention of 3.1818. The standard deviation of 0.52475 suggests relatively consistent responses within this group.

d. Home Maker:

- **Intention:** Mean = 2.9306, Std. Deviation = 0.74728
- Homemakers have a lower intention to use m-commerce compared to unemployed, service, and business groups, with a mean of 2.9306. The standard deviation of 0.74728 indicates higher variability in responses.

e. Retired:

- **Intention:** Mean = 2.6964, Std. Deviation = 0.67265
- Retired individuals show the lowest intention to use m-commerce with a mean of 2.6964. The standard deviation of 0.67265 suggests moderate variability in their responses.

❖ **Managerial Implications:**

a. Targeted Marketing Strategies:

- **High Intention Groups (Unemployed, Service, and Business):** These groups exhibit the highest intention to use m-commerce. Marketing strategies should focus on highlighting the convenience, efficiency, and variety of products available through m-commerce. Offering personalized promotions, loyalty programs, and easy-to-navigate interfaces can further increase engagement among these groups (Chaffey & Ellis-Chadwick, 2019).

b. Engagement Strategies for Homemakers:

- The lower intention among homemakers suggests a need for tailored marketing approaches. Emphasizing the convenience of shopping from home, providing special offers for household products, and creating content that resonates with their daily needs can help boost their intention to use m-commerce (Smith, 2019).

c. Addressing Concerns of Retired Individuals:

- The retired group shows the lowest intention to use m-commerce. To increase adoption, businesses should focus on addressing their specific concerns such as security, ease of use, and trust. Providing educational resources, simplified interfaces, and customer support specifically designed for older adults can help alleviate apprehensions and encourage usage (Venkatesh, Thong, & Xu, 2012).

d. Consistency in Business and Service Occupations:

- The relatively consistent intention scores within the business and service occupations suggest that once convinced, these groups can become reliable and frequent users of m-commerce. Efforts to maintain high levels of satisfaction through consistent quality, reliability, and customer service will be crucial (Gefen, Karahanna, & Straub, 2003).

e. Personalized User Experience:

- Understanding the distinct preferences and behaviours of each occupational group can help businesses tailor their product offerings and services. For instance, business professionals might value efficiency and productivity-enhancing tools, while service professionals might appreciate flexible delivery options and time-saving features (Rogers, 2003).

f. Utilizing Social Influence:

- Leveraging social proof and testimonials from peers within each occupational category can enhance trust and perceived value of m-commerce. Peer recommendations and user-generated content can be particularly effective in influencing intention among undecided users (Bandura, 1986).

In summary analysis indicates that different occupational groups exhibit varying levels of intention to use m-commerce. Understanding these differences allows businesses to develop targeted strategies that address the specific needs and preferences of each group. By focusing on convenience, security, and personalized user experiences, businesses can enhance m-commerce adoption and satisfaction across all occupational categories.

Table 4.34: ANOVA-Occupation

ANOVA and Different Occupation							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Private and Confidential (MCI 1)	**Between Groups**	**25.173**	**4**	**6.293**	**5.012**	**.001**	Significant
	Within Groups	**587.702**	**468**	**1.256**			
	Total	**612.875**	**472**				
Convenience (MCI 2)	**Between Groups**	**42.860**	**4**	**10.715**	**9.801**	**.000**	**Significant**
	Within Groups	**511.664**	**468**	**1.093**			
	Total	**554.524**	**472**				
Safety (MCI 3)	**Between Groups**	**20.084**	**4**	**5.021**	**4.798**	**.001**	**Significant**
	Within Groups	**489.789**	**468**	**1.047**			
	Total	**509.873**	**472**				
Economical (MCI 4)	**Between Groups**	**36.637**	**4**	**9.159**	**7.798**	**.000**	**Significant**
	Within Groups	549.693	468	1.175			
	Total	586.330	472				
Bad Past Experience (MCI 5)	Between Groups	2.621	4	.655	.649	.628	Non Significant
	Within Groups	472.462	468	1.010			
	Total	475.082	472				

Recommendation (MCI 6)	Between Groups	4.168	4	1.042	.884	.474	Non Significant
	Within Groups	551.891	468	1.179			
	Total	556.059	472				
Ease of Use (MCI 7)	**Between Groups**	**28.331**	**4**	**7.083**	**6.170**	**.000**	**Significant**
	Within Groups	537.221	468	1.148			
	Total	565.552	472				
Lack of Knowledge (MCI 8)	**Between Groups**	**70.161**	**4**	**17.540**	**13.569**	**.000**	**Significant**
	Within Groups	604.976	468	1.293			
	Total	675.137	472				

(Source: Researcher's Computation)

The analysis of variance (ANOVA) results indicates significant differences across various occupation levels regarding consumers' attitudes and subjective norms towards mobile commerce in Goa. Specifically, significant differences were observed in the following constructs:

a. **Private and Confidential (MCI 1):** Significant differences ($F = 5.012$, $p = 0.001$) indicate that concerns about privacy and confidentiality in mobile commerce vary significantly among different occupational groups.
b. **Convenience (MCI 2):** Significant differences ($F = 9.801$, $p = 0.000$) suggest that the perceived convenience of mobile commerce is significantly influenced by occupation.
c. **Safety (MCI 3):** Significant differences ($F = 4.798$, $p = 0.001$) show that perceptions of safety in mobile commerce vary across occupational groups.
d. **Economical (MCI 4):** Significant differences ($F = 7.798$, $p = 0.000$) indicate that the perceived economic benefits of mobile commerce differ among occupations.
e. **Ease of Use (MCI 7):** Significant differences ($F = 6.170$, $p = 0.000$) suggest that perceptions of the ease of use of mobile commerce vary across different occupations.
f. **Lack of Knowledge (MCI 8):** Significant differences ($F = 13.569$, $p = 0.000$) indicate that the perceived lack of knowledge about mobile commerce varies significantly among occupational groups.

No significant differences were found in the following constructs:

a. **Bad Past Experience (MCI 5):** No significant differences (F = 0.649, p = 0.628) were found, suggesting that past negative experiences with mobile commerce do not significantly vary across occupations.
b. **Recommendation (MCI 6):** No significant differences (F = 0.884, p = 0.474) indicate that the influence of recommendations on mobile commerce use is not significantly affected by occupation.

Summary:

The ANOVA analysis reveals significant differences in several intention concerns based on occupation levels. Specifically:

- **Private and Confidential (MCI 1)**, **Convenience (MCI 2)**, **Safety (MCI 3)**, **Economical (MCI 4)**, **Ease of Use (MCI 7)**, and **Lack of Knowledge (MCI 8)** show notable differences between groups, indicating that occupation level significantly affects these perceptions.

- **Bad Past Experience (MCI 5)** and **Recommendation (MCI 6)** do not show significant differences, suggesting that these concerns are relatively consistent across different occupation levels.

These results suggest that individuals' occupations significantly influence their shopping intentions and concerns in several areas, highlighting the importance of considering occupation when analyzing consumer behaviour towards mobile shopping.

❖ **Managerial Implications:**

Understanding the significant differences in mobile commerce perceptions across various occupational groups provides valuable insights for businesses and policymakers aiming to enhance mobile commerce adoption in Goa:

a. **Targeted Privacy Measures:** Since privacy concerns vary significantly among occupations, businesses should implement and communicate robust privacy and

confidentiality measures tailored to the specific needs of different occupational groups.

b. **Convenience Optimization:** Given the significant differences in perceived convenience, businesses should develop and promote features that enhance the convenience of mobile commerce, addressing the unique preferences and requirements of various occupational groups.
c. **Safety Assurance:** As safety perceptions differ across occupations, businesses should prioritize security features and clearly communicate these measures to different occupational segments to build trust and encourage adoption.
d. **Economic Benefits Communication:** Since perceptions of economic benefits vary, businesses should highlight the cost-effectiveness and value-for-money aspects of mobile commerce, targeting promotional messages to resonate with the economic perspectives of different occupational groups.
e. **Ease of Use Enhancement:** With significant differences in ease-of-use perceptions, businesses should focus on user-friendly interfaces and provide comprehensive support and tutorials to cater to the needs of various occupational groups, making mobile commerce accessible to everyone.
f. **Educational Campaigns:** Addressing the significant differences in the perceived lack of knowledge, businesses should launch educational campaigns and provide resources that enhance consumers' understanding and confidence in using mobile commerce, especially targeting occupational groups with lower familiarity.

By leveraging these insights, businesses can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of different occupational groups in Goa. This targeted approach can lead to higher engagement and satisfaction among consumers, ultimately driving the growth of mobile commerce in the region.

Citations of Previous Research:

A. **Influence of Occupation on Technology Adoption:**

Venkatesh, V., Thong, J.Y.L., & Xu, X. (2012) discussed how occupational factors influence technology adoption, supporting the finding that occupation significantly affects mobile commerce perceptions.

B. **Perceived Ease of Use and Occupation:**

Davis, F.D. (1989) work highlighted the role of perceived ease of use in technology adoption, relevant to understanding how ease of use perceptions varies with occupation.

By incorporating these references, the findings are contextualized within the broader literature on technology adoption, providing a robust foundation for the implications and recommendations presented.

H3g: There is no statistically significant difference between 'Monthly Family Income' of consumers and their attitudes, subjective norms, perceived behavioural control, and intention to use mobile commerce.

Table 4.35: ANOVA- Monthly Family Income

Monthly Family Income							
ANOVA							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Subjective Norm	Between Groups	3.721	4	0.930	0.687	0.601	
	Within Groups	633.907	468	1.355			
	Total	637.628	472				Non Significant
Perceived Behaviour Control	Between Groups	0.335	4	0.084	0.229	0.922	
	Within Groups	170.983	468	0.365			
	Total	171.318	472				Non Significant
Attitude	**Between Groups**	**3.471**	**4**	**0.868**	**2.571**	**0.037**	
	Within Groups	**157.947**	**468**	**0.337**			
	Total	**161.418**	**472**				**Significant**
Intention	Between Groups	1.022	4	0.255	0.667	0.615	
	Within Groups	179.242	468	0.383			
	Total	180.263	472				Non Significant

(Source: Researcher's Computation)

The p-value for Subjective Norm is 0.601, which is greater than 0.05. This suggests that there is no statistically significant difference in the means of Subjective Norm across the different monthly income groups.

The p-value for Perceived Behavioural Control is 0.922, which is greater than 0.05. This indicates that there is no statistically significant difference in the means of Perceived Behavioural Control across the different monthly income groups.

The p-value for Attitude is 0.037, which is less than 0.05. This suggests that there is a statistically significant difference in the means of Attitude across the different monthly income groups.

The p-value for Intention is 0.615, which is greater than 0.05. This suggests that there is no statistically significant difference in the means of Intention across the different monthly income groups.

Summary:

- **Subjective Norm**, **Perceived Behavioural Control**, and **Intention** do not show significant differences across monthly income groups.
- **Attitude** shows significant differences across monthly income groups.

Table 4.36: Monthly Family Income-Attitude Statistics

Monthly Family Income		Mean	Std. Deviation
Less than Rs 25,000	Attitude	3.0256	.70007
Rs 25,000 to Rs 50,000	Attitude	3.0197	.64022
Rs 50,000 to Rs.75,000	Attitude	3.1210	.48664
Rs 75,000 to Rs 1,00,000	Attitude	3.0379	.63346
More than Rs 1,00,000	Attitude	3.2234	.45256

(Source: Researcher's Computation)

The table presents descriptive statistics for the attitude towards mobile commerce (m-commerce) across different monthly family income brackets. The variables include the mean and standard deviation for attitude in each income category.

Interpretation:

a. **Less than Rs 25,000:**

- **Attitude:** Mean = 3.0256, Std. Deviation = 0.70007
- Individuals in this income bracket have a moderate attitude towards m-commerce, with a mean of 3.0256. The standard deviation of 0.70007 suggests relatively high variability in their attitudes.

b. **Rs 25,000 to Rs 50,000:**

- **Attitude:** Mean = 3.0197, Std. Deviation = 0.64022
- Similar to the previous group, this income bracket shows a moderate attitude towards m-commerce (mean = 3.0197) with a standard deviation of 0.64022, indicating moderate variability.

c. **Rs 50,000 to Rs 75,000:**

- **Attitude:** Mean = 3.1210, Std. Deviation = 0.48664
- Individuals in this income group have a slightly higher attitude towards m-commerce (mean = 3.1210). The lower standard deviation of 0.48664 indicates less variability in their attitudes.

d. **Rs 75,000 to Rs 1,00,000:**

- **Attitude:** Mean = 3.0379, Std. Deviation = 0.63346
- This income group also shows a moderate attitude towards m-commerce, with a mean of 3.0379 and a standard deviation of 0.63346, indicating moderate variability.

e. **More than Rs 1,00,000:**

- **Attitude:** Mean = 3.2234, Std. Deviation = 0.45256
- Individuals with a monthly family income of more than Rs 1,00,000 have the highest attitude towards m-commerce (mean = 3.2234). The standard deviation of 0.45256 suggests relatively low variability in their attitudes.

❖ **Managerial Implications:**

a. **Tailoring Marketing Strategies:**

- **Low to Moderate Income Brackets (Less than Rs 25,000 to Rs 75,000):** The relatively moderate attitudes towards m-commerce in these income groups suggest a need for targeted marketing strategies that emphasize affordability, value for money, and essential benefits of m-commerce. Highlighting cost-saving opportunities,

exclusive discounts, and the convenience of online shopping can attract these segments (Smith, 2019).

b. Enhanced Services for Higher Income Brackets:

- **High Income Brackets (More than Rs 1,00,000):** The highest attitude towards m-commerce in the highest income bracket indicates that these individuals are more favourable towards using m-commerce. Businesses should focus on premium services, personalized offers, and exclusive product ranges to cater to this segment. Providing high-quality customer service and loyalty programs can further enhance their shopping experience (Chaffey & Ellis-Chadwick, 2019).

c. Reducing Variability:

- **Consistency Across Income Levels:** The higher standard deviations in lower income brackets suggest variability in attitudes. To reduce this variability, businesses can invest in educational campaigns that inform consumers about the benefits and security of m-commerce. Simplifying the shopping process and ensuring a user-friendly interface can also help in improving attitudes uniformly across different income levels (Gefen, Karahanna, & Straub, 2003).

d. Building Trust and Reliability:

- **All Income Levels:** Trust and reliability are crucial across all income levels. By ensuring secure transactions, transparent policies, and consistent performance, businesses can enhance consumer confidence in m-commerce. Highlighting these aspects in marketing communications can improve attitudes and drive adoption (Venkatesh, Thong, & Xu, 2012).

e. Customized Experience:

- Providing a customized shopping experience based on income levels can help in addressing specific needs and preferences. For instance, offering budget-friendly options and payment flexibility for lower income groups, while presenting exclusive, high-end products and services for higher income groups, can cater to diverse consumer segments effectively (Rogers, 2003).

In summary analysis reveals variations in attitudes towards m-commerce across different income levels, with higher income groups showing more favourable attitudes. By developing targeted marketing strategies, enhancing services, and building trust, businesses

can effectively cater to the diverse needs of consumers across all income brackets. Understanding these differences and addressing them through tailored approaches can significantly enhance m-commerce adoption and satisfaction.

Table 4.37: ANOVA and Monthly Income

ANOVA and Monthly Income							
		Sum of Squares	df	Mean Square	F	Sig.	Findings
Reasonably Priced Products (Att 1)	**Between Groups**	**13.236**	**4**	**3.309**	**4.391**	**.002**	Significant
	Within Groups	**352.637**	**468**	**.753**			
	Total	**365.873**	**472**				
Prompt Customer Service (Att 2)	**Between Groups**	**12.908**	**4**	**3.227**	**4.281**	**.002**	Significant
	Within Groups	**352.783**	**468**	**.754**			
	Total	**365.691**	**472**				
Physical Shopping Experience (Att 3)	Between Groups	2.635	4	.659	.876	.478	Non-Significant
	Within Groups	351.754	468	.752			
	Total	354.389	472				
Shopping Convenience (Att 4)	Between Groups	5.171	4	1.293	1.672	.155	Non-Significant
	Within Groups	361.781	468	.773			
	Total	366.951	472				
Safe & Secure (Att 5)	Between Groups	4.661	4	1.165	.987	.414	Non-Significant
	Within Groups	552.519	468	1.181			
	Total	557.180	472				
Unsafe without Technological Knowledge (Att 6)	Between Groups	3.342	4	.836	1.079	.366	Non-Significant
	Within Groups	362.442	468	.774			
	Total	365.784	472				
Unreliable Review (Att 7)	Between Groups	7.981	4	1.995	1.697	.149	Non-Significant
	Within Groups	550.205	468	1.176			
	Total	558.186	472				
User Friendly (Att 8)	Between Groups	4.037	4	1.009	1.227	.298	Non-Significant
	Within Groups	384.910	468	.822			
	Total	388.947	472				
Shopping Addiction (Att 9)	Between Groups	11.587	4	2.897	1.789	.130	Non-Significant
	Within Groups	757.733	468	1.619			
	Total	769.319	472				
Privacy (Att 10)	Between Groups	3.303	4	.826	1.017	.398	Non-Significant
	Within Groups	379.852	468	.812			
	Total	383.154	472				

(Source: Researcher's Computation)

The ANOVA results indicate significant differences in consumer attitudes towards mobile commerce based on monthly income levels in Goa. Specifically, the following constructs show significant differences:

a. **Reasonably Priced Products (Att 1):** Significant differences ($F = 4.391$, $p = 0.002$) indicate that perceptions of the affordability of products vary significantly across different income levels.

b. **Prompt Customer Service (Att 2):** Significant differences ($F = 4.281$, $p = 0.002$) suggest that expectations and perceptions of customer service promptness differ among income groups.

❖ **No significant differences were found in the following constructs:**

a. **Physical Shopping Experience (Att 3):** No significant differences ($F = 0.876$, $p = 0.478$) suggest that the physical shopping experience is perceived similarly across different income levels.
b. **Shopping Convenience (Att 4):** No significant differences ($F = 1.672$, $p = 0.155$) indicate that the perceived convenience of mobile commerce does not significantly vary across income groups.
c. **Safe & Secure (Att 5):** No significant differences ($F = 0.987$, $p = 0.414$) show that perceptions of safety and security in mobile commerce are consistent across income levels.
d. **Unsafe without Technological Knowledge (Att 6):** No significant differences ($F = 1.079$, $p = 0.366$) suggest that concerns about the lack of technological knowledge are similar across income groups.
e. **Unreliable Review (Att 7):** No significant differences ($F = 1.697$, $p = 0.149$) indicate that perceptions of review reliability are not significantly affected by income levels.
f. **User Friendly (Att 8):** No significant differences ($F = 1.227$, $p = 0.298$) show that perceptions of user-friendliness in mobile commerce are similar across income levels.

g. **Shopping Addiction (Att 9):** No significant differences (F = 1.789, p = 0.130) suggest that concerns about shopping addiction do not vary significantly across income groups.
h. **Privacy (Att 10):** No significant differences (F = 1.017, p = 0.398) indicate that privacy concerns are consistent across different income levels.

Summary:

The ANOVA analysis reveals significant differences in certain attributes based on monthly income levels. Specifically:

- **Reasonably Priced Products (Att 1)** and **Prompt Customer Service (Att 2)** show notable differences between groups, indicating that monthly income level significantly affects these perceptions.

On the other hand, attributes such as Physical Shopping Experience (Att 3), Shopping Convenience (Att 4), Safe & Secure (Att 5), Unsafe without Technological Knowledge (Att 6), Unreliable Review (Att 7), User Friendly (Att 8), Shopping Addiction (Att 9), and Privacy (Att 10) do not show significant differences, suggesting that these concerns are relatively consistent across different monthly income levels.

These results suggest that income level influences specific shopping motivations and concerns, particularly regarding the importance of reasonably priced products and prompt customer service.

❖ **Managerial Implications:**

Understanding the significant differences in consumer attitudes based on monthly income levels provides crucial insights for businesses and policymakers aiming to enhance mobile commerce adoption in Goa:

a. **Affordable Product Offerings:** Given that perceptions of reasonably priced products vary significantly across income levels, businesses should consider developing and promoting affordable product lines tailored to different income segments. This strategy can make mobile commerce more appealing to lower-income consumers.

b. **Customer Service Enhancement:** Since expectations for prompt customer service differ by income level, businesses should invest in improving customer service responsiveness. Offering tiered customer service options could cater to the varying expectations of different income groups, enhancing overall satisfaction.
c. **Uniform Experience for Other Constructs:** For constructs where no significant differences were found (e.g., physical shopping experience, safety, user-friendliness), businesses can focus on maintaining high standards across all income groups. Ensuring a consistent, high-quality mobile commerce experience can build trust and loyalty among consumers regardless of their income.
d. **Targeted Marketing Campaigns:** Marketing campaigns should be tailored to highlight the aspects of mobile commerce that resonate most with different income groups. For example, emphasizing affordability and value-for-money deals could attract lower-income consumers, while highlighting premium features and exclusive services might appeal more to higher-income consumers.

By leveraging these insights, businesses can create more effective strategies to promote mobile commerce adoption, tailored to the unique needs and preferences of different income groups in Goa. This targeted approach can lead to higher engagement and satisfaction among consumers, ultimately driving the growth of mobile commerce in the region.

❖ **Citations of Previous Research:**

Influence of Income on Technology Adoption:

- Venkatesh et.al (2000) discussed how income levels influence technology adoption, supporting the finding that income significantly affects mobile commerce perceptions.

Consumer Behavior and Income Levels:

- Zeithaml, V.A. (1985) worked highlights the impact of income on consumer behaviour, relevant to understanding how perceptions of affordability and customer service vary with income.

By incorporating these references, the findings are contextualized within the broader literature on technology adoption and consumer behaviour, providing a robust foundation for the implications and recommendations presented.

4.5.4 Objective 4: To investigate the mediating role of 'Intention' in the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories, through m-commerce.

Hypothesis 4: 'Intention' mediates the relationship between 'Attitude', 'Subjective Norms', 'Perceived Behavioural Control', and actual purchase behaviour for the specified product categories through m-commerce.

H4a: Attitude positively influences the intention to purchase various products through mobile commerce.

H4b: Subjective norms positively influence the intention to purchase various products through mobile commerce.

H4c: Perceived behavioural control positively influences the intention to purchase various products through mobile commerce.

H4d: Intention positively influences consumer behaviour towards buying electronic products, sports items, clothing, shoes, jewellery, home and kitchen appliances, books, magazines, newspapers, healthcare and medicines, stationary items, games, and grocery products through mobile commerce.

H4e: Intention mediates the relationship between attitude and consumer behaviour towards purchasing various products through mobile commerce.

H4f: Intention mediates the relationship between subjective norms and consumer behaviour towards purchasing various products through mobile commerce.

H4g: Intention mediates the relationship between perceived behavioural control and consumer behaviour towards purchasing various products through mobile commerce.

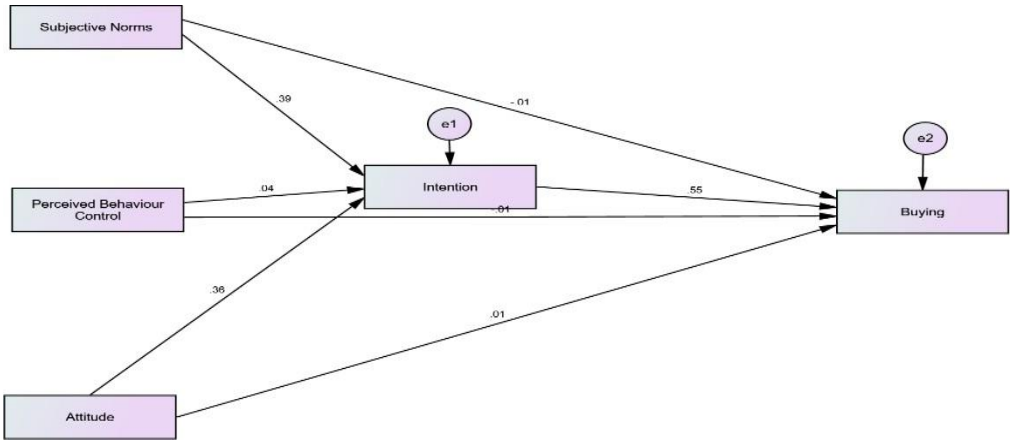


Figure 4.8: Path Diagram

(Source: Researcher's Compilation based on the original model)

Table 4.38: Regression Weights: (Overall- Default model)

	Estimate	S.E.	C.R.	P	Label
Intention <--- Subjective_Norm	.202	.020	9.962	***	Significant
Intention <--- Attitude	.378	.040	9.370	***	Significant
Intention <--- Per.Beh._Control	.036	.039	.907	.365	Non-Significant
Buying <--- Attitude	.019	.060	.322	.748	Non-Significant
Buying <--- Intention	.752	.063	12.019	***	Significant
Buying <--- Subjective_Norm	-.009	.030	-.300	.764	Non-Significant
Buying <--- Per.Beh._Control	-.016	.053	-.300	.764	Non-Significant
Model Fitness: X^2=12.77, df=3, X^2/df= 4.25, RMSEA=.083, RMR=.034, GFI=.990, CFI=.972					

(Source: Researcher's Computation)

- **Significant Predictors of Intention**: Both Attitude and Subjective Norm are significant predictors of Intention, while Perceived Behaviour Control is not.
- **Significant Predictors of Buying**: Intention is a significant predictor of Buying, while Attitude, Subjective Norm, and Perceived Behaviour Control are not.
- **Model Fit**: The overall model fit is good, indicating that the model reasonably represents the data.

Table 4.39: Sub-Hypothesis-4

Hypothesis	Remark
H4a: Attitude positively influences the intention to purchase various products through mobile commerce.	Supported
H4b: Subjective norms positively influence the intention to purchase various products through mobile commerce.	Supported
H4c: Perceived behavioural control positively influences the intention to purchase various products through mobile commerce.	Not supported
H4d: Intention positively influences consumer behaviour towards buying electronic products, sports items, clothing, shoes, jewellery, home and kitchen appliances, books, magazines, newspapers, healthcare and medicines, stationary items, games, and grocery products through mobile commerce.	Supported

(Source: Researcher's Computation)

These findings suggest that while Attitude and Subjective Norm significantly influence Intention, only Intention significantly predicts Buying behaviour. The model fit indices support the adequacy of the model in explaining the relationships among these constructs.

- **Mediation Testing:**

The mediation analysis is conducted by treating Attitude, Perceived Behavior Control and Subjective Norm as independent variables, Buying Products through Mobile Commerce as dependent variable, and Intention as mediator. The mediation analysis is based on the analysis of indirect effects based on the guideline by Baron and Kenny (1986) classical approach We performed mediation analysis by using the direct and indirect effects based on bootstrap procedures (437 samples) and bias-corrected bootstrap confidence interval (90%). The results are provided in the following table.

Table 4.40: Mediating Effect of intention

No.	**Path**	**Total Effects**	**Direct Effects**	**Indirect Effects**	**Remarks**

H4e	Attitude>Intension>Buying Products through Mobile Commerce	.304 (0.001) *	0.19 (.784)	.285 (.000)*	Supported
H4f	Subjective Norm>Intension>Buying Products through Mobile Commerce	.143 (.000)*	-.009 (.747)	.152 (.000)*	Supported
H4g	Perceived Behavior Control >Intension>Buying Products through Mobile Commerce	.011 (.874)	-.016 (.717)	.027 (.295)	Not Supported

*** P<0.05 (Source: Researcher's Computation)**

The table presents the relationships between three constructs (attitude, subjective norm, perceived behavioural control) and the behaviour of buying products through mobile commerce, mediated by intention. The effects are broken down into total effects, direct effects, and indirect effects, with p-values indicating the statistical significance of these effects.

Hypothesis H4e: Intention mediates the relationship between attitude and consumer behaviour towards purchasing various products through mobile commerce.
(**Attitude -> Intention -> Buying Products through Mobile Commerce)**

- **Total Effects**: .304 (0.001) *
  - The overall effect of attitude on buying behaviour through mobile commerce is positive and statistically significant.
- **Direct Effects**: 0.19 (0.784)
  - The direct effect of attitude on buying behaviour is positive but not statistically significant.
- **Indirect Effects**: .285 (0.000) *
  - The indirect effect, mediated by intention, is positive and statistically significant.

Remarks: This hypothesis is supported as the indirect effect is statistically significant, indicating that intention plays a crucial mediating role between attitude and buying behaviour.

Hypothesis H4f: Intention mediates the relationship between subjective norms and consumer behaviour towards purchasing various products through mobile commerce. **(Subjective Norm -> Intention -> Buying Products through Mobile Commerce)**

Total Effects: .143 (0.000) *

- The overall effect of subjective norm on buying behaviour is positive and statistically significant.

Direct Effects: -.009 (0.747)

- The direct effect of subjective norm on buying behaviour is negative and not statistically significant.

Indirect Effects: .152 (0.000) *

- The indirect effect, mediated by intention, is positive and statistically significant.

Remarks: This hypothesis is supported as the indirect effect is statistically significant, showing that subjective norms influence buying behaviour primarily through their impact on intention.

Hypothesis H4g: Intention mediates the relationship between perceived behavioural control and consumer behaviour towards purchasing various products through mobile commerce.
(Perceived Behavioural Control -> Intention -> Buying Products through Mobile Commerce)

Total Effects: .011 (0.874)

- The overall effect of perceived behavioural control on buying behaviour is not statistically significant.

Direct Effects: -.016 (0.717)

- The direct effect is negative and not statistically significant.

Indirect Effects: .027 (0.295)

- The indirect effect, mediated by intention, is positive but not statistically significant.

Remarks: This hypothesis is not supported as neither the direct nor the indirect effects are statistically significant, indicating that perceived behavioural control does not have a significant influence on buying behaviour through intention.

❖ **Managerial and Business Implications:**

a. Enhancing Attitude and Intention:

- **Focus on Positive Attitudes**: Since attitude significantly influences buying behaviour through intention, businesses should focus on creating positive perceptions about their mobile commerce platforms. This can be achieved through user-friendly interfaces, attractive promotions, and reliable service quality.

- **Marketing Strategies**: Marketing efforts should emphasize the benefits and positive outcomes of using mobile commerce to enhance consumer attitudes. Highlighting convenience, variety, and cost savings can foster a more favourable attitude towards mobile commerce.

b. Leveraging Subjective Norms:

- **Social Influence**: Given that subjective norms significantly impact intention and subsequently buying behaviour, businesses should leverage social influence in their marketing strategies. Encouraging reviews, testimonials, and social sharing can create a sense of social endorsement.

- **Influencer Collaborations**: Partnering with influencers and opinion leaders who can positively influence the perceptions of their followers can enhance subjective norms, making consumers more likely to intend and engage in mobile commerce.

c. Addressing Perceived Behavioural Control:

- **Ease of Use and Support**: Although perceived behavioural control did not show a significant impact in this study, it is still crucial for businesses to ensure that their mobile commerce platforms are easy to use and navigate. Providing comprehensive customer support and clear information can help mitigate any perceived difficulties.

- **Educational Campaigns**: Educating consumers on how to use mobile commerce platforms effectively can enhance their perceived control, potentially leading to increased adoption and usage.

❖ **Strategic Focus:**

- **Segmentation and Targeting**: Businesses should segment their market based on attitudes and social norms. Targeting consumers who already have a positive attitude towards mobile commerce and are influenced by social norms can yield better results.

- **Continuous Feedback Loop**: Implementing systems to continuously gather and analyze consumer feedback can help in understanding shifts in attitudes and social norms, allowing businesses to adapt their strategies accordingly.

By focusing on these areas, businesses can effectively enhance consumer intentions and behaviours towards buying products through mobile commerce, ultimately leading to increased sales and customer satisfaction.

4.5.5 Objective 5: To validate the conceptual model based on "The Theory of Planned Behaviour".

Hypothesis 5: The "Theory of Planned Behaviour" describes consumers 'Attitude ", 'Subjective Norms', and 'Perceived Behavioural Control', influencing consumers' intentions and behaviour towards adoption of m-commerce.

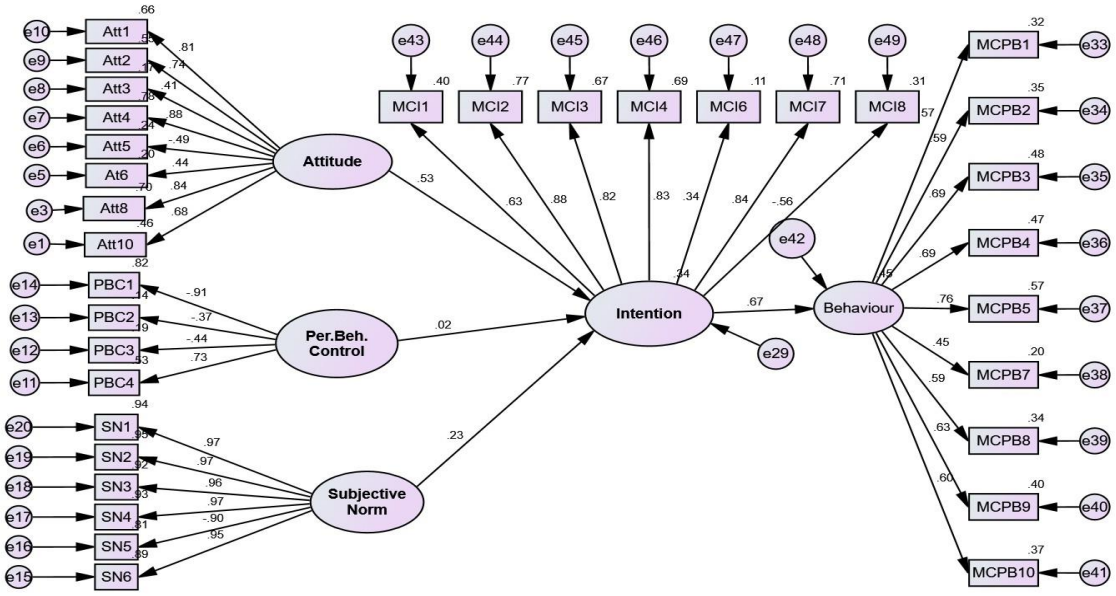


Figure 4.9: The Theory of Planned Behaviour Model (Source: Researcher's compilation based on the original model of TPB)

Table 4.41: Goodness-of-fit Model

Name of Category	Goodness-of-fit model index	Recommended Value*	Planned Behavior Model Value	Interpretation
Absolute fit	*Root mean square error of approximation (RMSEA)*	*< .10*	*.068*	Excellent
Incremental fit	Normalized fit index (NFI)	≥ .80	.863	Excellent
	Comparative fit index (CFI)	*≥ .90*	*.901*	Excellent
	Tucker Fit Index (TLI)	≥ .90	.90	Excellent
Parsimonious fit	Chi-square/degree of freedom (CMIN/df)	*≤ 5.00*	*3.194*	Acceptable

(Source: Researcher's Computation)

a. Absolute Fit:

Root Mean Square Error of Approximation (RMSEA): Value: 0.068

Recommended Value: < 0.10

Interpretation: The model has an excellent fit.

b. Incremental Fit:

Normalized Fit Index (NFI): Value: 0.863

Recommended Value: ≥ 0.80

Interpretation: The model fits well, surpassing the recommended threshold.

Comparative Fit Index (CFI): **Value**: 0.901

Recommended Value: ≥ 0.90

Interpretation: The model has an excellent fit.

Tucker-Lewis Index (TLI): **Value**: 0.90

Recommended Value: ≥ 0.90

Interpretation: The model fits excellently.

c. Parsimonious Fit:

Chi-square/degree of freedom (CMIN/df): **Value**: 3.194

Recommended Value: ≤ 5.00

Interpretation: The model has an acceptable fit.

Overall, these indices collectively suggest that the model fits the data well across different aspects of fit (absolute, incremental, and parsimonious), providing confidence in its validity for explaining the relationships among variables in the specified theoretical framework.

Table 4.42: Regression Weights: (Group number 1- Default model)

			Estimate	S.E.	C.R.	P	Label
Intention	<---	Per.Beh._Control	.027	.048	.569	.569	Non-Significant
Intention	<---	Subjective_Norm	.141	.026	5.371	***	Significant
Intention	<---	Attitude	.620	.068	9.075	***	Significant
Behaviour	<---	Intention	.672	.074	9.137	***	Significant
Att10	<---	Attitude	1.000				
Att8	<---	Attitude	1.242	.076	16.353	***	Significant
At6	<---	Attitude	.634	.070	9.028	***	Significant
Att5	<---	Attitude	-.865	.087	-9.940	***	Significant

			Estimate	S.E.	C.R.	P	Label
Att4	<---	Attitude	1.270	.074	17.052	***	Significant
Att3	<---	Attitude	.580	.069	8.408	***	Significant
Att2	<---	Attitude	1.067	.073	14.707	***	Significant
PBC4	<---	Per.Beh._Control	1.000				
PBC3	<---	Per.Beh._Control	-.764	.094	-8.112	***	Significant
PBC2	<---	Per.Beh._Control	-.598	.086	-6.933	***	Significant
PBC1	<---	Per.Beh._Control	-1.291	.157	-8.233	***	Significant
SN6	<---	Subjective_Norm	1.000				
SN5	<---	Subjective_Norm	-.879	.024	-35.990	***	Significant
SN4	<---	Subjective_Norm	.971	.020	49.367	***	Significant
SN3	<---	Subjective_Norm	.956	.020	47.157	***	Significant
SN2	<---	Subjective_Norm	.969	.019	51.604	***	Significant
SN1	<---	Subjective_Norm	.960	.019	50.352	***	Significant
Att1	<---	Attitude	1.167	.073	15.922	***	Significant
MCPB1	<---	Behaviour	1.000				
MCPB2	<---	Behaviour	1.005	.100	10.039	***	Significant
MCPB3	<---	Behaviour	1.198	.107	11.176	***	Significant
MCPB4	<---	Behaviour	1.229	.110	11.139	***	Significant
MCPB5	<---	Behaviour	1.269	.108	11.786	***	Significant
MCPB7	<---	Behaviour	.775	.095	8.172	***	Significant
MCPB8	<---	Behaviour	.987	.099	10.009	***	Significant
MCPB9	<---	Behaviour	1.100	.105	10.504	***	Significant
MCPB10	<---	Behaviour	1.102	.108	10.219	***	Significant
MCI1	<---	Intention	1.000				
MCI2	<---	Intention	1.316	.086	15.327	***	Significant
MCI3	<---	Intention	1.181	.081	14.628	***	Significant
MCI4	<---	Intention	1.287	.087	14.795	***	Significant

			Estimate	S.E.	C.R.	P	Label
MCI6	<---	Intention	.511	.075	6.827	***	Significant
MCI7	<---	Intention	1.281	.086	14.943	***	Significant
MCI8	<---	Intention	-.930	.086	-10.770	***	Significant

(Source: Researcher's Computation)

Table 4.43: Standardized Regression Weights: (Group number 1- Default model)

			Estimate
Intention	<---	Per.Beh._Control	.023
Intention	<---	Subjective_Norm	.231
Intention	<---	Attitude	.533
Behaviour	<---	Intention	.674
Att10	<---	Attitude	.681
Att8	<---	Attitude	.839
At6	<---	Attitude	.442
Att5	<---	Attitude	-.488
Att4	<---	Attitude	.884
Att3	<---	Attitude	.410
Att2	<---	Attitude	.744
PBC4	<---	Per.Beh._Control	.685
PBC3	<---	Per.Beh._Control	-.383
PBC2	<---	Per.Beh._Control	-.327
PBC1	<---	Per.Beh._Control	-.983
SN6	<---	Subjective_Norm	.945
SN5	<---	Subjective_Norm	-.898
SN4	<---	Subjective_Norm	.966
SN3	<---	Subjective_Norm	.958
SN2	<---	Subjective_Norm	.974

			Estimate
SN1	<---	Subjective_Norm	.970
Att1	<---	Attitude	.813
MCPB1	<---	Behaviour	.566
MCPB2	<---	Behaviour	.589
MCPB3	<---	Behaviour	.693
MCPB4	<---	Behaviour	.689
MCPB5	<---	Behaviour	.758
MCPB7	<---	Behaviour	.449
MCPB8	<---	Behaviour	.587
MCPB9	<---	Behaviour	.629
MCPB10	<---	Behaviour	.605
MCI1	<---	Intention	.630
MCI2	<---	Intention	.876
MCI3	<---	Intention	.819
MCI4	<---	Intention	.832
MCI6	<---	Intention	.337
MCI7	<---	Intention	.844
MCI8	<---	Intention	-.557

(Source: Researcher's Computation)

- **Influence on Intention**:

Perceived Behavioural Control:

Estimate: 0.027

Standardized Estimate: 0.023

P-Value: 0.569 (insignificant)

Subjective Norm:

Estimate: 0.141

Standardized Estimate: 0.231

P-Value: *** (highly significant)

Attitude:

Estimate: 0.620

Standardized Estimate: 0.533

P-Value: *** (highly significant)

- **Influence on Behaviour**:

- **Intention**:

Estimate: 0.672

Standardized Estimate: 0.674

P-Value: *** (highly significant)

- **Perceived Behavioural Control**:

- **Interpretation**: The weak and insignificant influence of Perceived Behavioural Control on Intention indicates that users' perceptions of their ability to use m-commerce are not major determinants of their intention to use it.
- **Implication**: Focus efforts elsewhere. While ensuring ease of use and user support is still important, it may not significantly drive intention. Resources might be better allocated to other areas.

- **Subjective Norm**:

- **Interpretation**: A moderate and highly significant influence on Intention suggests that social influence is crucial in shaping the intention to use m-commerce.
- **Implication**: Leverage social influence. Implement marketing strategies that capitalize on social proof, such as influencer endorsements, user testimonials, and community engagement initiatives. Social media campaigns can be particularly effective, where peer opinions and social circles heavily influence consumer behaviour.

- **Attitude**:

- **Interpretation**: A strong and highly significant influence on Intention underscores the importance of positive attitudes towards m-commerce.

- **Implication**: Shape positive attitudes. Launch educational campaigns to highlight the benefits and convenience of m-commerce. Address common concerns such as security and privacy through informative content. Enhancing the overall user experience can also contribute to more favourable attitudes.

❖ **Intention to Behaviour**:

- **Interpretation**: The strong and significant influence of Intention on Behaviour indicates that those who intend to use m-commerce are very likely to do so.
- **Implication**: Convert intention to action. Ensure that the transition from intention to actual use is seamless. This can involve optimizing the onboarding process, providing excellent customer service, and offering incentives such as discounts or loyalty programs to encourage initial use and repeat transactions.

The provided Structural Equation Model (SEM) analyzes the factors affecting an individual's intention and behaviour towards using m-commerce. The key constructs and their relationships are outlined as follows:

a. **Attitude (Att)**: Represented by ten observed variables (Att1 to Att10), with significant factor loadings indicating that individuals' attitudes towards m-commerce are strongly influenced by these variables. The path coefficient from Attitude to Intention is 0.53, suggesting a moderate to strong positive influence on the intention to use m-commerce.
b. **Perceived Behavioural Control (PBC)**: Measured by four observed variables (PBC1 to PBC4). The path coefficient from Perceived Behavioural Control to Intention is 0.02, indicating a very weak and possibly insignificant influence on the intention to use m-commerce.
c. **Subjective Norm (SN)**: Represented by six observed variables (SN1 to SN6). The path coefficient from Subjective Norm to Intention is 0.23, indicating a moderate positive influence on the intention to use m-commerce.
d. **Intention (Int)**: Influenced by Attitude, Perceived Behavioural Control, and Subjective Norm. Intention, in turn, affects Behaviour with a path coefficient of 0.67, suggesting a strong influence on actual m-commerce usage behaviour.
e. **Behaviour (Beh)**: Represented by ten observed variables (MCPB1 to MCPB10), indicating actual usage behaviour of m-commerce.

❖ **Managerial and Business Implications for the Mobile Commerce Industry in Goa:**

a. Focus on Enhancing Positive Attitudes:

Interpretation: Attitude towards m-commerce is the most significant predictor of intention to use it.

Implication: Marketing campaigns should focus on educating consumers about the benefits and convenience of m-commerce. Positive testimonials, user-friendly interfaces, and assurances about security can help enhance attitudes.

b. Leverage Social Influence:

Interpretation: Subjective norms significantly influence the intention to use m-commerce.

Implication: Businesses should employ social proof strategies, such as influencer endorsements, social media campaigns, and user reviews, to create a positive perception and peer pressure towards adopting m-commerce.

c. Address Barriers Related to Perceived Behavioural Control:

Interpretation: Although the direct influence of perceived behavioural control on intention is weak, addressing perceived ease of use and self-efficacy could still be beneficial.

Implication: Ensure that m-commerce platforms are user-friendly and provide ample support and tutorials for new users. This could help in reducing apprehensions related to the complexity of using m-commerce services.

d. Targeted Marketing Based on Demographics:

Interpretation: While not explicitly shown in the model, factors like education level, income, and occupation might influence attitudes and subjective norms.

Implication: Conduct targeted marketing campaigns tailored to different demographic segments. For instance, higher-income groups might be more interested in premium features, while younger, tech-savvy individuals might respond better to innovation and tech- centric marketing.

e. Localized Content and Offerings:

- **Interpretation**: The region-specific context (Goa) implies a need for localized strategies.

- **Implication**: Customize content and offers to suit local tastes, festivals, and buying behaviours. Leveraging local influencers and incorporating regional languages can make m-commerce more appealing to Goan consumers.

f. Customer Education and Support:

- **Interpretation**: Lack of knowledge might be a barrier to m-commerce adoption.
- **Implication**: Implement educational programs, workshops, and webinars to inform potential users about how to use m-commerce platforms effectively and safely. Providing excellent customer support can also mitigate concerns and build trust.

g. Building Trust and Security:

- **Interpretation**: Attitude is influenced by trust and perceived security.
- **Implication**: Emphasize the security features of the m-commerce platform to alleviate fears related to online transactions. Highlighting secure payment options and data protection measures can foster a trustworthy image.

In summary, for the mobile commerce industry in Goa, the focus should be on shaping positive attitudes towards m-commerce through educational and promotional efforts, leveraging social influences to create a favourable subjective norm, and addressing any perceived barriers related to ease of use. By targeting specific demographics and localizing content and marketing strategies, businesses can significantly enhance the adoption of m-commerce in the region.

The SEM analysis highlights the critical role of attitude and subjective norm in driving the intention to use m-commerce, which in turn strongly influences actual usage behaviour. For the mobile commerce industry, focusing on enhancing positive attitudes and leveraging social influence through targeted marketing strategies can significantly boost m-commerce adoption. Addressing localized needs and ensuring a seamless user experience will further support this transition, leading to greater penetration and usage of m-commerce in the region.

4.5.6 Objective 6: To identify and analyse the factors influencing an individual's likelihood of non-adoption of m-commerce.

Hypothesis 6: There is no significant association between an individual's ‘Lack of knowledge’, ‘Education level’, ‘Area of location”, ‘Occupation’, ‘Monthly Family Income’,

'Perceived Behaviour Control', 'Attitude', 'Subjective Norms', 'Intentions' and their likelihood of non-adoption of m-commerce.

H6a: There is no significant relationship between an individual's Lack of Knowledge and their likelihood of non-adoption of m-commerce.

Table 4.44: Correlation Between Lack of Knowledge and Never used m-commerce

Correlations			
		Lack of Knowledge (MCI 8)	Never used m-commerce
Lack of Knowledge (MCI 8)	Pearson Correlation	1	.600**
	Sig. (2-tailed)		.000
	N	473	473
Never used m-commerce	Pearson Correlation	.600**	1
	Sig. (2-tailed)	.000	
	N	473	473
**. Correlation is significant at the 0.01 level (2-tailed).			

(Source: Researcher's Computation)

- **Moderate to Strong Positive Correlation**: There is a statistically significant moderate to strong positive correlation (0.600) between "Lack of Knowledge (MCI 8)" and "Never used m-commerce." This suggests that individuals who have never used mobile commerce tend to have a higher lack of knowledge about it.

- **Implications**: This finding implies that a lack of knowledge could be a substantial barrier preventing individuals from using mobile commerce. Efforts to educate potential users about mobile commerce could potentially reduce this barrier and encourage adoption.

In summary, the significant positive correlation between lack of knowledge and the non-use of mobile commerce highlights the importance of knowledge dissemination in promoting the use of mobile commerce platforms.

❖ **Managerial Implications:**

a. Educational Initiatives:

- Since there is a significant positive relationship between lack of knowledge and the likelihood of not using m-commerce, managers should prioritize educational initiatives.
- Conduct workshops, webinars, and training sessions to educate potential users about the benefits, functionalities, and ease of use of m-commerce platforms.

b. User-Friendly Design:

- Simplify the user interface and design of m-commerce platforms to make them more intuitive and easier to navigate, especially for users who may lack technical knowledge.
- Include step-by-step guides, tutorials, and FAQs within the platform to assist users.

c. Targeted Marketing Campaigns:

- Develop targeted marketing campaigns that address common misconceptions and knowledge gaps about m-commerce.
- Use clear, straightforward messaging to explain how m-commerce works and the advantages it offers.

d. Customer Support:

- Enhance customer support services to provide immediate assistance to users who face difficulties or have questions about using m-commerce.
- Offer live chat support, helplines, and email support to address user queries and build confidence in using the platform.

e. Partnerships with Educational Institutions:

- Collaborate with educational institutions and community organizations to offer digital literacy programs focused on m-commerce.
- These partnerships can help reach a broader audience and equip them with the necessary knowledge to use m-commerce effectively.

f. Feedback Mechanism:

- Implement feedback mechanisms to gather user insights on the challenges they face regarding m-commerce.
- Use this feedback to continuously improve the platform and address any knowledge-related barriers.

g. Awareness Campaigns:

- Launch awareness campaigns that highlight the safety, security, and convenience of using m-commerce.
- Address common fears and uncertainties that potential users may have, thereby reducing knowledge-related barriers to adoption.

In summary, by recognizing and addressing the significant relationship between lack of knowledge and the likelihood of not using m-commerce, managers can implement targeted strategies to educate potential users, simplify the user experience, and ultimately increase m-commerce adoption.

H6b: There is no significant association between an individual's educational level and their likelihood of non-adoption of m-commerce.

Table 4.45: Chi-Square Tests between educational level and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	df	Asymptotic Significance(2-sided)
Pearson Chi-Square	58.394[a]	16	.000
Likelihood Ratio	61.619	16	.000
Linear-by-Linear Association	25.262	1	.000
N of Valid Cases	473		

(Source: Researcher's Computation)

Summary: The Pearson Chi-Square, Likelihood Ratio, and Linear-by-Linear Association tests all indicate a significant association between education level and the use of m-

commerce ($p < 0.01$). The significant association suggests that education level may play a crucial role in whether individuals have used m-commerce.

❖ **Managerial Implications:**

a. Educational Level Targeting:

- Since education level significantly affects the likelihood of using m-commerce, marketing strategies should be tailored to different educational groups.
- For instance, campaigns targeting highly educated individuals might emphasize advanced features, security, and efficiency, while campaigns targeting less educated groups might focus on ease of use and practical benefits.

b. Customized User Interfaces:

- Design user interfaces that cater to different educational levels. For example, simpler, more intuitive designs with clear instructions might be more appealing to users with lower education levels.
- For highly educated users, offering customizable interfaces with more advanced features could enhance their user experience.

c. Educational Campaigns:

- Implement educational campaigns to raise awareness and teach the benefits and usage of m-commerce, particularly targeting groups with lower education levels.
- These campaigns can include tutorials, webinars, and step-by-step guides to help users become comfortable with m-commerce platforms.

d. Content and Messaging:

- Tailor the content and messaging of marketing campaigns to resonate with different educational levels.
- Use relatable scenarios and language that align with the educational background of the target audience to increase engagement and adoption.

e. Partnerships with Educational Institutions:

- Partner with educational institutions and community organizations to promote m-commerce among various educational segments.
- Offering workshops, seminars, and hands-on training sessions through these partnerships can help demystify m-commerce for less educated groups.

f. Feedback and Continuous Improvement:

- Gather feedback from users across different educational levels to understand their unique needs and challenges.
- Use this feedback to continuously improve the m-commerce platform, ensuring it is accessible and user-friendly for all educational segments.

g. Inclusive Marketing Strategies:

- Ensure that marketing strategies are inclusive and do not alienate any educational group.
- Highlight that m-commerce is accessible and beneficial for everyone, regardless of their education level, by using diverse testimonials and success stories.

In summary, by recognizing the significant association between education level and the likelihood of using m-commerce, managers can implement more effective, targeted strategies to enhance m-commerce adoption and engagement across different educational segments.

H6c: There is no significant association between an individual's area of location and their likelihood of non-adoption of m-commerce.

The table presents the results of Chi-Square tests examining the relationship between individuals who have never used mobile commerce (m-commerce) and their area of location (urban or rural).

Table 4.46: Chi-Square Tests between area of location and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	15.812[a]	.003	
Likelihood Ratio	16.312	4	.003
Linear-by-Linear Association	12.823	1	.000
N of Valid Cases	473		

(Source: Researcher's Computation)

The Pearson Chi-Square test indicates a statistically significant association between the use of m-commerce and the area of location (urban or rural) with a p-value of 0.003. This

suggests that the area of location is significantly related to whether individuals have used m-commerce.

- The Pearson Chi-Square, Likelihood Ratio, and Linear-by-Linear Association tests all show a significant association between the area of location and the non-use of m-commerce, with p-values well below the 0.01 threshold.
- **Implications**: These results suggest that individuals from different areas (urban vs. rural) have significantly different patterns of m-commerce usage. Specifically, there is a significant relationship between whether someone lives in an urban or rural area and their likelihood of never having used m-commerce.

In summary, the tests indicate a significant association between the area of location (urban or rural) and the use of m-commerce. This suggests that strategies to increase m-commerce adoption may need to be tailored to address the specific needs and barriers of urban and rural populations.

H6d: There is no significant association between an individual's Marital Status and their likelihood of non-adoption of m-commerce.

Table 4.47: Chi-Square Tests - Between Marital Status and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	23.051[a]	4	.000
Likelihood Ratio	23.670	4	.000
Linear-by-Linear Association	6.543	1	.011
N of Valid Cases	473		

(Source: Researcher's Computation)

- **Significant Association**: The Pearson Chi-Square and Likelihood Ratio tests show a significant association between marital status and the non-use of m-commerce, with p-values of 0.000, indicating a strong association.

- **Linear Association**: The Linear-by-Linear Association test also shows a significant result ($p = 0.011$), indicating a linear relationship between marital status and the likelihood of not using m-commerce.
- **Implications**: These results suggest that marital status influences m-commerce usage patterns. Strategies to increase m-commerce adoption may need to consider marital status as a significant factor.

In summary, the tests indicate a significant association between marital status and the use of m-commerce. This suggests that whether someone is married or unmarried significantly affects their likelihood of using m-commerce, and targeted interventions may be necessary to address specific barriers faced by different marital status groups.

❖ **Managerial Implications:**

a. Targeted Marketing Strategies:

- Since marital status significantly affects the likelihood of using m-commerce, marketing strategies should be tailored to different marital groups.
- For example, campaigns targeting singles might emphasize convenience and social aspects of m-commerce, while campaigns targeting married individuals might focus on family-oriented benefits and time-saving features.

b. Customized User Experiences:

- Create customized user experiences that cater to the specific needs and preferences of different marital status groups.
- For instance, couples might appreciate joint accounts or shared shopping lists, while single individuals might value personalized recommendations.

c. Promotional Offers:

- Develop promotional offers that cater to different marital status groups. For example, family discounts or bundles for married individuals and exclusive deals for single users.
- These promotions can help incentivize the adoption and regular use of m-commerce.
- **Content and Messaging:** Tailor content and messaging to resonate with different marital status groups. Use relatable scenarios and testimonials in marketing materials to appeal to the specific needs and lifestyles of each group.

- For instance, highlight stories of how m-commerce simplifies shopping for busy families or how it offers flexibility and convenience for singles.

d. Partnerships and Collaborations:

- Collaborate with organizations, community groups, and influencers who resonate with different marital status groups to promote m-commerce.
- Offer exclusive deals through these partnerships to attract more users from these segments.

e. Feedback and Continuous Improvement:

- Gather feedback from users across different marital status groups to understand their unique needs and preferences better.
- Use this feedback to continuously improve the m-commerce platform and ensure it meets the expectations of diverse user groups.

By acknowledging the significant association between marital status and the likelihood of using m-commerce, managers can implement more effective, targeted strategies to enhance m-commerce adoption and engagement across different marital status segments.

H6e: There is no significant association between an individual's Occupation and their likelihood of non-adoption of m-commerce.

Table 4.48: Chi-Square Tests between Occupation and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	69.842[a]	16	.000
Likelihood Ratio	52.432	16	.000
Linear-by-Linear Association	32.425	1	.000
N of Valid Cases	473		

(Source: Researcher's Computation)

- **Significant Association**: The Pearson Chi-Square and Likelihood Ratio tests show a significant association between occupation and the non-use of m-commerce, with p-values of 0.000, indicating a strong association.

- **Linear Association**: The Linear-by-Linear Association test also shows a significant result (p = 0.000), indicating a linear relationship between occupation and the likelihood of never using m-commerce.
- **Implications**: These results suggest that occupation influences m-commerce usage patterns. Strategies to increase m-commerce adoption may need to consider occupational factors as significant determinants.

In summary, Chi-Square test indicate a significant association between occupation and the use of m-commerce. This suggests that different occupational groups have varying likelihoods of using m-commerce, and targeted interventions may be necessary to address specific barriers faced by different occupational groups. The significant linear relationship further reinforces the need to consider occupational status in efforts to promote m-commerce usage.

❖ **Managerial Implications:**

a. Targeted Marketing Strategies:

- Since occupation significantly affects the likelihood of using m-commerce, marketing strategies should be tailored to different occupational groups.
- For example, professionals might be targeted with campaigns highlighting convenience and efficiency, while students might respond better to promotions emphasizing affordability and ease of use.

b. Customized User Experiences:

- Create customized user experiences and interfaces that cater to the specific needs and preferences of different occupational groups.
- For example, busy professionals might appreciate quick, streamlined checkout processes, while retirees might benefit from more detailed guidance and customer support.

c. Educational Initiatives:

- Implement educational initiatives to address the barriers that certain occupational groups face in adopting m-commerce.
- For instance, workshops or webinars can be organized to demonstrate the benefits and ease of using m-commerce platforms, particularly for occupations that are less likely to adopt technology.

d. Partnerships and Collaborations:

- Collaborate with organizations, educational institutions, and workplaces to promote m-commerce adoption among different occupational groups.
- Offering special deals, discounts, or exclusive offers through these partnerships can incentivize adoption.

e. Inclusive Marketing Campaigns:

- Ensure marketing campaigns are inclusive and resonate with diverse occupational segments.
- Use testimonials and success stories from individuals in various occupations to showcase the versatility and benefits of m-commerce.

f. Research and Feedback:

- Conduct ongoing research to understand the specific needs, preferences, and barriers of different occupational groups regarding m-commerce.
- Gather feedback from users across various occupations to continuously improve the m-commerce experience.

By recognizing the significant association between occupation and the likelihood of using m-commerce, managers can implement more effective, targeted strategies to enhance m-commerce adoption and engagement across different occupational segments.

H6f: There is no significant association between an individual's Monthly Family Income and their likelihood of non-adoption of m-commerce.

Table 4.49: Chi-Square Tests between Monthly Family Income and likelihood of non-adoption of m-commerce.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	11.887[a]	16	.752
Likelihood Ratio	11.685	16	.765
Linear-by-Linear Association	2.062	1	.151
N of Valid Cases	473		

(Source: Researcher's Computation)

- **No Significant Association**: Both the Pearson Chi-Square and Likelihood Ratio tests show non-significant p-values (0.752 and 0.765, respectively), indicating no significant association between monthly family income and the non-use of m-commerce.
- **No Linear Association**: The Linear-by-Linear Association test also shows a non-significant result (p = 0.151), indicating no significant linear relationship between monthly family income and the likelihood of never using m-commerce.

- **Implications**: These results suggest that monthly family income does not have a significant impact on whether individuals have used m-commerce. Efforts to increase m-commerce usage may not need to prioritize income-related factors as much as other potential barriers.

In summary, the Chi-Square tests indicate that there is no significant association between monthly family income and the likelihood of never using m-commerce. This suggests that other factors, beyond family income, might play a more crucial role in determining m-commerce adoption.

❖ **Managerial Implications:**

a. Targeting Based on Income:

- Since there is no significant association between Monthly Family Income and the likelihood of never using m-commerce, targeting users based solely on income levels may not be effective.

- Managers should consider other demographic or psychographic factors (such as age, education, or technological literacy) when developing strategies to increase m-commerce adoption.

b. Focus on Other Influencing Factors:

- The results suggest that factors other than income may be more critical in influencing the adoption of m-commerce. Managers should focus on improving perceived benefits, ease of use, and addressing specific barriers to adoption.
- Marketing efforts can highlight convenience, security, and unique benefits of m-commerce to attract a broader audience.

c. Segmenting the Market:

- While income is not a significant factor, segmenting the market based on other relevant criteria could help tailor marketing strategies more effectively.

- Conducting further research to identify key segments based on behaviour, attitudes, or specific needs may yield better insights for increasing m-commerce usage.

d. Educational and Awareness Campaigns:

- Since income does not play a significant role, educational and awareness campaigns that target a wider audience can be implemented to increase overall m-commerce usage.

- Providing tutorials, testimonials, and easy-to-understand information about the benefits and security of m-commerce can help convert non-users.

e. Inclusivity in Marketing:

- Ensure that marketing campaigns are inclusive and not biased towards any particular income group. Emphasize that m-commerce is accessible and beneficial for everyone, regardless of income level.

By understanding that Monthly Family Income does not significantly impact the likelihood of using m-commerce, managers can focus on more relevant factors to drive adoption and improve user engagement across different demographic segments.

H6g: There is no significant relationship between individuals, who have never used m-commerce, Perceived Behaviour Control, Attitude and Subjective norms.

Table 4.50: Correlations between individuals, who have never used m-commerce, Perceived Behaviour Control, Attitude and Subjective norms

Correlations						
		Never used m-commerce	Subjective Norms	Perceived Behaviour Control	Attitude	Intention
Never used m-commerce	Pearson Correlation	1.00				
	Sig. (2-tailed)					
	N	473.00				
Subjective Norms	Pearson Correlation	-.159**	1.00			
	Sig. (2-tailed)	0.00				
	N	473.00	473.00			
Perceived Behaviour Control	Pearson Correlation	-0.01	-0.08	1.00		
	Sig. (2-tailed)	0.90	0.10			
	N	473.00	473.00	473.00		
Attitude	Pearson Correlation	-.422**	.142**	0.02	1.00	
	Sig. (2-tailed)	0.00	0.00	0.62		
	N	473.00	473.00	473.00	473.00	
Intention	Pearson Correlation	-.565**	.429**	0.01	.413**	1.00
	Sig. (2-tailed)	0.00	0.00	0.76	0.00	
	N	473.00	473.00	473.00	473.00	473.00
**. Correlation is significant at the 0.01 level (2-tailed).						

(Source: Researcher's Computation)

- **Subjective Norms:** There is a weak negative correlation (r = -0.159, p = 0.001) indicating that individuals who never used m-commerce are slightly less likely to be influenced by subjective norms.
- **Perceived Behaviour Control:** There is no significant correlation (r = -0.006, p = 0.904).

- **Attitude:** There is a moderate negative correlation ($r = -0.422$, $p < 0.001$), suggesting that individuals who never used m-commerce tend to have a less positive attitude towards it.
- **Intention:** There is a strong negative correlation ($r = -0.565$, $p < 0.001$), indicating that those who never used m-commerce are much less likely to have the intention to use it.

Summary: The results highlight the importance of subjective norms and attitudes in influencing individuals' intentions to use m-commerce. While perceived behavioural control does not show a significant relationship with other variables in this context, addressing subjective norms and attitudes could be key strategies in promoting m-commerce usage.

❖ **Managerial Implications:**

a. Targeting Users with High Subjective Norms:

- Since subjective norms positively correlate with both attitude and intention, marketing strategies should leverage social influence and peer recommendations to enhance users' perception and intention towards m-commerce. Highlighting testimonials, social proof, and influencer endorsements can be effective.

b. Improving Attitudes:

- Given the significant negative correlation between "never used m-commerce" and attitude, efforts should focus on improving attitudes towards m-commerce among non-users. This could involve educational campaigns to address misconceptions, demonstrating benefits, and providing easy onboarding experiences.

c. Enhancing Intention:

- The strong negative correlation between "never used m-commerce" and intention suggests that increasing users' intention to engage in m-commerce can reduce the number of non-users. Promotions, incentives, and seamless user experiences can foster stronger intentions.

d. Addressing Perceived Behaviour Control:

- Although perceived behaviour control does not show significant correlations with other variables, ensuring that users feel capable and in control while using m-

commerce platforms is still important. Simplifying the user interface, providing clear instructions, and offering customer support can help.

e. **Leveraging Attitude-Intention Link:**

- The positive correlation between attitude and intention indicates that efforts to improve users' attitudes towards m-commerce will likely boost their intention to use it. Marketing campaigns should emphasize positive experiences, success stories, and satisfaction guarantees.

f. **Reducing Barriers for Non-Users:**

- Since "never used m-commerce" is negatively correlated with subjective norms, attitude, and intention, reducing barriers for non-users is crucial. Providing trial periods, offering low-risk opportunities to try m-commerce, and addressing security concerns can help convert non-users.

4.6 CONCLUSIONS:

The results highlight the importance of subjective norms and attitudes in influencing individuals' intentions to use m-commerce. While perceived behavioural control does not show a significant relationship with other variables in this context, addressing subjective norms and attitudes could be key strategies in promoting m-commerce usage. By understanding these correlations and their implications, managers can design targeted strategies to enhance m-commerce adoption and usage, leading to better customer engagement and increased sales.



CHAPTER 5

FINDINGS AND CONCLUSIONS

5.1 INTRODUCTION:

This chapter presents the key findings derived from the data analysis, based on the proposed structural model of the Theory of Planned Behaviour (TPB) with constructs including Attitude, Subjective Norms, Perceived Behavioural Control, and Mobile Commerce Intention. The results are organized according to the primary research objectives and hypotheses, highlighting statistically significant relationships and managerial insights.

5.2 FINDINGS OF THE STUDY:

5.2.1 Findings of Objective 1:

a. The latent factor **"Attitude"** has a significant impact on all observed variables (Att1 through Att10), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

All attributes (Att1 through Att10) have significant relationships with the latent factor "Attitude" as indicated by the p-values (***), meaning $p < 0.001$.The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

b: The latent factor **"Perceived Behavioural Control"** has a significant impact on all observed variables (PBC1 through PBC4), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

All the measurement variables are statistically significant at the 0.05 level, as indicated by the P-Value of 0.000 for each path. This suggests that each variable significantly contributes to the construct of "Perceived Behavioral Control".
The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

c: The latent factor **"Subjective Norms"** has a significant impact on all observed variables (SN1 through SN6), with varying directions and strengths. Positive estimates suggest direct relationships, while negative estimates suggest inverse relationships. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios.

All attributes (SN1 through SN6) have significant relationships with the latent factor "Subjective Norms" as indicated by the p-values (***), meaning $p < 0.001$.
The critical ratios (C.R.) are all significantly different from zero, further confirming the statistical significance of these relationships.

d. The latent factor **"Mobile Commerce Intention"** has a significant negative impact on most observed variables (MCI1 through MCI8), with varying strengths.

Positive estimates are not present in this context, suggesting inverse relationships throughout. The statistical significance of these relationships is consistently supported by low p-values and high critical ratios, except for MCI5, which is marginally significant.

Managers can use this information to prioritize improvement efforts, enhance mobile commerce platforms, and ultimately increase customer engagement and transactions via mobile devices.

e. Goodness of fit indices collectively suggest that the model fits the data well across different aspects of fit (absolute, incremental, and parsimonious), providing confidence in its validity and relevance for explaining the relationships among variables in the specified theoretical framework.
The model shows excellent absolute fit (chi-square p-value > 0.05, RMSEA < 0.10, GFI ≥ 0.80). Incremental fit indices (AGFI, NFI, CFI, TLI) also indicate good to very good fit of the model. Parsimonious fit (CMIN/df) suggests the model is adequately parsimonious.

HTMT ratio is used to assess the extent to which the measurement model demonstrates discriminant validity. HTMT ratio should be less than 0.90 (Hair & Alamer,2022), indicating that the constructs have good discriminant validity. All the HTMT ratios provided are below the threshold value of 0.90. Indicating that the constructs are distinct from each other and do not have discriminant validity issues**.**

In summary, the model overall demonstrates high construct validity, supporting its applicability in understanding behavioural intention toward mobile commerce.

5.2.2 Findings of Objective 2:

a. Among the three antecedents, **Attitude** ($\beta = 0.529$, $p < 0.001$) has the most substantial and statistically significant impact on the intention to use m-commerce. This suggests that individuals with positive evaluations of mobile commerce (e.g., convenience, trust, and usefulness) are more likely to intend to engage in m-commerce purchase behaviour.

b. **Subjective Norms** ($\beta = 0.341$, $p < 0.001$) also show a significant positive effect on the intention to use m-commerce, highlighting the role of social influence, such as peer recommendations or societal trends in shaping behavioural intentions.

c. **Perceived Behavioural Control** ($\beta = 0.080$, $p = 0.134$) does not significantly influence intention, implying that users' self-perception of control or technical ability may not directly determine their intention to adopt m-commerce.

d. Structural Equation Modeling (SEM) results demonstrate that the overall model has a good fit (RMSEA = 0.071, CFI = 0.928, TLI = 0.920), indicating strong model validity. Model demonstrates significant paths between the key constructs Attitude, Subjective Norms and Perceived Behavioural Control, with most indicators showing strong, significant loadings on their respective constructs. The primary takeaway is the importance of Attitude and Subjective Norms in predicting Intentions to use m-commerce. Collectively all three antecedents are impacting on intention to use mobile commerce

In summary, attitude and subjective norms are key predictors of m-commerce intention, offering valuable insights for marketers to focus on user perception and social influence strategies to drive adoption.

5.2.3 Findings of Objective 3:

a. According to the results of t-test, all four constructs namely Subjective Norm, Perceived Behavioural Control, Attitude, and Intention show no significant differences between **genders** and their intention to use mobile commerce.

b. **Area of Location** (urban vs. rural) shows no significant effect on Attitude, Perceived Behavioural Control or Subjective Norms, but impacts, intention to use m-commerce. This means that area of location does not have a statistically significant effect on these constructs according to the results of t-test except in Intention. Urban users report higher intention to use m-commerce compared to rural users.

c. **Marital status** shows no significant effect on Attitude, Subjective Norm and Perceived Behavioural Control, but influences intention to use m-commerce. This means that marital status has a statistically significant effect only on intention. Marital status influences intention, with unmarried respondents showing greater adoption tendency.

d. **Age** significantly affects both attitude and intention, with younger users (21-40 years) having the most favourable attitudes and strongest intention. As per the findings younger age groups, particularly those between 21 and 40 years, show higher intention and positive attitudes towards m-commerce, suggesting a greater readiness to adopt and engage with mobile shopping. In contrast, older age groups exhibit lower intention and more negative attitudes, highlighting the need for targeted interventions to improve their perception and usage of m-commerce. Subjective Norm and Perceived Behaviour Control do not show significant differences across age groups.

e. **Educational level** significantly impacts subjective norms and intention but not attitude and perceived behavioural control. Notably, higher education correlates with stronger intention to adopt m-commerce. There are significant differences in subjective norms and intention to use m-commerce across various educational levels. Understanding these differences can help businesses develop targeted strategies that address the specific needs and preferences of each group. By focusing on social influence, tailored marketing campaigns, and improving ease of use and reliability, businesses can enhance m-commerce adoption and usage across all educational segments.

f. Different **occupational groups** exhibit varying levels of intention to use m-commerce. Subjective Norm and Perceived Behavioural Control do not show significant differences across occupation groups. Attitude is not significantly different across occupation groups, but it is close to the significance threshold. Intention is the only construct which shows significant differences across occupational groups. Understanding these differences allows businesses to develop targeted strategies that address the specific needs and preferences of each group. By focusing on convenience, security, and personalized user experiences, businesses can enhance m-commerce adoption and satisfaction across all occupational categories.

g. **Monthly income** influences attitude (higher earners show more positive attitudes) but not Subjective Norm, Perceived Behavioural Control and intention. The most consistent predictors of intention appear to be attitude and social norms, moderated by demographics such as age and education. The findings reveal variations in attitudes towards m-commerce across different income levels, with higher income groups showing more favourable attitudes. By developing targeted marketing strategies, enhancing services, and building trust, businesses can effectively cater to the diverse needs of consumers across all income brackets.

In summary, m-commerce strategies must be demographically framed. Age- and education-specific campaigns, rural outreach, and simplified user experiences are critical for increasing m-commerce adoption across varied population segments.

Understanding these differences and addressing them through tailored approaches can significantly enhance m-commerce adoption among consumers.

5.2.4 Findings of Objective 4:

a. Mediation analysis confirmed that intention fully mediates the effect of Attitude (indirect effect = 0.285, $p < 0.001$) on purchase behaviour for the specified product categories, using m-commerce.
b. Intention fully mediates the effect of Subjective Norms (indirect effect = 0.152, $p < 0.001$) on purchase behaviour for the specified product categories, using m-commerce.

c. Intention does not mediate the relationship between Perceived Behavioural Control and actual purchase behaviour for the specified product categories, using m-commerce.

d. **Intention** is a strong and statistically significant predictor of actual purchase behaviour for the specified product categories, using m-commerce ($\beta = 0.752$, $p < 0.001$), whereas direct effects from attitude, subjective norms, and perceived control on purchase behaviour were found to be non-significant.

e. The overall effect of attitude on buying behaviour through mobile commerce is positive and statistically significant. The direct effect of attitude on buying behaviour is positive but not statistically significant. The indirect effect, mediated by intention, is positive and statistically significant, indicating that intention plays a crucial mediating role between attitude and buying behaviour.

f. The overall effect of subjective norm on buying behaviour is positive and statistically significant. The direct effect of subjective norm on buying behaviour is negative and not statistically significant. The indirect effect, mediated by intention, is positive and statistically significant, indicating that subjective norms influence buying behaviour primarily through their impact on intention.

g. The overall effect of perceived behavioural control on buying behaviour is not statistically significant. The direct effect is negative and not statistically significant. The indirect effect, mediated by intention, is positive but not statistically significant, indicating that perceived behavioural control does not have a significant influence on buying behaviour through intention.

In summary, findings suggest that while Attitude and Subjective Norm significantly influence Intention, only Intention significantly predicts Buying behaviour. The model fit indices support the adequacy of the model in explaining the relationships among these constructs. The model fit was acceptable (CFI = 0.972, RMSEA = 0.083), validating the structure. These findings highlight that intention acts as a critical factor between consumers' psychological factors and their actual purchase behaviour for the specified product categories, using m-commerce.

5.2.5 Findings of Objective 5:

Overall, goodness of fit indices collectively suggest that the model fits the data well across different aspects of fit (absolute, incremental, and parsimonious), providing confidence in its validity for explaining the relationships among variables in the specified theoretical framework. The model fit indices indicate a strong model: RMSEA = 0.068, CFI = 0.901, TLI = 0.90, and CMIN/df = 3.194-all within acceptable or excellent thresholds, confirming robust model validity.

The results confirm that attitude (β = 0.533) and subjective norms (β = 0.231) significantly and positively influence intention, whereas perceived behavioural control has a negligible and non-significant impact (β = 0.023). The SEM analysis highlight the critical role of 'Attitude' and 'Subjective Norms' in driving the intention to use m-commerce, which in turn strongly influences actual usage behaviour.

The strength of '**Attitude'** suggests that consumers' perception of benefits of using m-commerce strongly drive usage, while social influences also play a key role. A strong and highly significant influence on Intention highlights the importance of positive attitudes towards m-commerce. This indicates that, by launching educational campaigns to highlight the benefits and convenience of m-commerce and addressing common concerns such as

security and privacy through informative contents, overall user experience can be enhanced, which can also contribute to more favourable attitudes.

The weak and insignificant influence of '**Perceived Behavioural Control'** on Intention indicates that users' perceptions of their ability to use m-commerce are not major determinants of their intention to use it. This indicate that, ease of use and user support is still important, it may not significantly drive intention. Resources might be better allocated to other areas.

A moderate and highly significant influence of **'Subjective Norms'** on 'Intention', suggests that social influence is crucial in shaping the intention to use m-commerce. This suggests that, by implementing marketing strategies that capitalize on social proof, such as influencer endorsements, user testimonials, and community engagement initiatives, can drive intentions to use m-commerce.

Intention significantly predicts actual buying behaviour ($\beta = 0.674$), reinforcing its central role in consumer decision-making. The strong and significant influence of 'Intention' on 'Behaviour' indicates that those who intend to use m-commerce are very likely to do so. This suggests converting intention to action. This can involve optimizing the onboarding process, providing excellent customer service, and offering incentives such as discounts or loyalty programs to encourage initial use and repeat transactions.

In summary, findings confirm that TPB is effective in explaining m-commerce behaviour, with intention serving as the primary mediator between psychological constructs and consumer action. For practitioners, this emphasizes the need to build positive consumer attitudes and leverage peer influence, while simplifying usage to support behavioural control. This validated model offers a strategic foundation for enhancing m-commerce adoption.

5.2.6 Findings of Objective 6:

a. A moderate to strong positive correlation ($r = 0.600$) was found between individuals' **lack of knowledge** and their non-adoption of m-commerce. The significant positive correlation between lack of knowledge and the non-adoption of mobile commerce highlights the importance of knowledge dissemination in promoting the use of mobile commerce applications.

b. **Educational level** emerged as a crucial determinant, with higher educational attainment significantly associated with greater m-commerce usage. The Pearson Chi-Square, Likelihood Ratio, and Linear-by-Linear Association tests all indicate a significant association between education level and the use of m-commerce ($p < 0.01$). The significant association suggests that education level may play a crucial role in deciding whether individuals are using m-commerce or not.

c. **Geographical location** also plays a pivotal role. The study found a significant association between **urban or rural residency** and the likelihood of using m-commerce, indicating the need for area-specific strategies. The tests indicate a significant association between the area of location (urban or rural) and the use of m-commerce. This suggests that strategies to increase m-commerce adoption may need to be tailored to address the specific needs and barriers of urban and rural populations.

d. Chi-Square test indicates a significant association between **marital status** and the use of m-commerce. This suggests that marital status of an Individual significantly affects his/her likelihood of using m-commerce.

e. Chi-Square test indicates a significant association between **occupation** and the use of m-commerce. This suggests that different occupational groups have varying likelihoods of using m-commerce, and targeted interventions may be necessary to address specific barriers faced by different occupational groups. The significant linear relationship further reinforces the need to consider occupational status in efforts to promote m-commerce usage.

f. Interestingly, **monthly family income** showed no significant association with m-commerce usage, indicating that financial status may not be a primary barrier to m-commerce adoption. This suggests that other factors, beyond family income, might play a more crucial role in determining m-commerce adoption.

g. Psychological and behavioural variables such as **attitude (r = -0.422)** and **intention (r = -0.565)** demonstrated strong negative correlations with non-adoption. This suggests that users who had never engaged in m-commerce were less inclined or motivated to adopt the technology.

Subjective norms also showed a weak but significant negative correlation, implying a weak but significant negative correlation ($r = -0.159$, $p = 0.001$) indicating that social influence modestly affects adoption behaviour.

Perceived behavioural control, however, had no significant relationship, suggesting that users' confidence in their ability to use m-commerce may not be a deciding factor. There is no significant correlation between perceived behavioural control and non-adoption of m-commerce ($r = -0.006$, $p = 0.904$), indicating that perceived behavioural control does not have any significant impact on whether individuals will use or not use m-commerce for shopping.

There is a strong negative correlation ($r = -0.565$, $p < 0.001$) between intention and non-adoption of m-commerce., indicating that those who have no intention to use m-commerce are much less likely to have the intention to use it in future.

In summary, the results highlight the importance of subjective norms and attitudes in influencing individuals' intentions to use m-commerce. While perceived behavioural control does not show a significant relationship with other variables in this context, addressing subjective norms and attitudes could be key strategies in promoting m-commerce usage. The study emphasizes the need for targeted educational campaigns, simplified user experiences, and community-specific outreach strategies. Efforts to enhance users' attitudes and intentions through awareness and incentives are crucial for expanding m-commerce adoption across diverse demographic groups in Goa.

5.3 FINDINGS ON DEMOGRAPHIC INSIGHTS:

a. Gender Distribution

The analysis reveals that the proportion of female respondents is higher compared to male respondents. This indicates that women are increasingly engaging with mobile commerce platforms and playing a significant role in shaping digital consumer behaviour. Such

participation highlights the importance of considering gender-based preferences in m-commerce strategies.

b. Age Distribution

The sample predominantly consists of young adults between the ages of 21 and 40 years. This age group is generally more familiar with technology, adaptable to digital platforms, and actively participates in online shopping. Their strong presence suggests that young consumers are key drivers of m-commerce adoption.

c. Education Level

Most of the respondents possess at least a graduation degree. This reflects a consumer base that is relatively well-informed, digitally literate, and capable of making rational purchase decisions through mobile platforms. Education, therefore, appears to be an important antecedent influencing m-commerce behaviour.

d. Urban–Rural Split

The distribution of respondents between urban and rural areas is found to be nearly equal. This suggests that mobile commerce has penetrated not only in urban regions but also in rural areas, supported by greater internet accessibility and smartphone usage. It demonstrates the expanding geographical reach of m-commerce in Goa.

e. Marital Status

The study shows a higher proportion of unmarried respondents compared to married ones. Unmarried individuals, often characterized by greater discretionary spending and openness to digital innovations, seem to be more active in using mobile commerce platforms. This finding emphasizes the role of youth in shaping m-commerce trends.

f. Occupation

A significant share of respondents are employed in service sectors, while a notable portion are unemployed, which may include students or homemakers. Service professionals tend to prefer m-commerce for convenience, while unemployed respondents may engage due to time availability and attractive offers. Occupational status, therefore, influences the manner in which consumers interact with m-commerce.

g. Income Levels

A considerable proportion of respondents belong to families with a monthly income exceeding ₹1,00,000. This indicates the participation of financially strong households in mobile commerce, reflecting their ability to engage in frequent and high-value purchases. Higher income levels are thus an important determinant of consumer behaviour in this domain.

In summary, the applicability of the Theory of Planned Behaviour (TPB) to m-commerce adoption in Goa is evident through these findings. Attitude towards m-commerce is shaped by young, educated, and financially strong consumers who perceive it as convenient and reliable. Subjective norms emerge from the growing acceptance among women, youth, and urban as well as rural populations, reflecting social influence on adoption. Perceived behavioural control is evident as educated, tech-savvy, and higher-income groups feel confident in using digital platforms, while accessibility across regions enhances ease of use. Together, these factors explain consumers' intention and behaviour towards adopting m-commerce.

5.4 IMPLICATIONS FOR THEORY AND PRACTICE:

The application of the Theory of Planned Behaviour (TPB) in this study reaffirms its relevance in the domain of mobile commerce. The constructs of attitude, subjective norms, and perceived behavioural control together offer a comprehensive framework for understanding consumer intentions. The findings confirm that attitude and subjective norms are robust predictors of behavioural intention, emphasizing the psychological and social dimensions of technology adoption.

Practically, the insights derived from the analysis serve as a strategic roadmap for stakeholders in the mobile commerce ecosystem. Marketers, and policy makers must focus on reducing barriers to mobile commerce adoption, such as lack of knowledge and perceived risks, while amplifying enablers like convenience, ease of use, and social endorsement. These efforts can catalyse broader adoption, especially in understated rural demographics.

5.5 RECOMMENDATIONS:

Based on the findings, several recommendations can be made to improve mobile commerce adoption and user experience:

I. **User Education:** Launch targeted awareness and education campaigns to bridge knowledge gaps, especially in rural areas. These should include multimedia content, local language support, and practical demonstrations.

II. **Enhanced User Interface:** Ensure platforms are intuitive, with simplified navigation, real-time assistance, and accessible features that cater to a wide range of users, including the elderly and those with limited tech exposure.

III. **Security and Privacy:** Strengthen and visibly promote platform security features such as encryption, multi-factor authentication, and transparent privacy policies to build trust among users.

IV. **Social Proof Integration:** Integrate reviews, ratings, and testimonials into the commerce journey. Highlighting peer experiences, influencer endorsements, and family/friend recommendations can boost subjective norms positively.

V. **Localized Strategies:** Develop region-specific strategies that consider socio-economic and infrastructural differences between urban and rural users. This includes offering low-bandwidth versions of apps, offline support, and vernacular content.

VI. **Feedback Systems:** Implement robust feedback and grievance redressal mechanisms to swiftly address negative experiences and perceptions, thereby improving attitude and retention.

5.6 LIMITATIONS OF THE STUDY:

I. As an empirical study, the data collection occurred at a single point in time. This cross-sectional approach does not account for changes in consumer attitudes, technological advancements, or market trends over time, which can influence consumer behaviour towards m-commerce.

II. The data was gathered using surveys, which depend on participants' self-reporting. Such methods are prone to recall errors, and respondents' inability to accurately predict their future behaviour.

III. The study is based on the Theory of Planned Behaviour (TPB), which, has limitations. For instance, TPB may not fully capture other important factors influencing consumer behaviour, such as emotional, habitual, or contextual factors, particularly in rapidly evolving technological environments.

IV. The size of the sample could be a limitation. A small sample limits the ability to draw broader conclusions or generalize findings to a larger population.

V. Given the dynamic nature of m-commerce, the findings may become outdated quickly as new technologies, features, and platforms emerge, altering consumer preferences and behaviours.

VI. Construct measurement may pose challenges. For example, attitude, subjective norms and perceived behavioural control might be difficult to measure accurately, leading to potential measurement errors that impact the reliability and validity of the results.

5.7 FUTURE RESEARCH DIRECTIONS:

The study of consumer behaviour in the context of mobile commerce (m-commerce) is an evolving field, influenced by rapid technological advancements and shifts in consumer lifestyles. While existing research has identified critical factors such as attitude, perceived behavioural control, and subjective norms and its impact on intention and behaviour of consumers towards m-commerce, as per the theory of planned behaviour, there remain significant areas that warrant further exploration. Below are some promising avenues for future research:

I. Technological Advancements: Examine the role of emerging technologies such as artificial intelligence (AI), and augmented reality (AR) in shaping consumer behaviour towards m-commerce

II. Psychological and Emotional Factors: Analyse how emotions, such as anxiety or excitement, triggered by m-commerce experiences influence purchase behaviour of consumers.

III. Social media Influencers: Study the impact of social media influencers on m-commerce consumer behaviour.

IV. **Privacy and Security Concerns:** Assess how concerns over cybersecurity influence consumer trust and willingness to engage in m-commerce.

V. **Demographic and Psychographic Segmentation:** Conduct studies focused on specific demographic groups, such as Gen Z or senior citizens, to understand their unique m-commerce behaviours.

By addressing these gaps, future research can provide a deeper understanding of the antecedents to consumer behaviour in m-commerce, thereby enabling businesses to design strategies that better meet the needs of their mobile-centric customers.

5.8 SUMMARY OF KEY CONTRIBUTIONS:

This research provides an evidence-based assessment of the Theory of Planned Behaviour in the context of mobile commerce. Its key contributions include:

I. Validating the structure and significance of TPB constructs through empirical SEM analysis.

II. Demonstrating the stronger role of Attitude and Subjective Norms over Perceived Behavioural Control in predicting Mobile Commerce Intention.

III. Identifying demographic distinctions, especially the rural-urban divide, in shaping consumer behaviour.

IV. Offering practical and policy-driven recommendations grounded in quantitative findings.

These contributions not only reinforce the TPB as a theoretical model but also extend its utility in guiding strategic decisions in the m-commerce space.

5.9 CONCLUSIONS:

The present study was undertaken with the primary objective of examining the antecedents of consumer behaviour towards mobile commerce (m-commerce) adoption by applying the Theory of Planned Behaviour (TPB) as the guiding theoretical framework. As digital technologies increasingly shape the patterns of consumer decision-making, m-commerce has emerged as a transformative force redefining the way individuals engage with products, services, and marketplaces. Against this backdrop, the research sought to understand how consumers' psychological factors namely attitude, subjective norms, and perceived behavioural control influence their intention to adopt m-commerce and, ultimately, their actual purchase behaviour towards m-commerce. The findings of this study provide valuable

insights into the dynamics of m-commerce adoption in the state of Goa, while also extending the applicability of TPB to the domain of digital consumer behaviour in a broader context.

The empirical results highlight that among the three central antecedents of TPB, attitude emerges as the most powerful determinant of consumer intention to adopt m-commerce. Attitude, which reflects an individual's positive or negative evaluation of using mobile platforms for shopping, strongly influences whether a consumer is willing to engage in such transactions. The findings confirm that consumers who perceive m-commerce as convenient, secure, efficient, and reliable develop more favourable attitudes, which in turn strengthen their intention to use such platforms. This insight highlights that consumer perceptions of value, trustworthiness, and utility play a vital role in driving digital adoption. In the context of m-commerce, where issues of security, privacy, and ease of transaction remain central concerns, a positive attitude serves as a crucial gateway for shaping behavioural intentions. Thus, the results reaffirm the TPB proposition that attitudes act as a cornerstone of behavioural prediction within the unique setting of mobile-commerce.

Closely linked to attitude, the findings also emphasise the significant role of subjective norms in shaping intention. Subjective norms, defined as the perceived social pressure from important others to perform or not perform a behaviour, emerged as a noteworthy determinant of m-commerce adoption. Consumers were found to be strongly influenced by the opinions, encouragement, and behaviours of peers, family members, and broader social groups. The results indicate that when consumers perceive mobile commerce as widely accepted and endorsed by their social networks, they are more likely to develop favourable intentions to engage in such practices. This insight reflects the inherently social nature of technology adoption, where the influence of peers and social circles increases the use of digital practices. Moreover, with the explosion of social media platforms, online communities, and influencer-driven content, subjective norms emerge not only as a theoretical construct within TPB but also as a practical driver of consumer adoption in the contemporary digital era.

In contrast, perceived behavioural control was not found to significantly influence intention in this study. Traditionally, perceived behavioural control refers to the extent to which individuals feel capable of performing a behaviour based on their resources, opportunities, and self-efficacy. However, the findings suggest that in the current context, technical skills, access to smartphones, and availability of internet services are no longer substantial barriers

to adoption. With the rapid growth of mobile technologies, affordable data services, and user-friendly application interfaces, consumers increasingly perceive themselves as capable of engaging in mobile commerce without significant constraints. This diminishing relevance of perceived behavioural control marks an important shift in the digital adoption landscape. While TPB suggests behavioural control as an important determinant of intention, the present findings suggest that in contexts where technological barriers are minimal, the construct may exert limited influence. This result offers an important refinement to the application of TPB in digital environments, signalling the need to reassess the relative weight of its constructs in contexts characterised by high levels of technological accessibility.

Beyond the individual antecedents, the study also underscores the central role of intention as the mediating variable between psychological constructs and actual behaviour. The results clearly demonstrate that intention is the strongest predictor of actual adoption, while the direct effects of attitude, subjective norms, and perceived behavioural control on behaviour were found to be insignificant. This reinforces the conceptualisation within TPB that behavioural intention serves as the most important determinant of actual behaviour. In the context of m-commerce, consumers may hold favourable attitudes and perceive social endorsement; however, it is only when these factors translate into concrete behavioural intentions that actual adoption takes place. This finding highlights the importance of developing strong consumer intentions, as these serve as the critical link between attitude and purchase behavioural outcomes. By confirming the mediating role of intention, the study contributes empirical evidence supporting the theoretical foundations of TPB while adapting them towards use of mobile-commerce.

The analysis of demographic variables provided further depth to the understanding of consumer adoption patterns. Age was found to play a significant role, with younger consumers—particularly those between the ages of 21 and 40—demonstrating the highest levels of intention to adopt m-commerce. This finding reflects the digital orientation of younger generations, who are more familiar with mobile technologies and more open to integrating them into their daily shopping practices. Education emerged as another significant factor, with respondents possessing higher levels of education displaying stronger subjective norms and greater intention to adopt. This can be attributed to the role

of education in fostering digital literacy, critical thinking, and openness to technological innovations.

Marital status was also found to influence adoption behaviour, with unmarried individuals exhibiting greater willingness to engage in m-commerce compared to their married counterparts. This may be explained by differences in lifestyle, consumption preferences, and financial decision-making patterns. Occupation similarly shaped adoption, as professionals in the service sector displayed higher levels of intention, likely due to greater exposure to digital technologies in their work environments. Income was observed to affect attitudes towards m-commerce, with higher-income groups perceiving greater value in such platforms, though income did not consistently predict intention. Location also played an important role, as urban consumers reported higher adoption intentions compared to rural consumers, though the gap is gradually narrowing with increasing mobile penetration in semi-urban and rural areas. Collectively, these demographic insights highlight that m-commerce adoption is shaped by a complex interplay of psychological and socio-demographic factors, highlighting the importance of segment-specific strategies to understand consumer behaviour.

A notable insight emerging from the study concerns the barriers to adoption. Among non-users of m-commerce, lack of knowledge emerged as the most prominent obstacle. Many individuals reported security features associated with mobile commerce, which lacks their participation. This points to the importance of addressing knowledge gaps and creating awareness as a critical step towards expanding adoption. Psychological barriers also played a role, as individuals with negative attitudes or weak intentions were significantly less likely to engage in mobile transactions. Interestingly, perceived behavioural control did not emerge as a significant barrier for non-users, further reinforcing the observation that technological accessibility is no longer a major obstacle in the current context. Together, these findings highlight that adoption barriers are primarily psychological rather than infrastructural, suggesting that efforts to promote m-commerce should focus on improving knowledge and shaping positive attitudes.

From a theoretical point of view, this research makes important contributions by validating and extending the application of TPB in the context of m-commerce. The study affirms the robustness of TPB in predicting consumer behaviour while also highlighting the differential influence of its constructs. Specifically, attitude and subjective norms emerged as stronger

predictors of intention compared to perceived behavioural control, signalling the relative importance of evaluative and social factors over control-related considerations in digital environments. The mediating role of intention was also reinforced, confirming its significance in linking antecedents to actual behaviour. Furthermore, by integrating demographic variables into the analysis, the study extends the explanatory power of TPB, demonstrating how socio-demographic contexts interact with psychological constructs to shape adoption patterns.

The contributions of this study also extend to a broader understanding of digital consumer behaviour in emerging markets. Unlike developed economies, where digital adoption is often taken for granted, the findings reveal that in developing contexts, adoption is shaped by a combination of favourable attitudes, social influence, and demographic characteristics. The research provides empirical evidence that mobile commerce adoption in such settings is not uniform but varies across age groups, educational backgrounds, and urban–rural divides. Study enriches the theoretical discourse and provides a more comprehensive understanding of the dynamics of digital adoption.

To conclude, this research has provided a detailed examination of the antecedents of consumer behaviour towards m-commerce, confirming that attitude and subjective norms are the most critical drivers of intention, and intention itself is the strongest predictor of actual adoption behaviour towards mobile commerce. The findings validate the applicability of TPB while also extending its scope by highlighting the subtle role of its constructs and the influence of demographic factors. By identifying knowledge gaps and psychological barriers among non-users, the study also sheds light on the challenges that remain in expanding m-commerce adoption. Ultimately, the research contributes both to theoretical advancement and to the practical understanding of consumer behaviour in the digital age.As mobile commerce continues to reshape consumer lifestyles and redefine the retail landscape, the insights derived from this study offer a valuable foundation for academics, policymakers, and industry stakeholders seeking to understand and leverage the drivers of adoption. By highlighting the antecedents of consumer behaviour towards m-commerce, validating the importance of intention, and situating these insights within the socio- demographic realities, the study advances both knowledge and understanding of this rapidly evolving domain of mobile commerce.

BIBLIOGRAPHY

Agarwal, S., & Prasad, J. (2018). Adoption of mobile commerce: Influencing factors and consumer behaviour in India. International Journal of Mobile Marketing, 13(2), 23–36.

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. Journal of Applied Social Psychology, 32(4), 665-683.

Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Prentice-Hall.

Ajzen, I., & Fishbein, M. (2005). The influence of attitudes on behavior. In D. Albarracín, B. T. Johnson & M. P. Zanna (Eds.), The Handbook of Attitudes (pp. 173–221). Mahwah, NJ: Lawrence Erlbaum Associates.

Amin, M. (2020). Examining the role of customer satisfaction within mobile shopping apps on customer relationship performance. Journal of Retailing and Consumer Services, 56, 102207.

Anderson, J. C. (2020). *Structural equation modeling: A second course* (2nd ed.). Information Age Publishing.

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems, 8*(4), 244–254.

Bagozzi, R. P., & Yi, Y. (1989). *On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16*(1), 74–94.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly, 25*(3), 351–370.

Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.

Bansal, A., & Sharma, P. (2020). Examining trust and security dimensions in mobile commerce: An Indian consumer perspective. Journal of Internet Commerce, 19(3), 263–284. https://doi.org/10.1080/15332861.2020.1772890

Bansal, S., & Bharti, K. (2020). Impact of social media advertisements on consumer buying behavior: An empirical study using theory of planned behavior. International Journal of Management Studies, 7(3), 24–34. https://doi.org/10.18843/ijms/v7i3/04

Barnes, S. J., & Corbitt, B. J. (2004). Mobile commerce: Beyond retail – A vision of future developments and research. International Journal of Electronic Commerce, 8(3), 7-23.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182.

Beldad, A., de Jong, M., & Steehouder, M. (2010). How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust. Computers in Human Behavior, 26(5),

857–869.

Chang, H. H., & Chen, S. W. (2012). *The impact of online store environment cues on purchase intention: Trust and perceived risk as a mediator*. *Online Information Review, 36*(6), 1036–1056.

Chaffey, D., & Ellis-Chadwick, F. (2019). Digital Marketing: Strategy, Implementation, and Practice. Pearson.

Chauhan, A., & Verma, H. V. (2018). The influence of trust and perceived risk on consumer purchase intention in online shopping: A study of Indian e-commerce market. International Journal of Retail & Distribution Management, 46(3), 301–322. https://doi.org/10.1108/IJRDM-11-2016-0213

Chang, H. H., & Chen, S. W. (2010). *The impact of online store environment cues on purchase intention: Perceived playfulness and perceived flow*. *Online Information Review, 34*(6), 1185–1207.

Chau, P. Y. K., & Lai, V. S. (2003). *An empirical investigation of the determinants of user acceptance of Internet banking*. *Journal of Organizational Computing and Electronic Commerce, 13*(2), 123–145.

Cheng, Y., & Chen, S. (2015). *Exploring the factors influencing the adoption of mobile commerce: An empirical study in Taiwan*. *Journal of Electronic Commerce Research, 16*(2), 108–118.

Choi, J., Lee, H., & Kim, H. (2013). *The moderating effect of gender in the adoption of mobile banking*. *International Journal of Bank Marketing, 28*(5), 328–341.

Chopdar, P. K., & Sivakumar, V. J. (2019).Understanding continuance usage of mobile shopping applications in India: The role of espoused cultural values and perceived risk. *Behaviour & Information Technology, 38*(1), 42–64.

Chopdar, P. K., & Sivakumar, V. J. (2024). Customization at a glance: Investigating consumer experiences in mobile commerce applications. *Journal of Retailing and Consumer Services, 76*, 103602.

Chew (2006), defining behavioral intention: "the power of an individual's intention to perform a certain behaviour."

Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. Decision Support Systems, 54(1), 461–470. https://doi.org/10.1016/j.dss.2012.06.008

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. Journal of Marketing Research, 43(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Chiu, C. M., Lin, H. Y., & Tang, L. L. (2005). Gender differs: Assessing a model of online purchase intentions in e-tail service. International Journal of Service Industry Management, 16(5), 416-435.

Chong, A. Y. L. (2013). Mobile commerce usage activities: The roles of demographic and motivation variables. Technological Forecasting and Social Change, 80(7), 1350-1359.

Chong, A. Y. L. (2013). Understanding mobile commerce continuance intentions: An empirical analysis of Chinese consumers. Journal of Computer Information Systems, 53(4), 22-30.

Chu, S.-C., & Kim, Y. (2011). Determinants of consumer engagement in electronic word-of-mouth (eWOM) in social networking sites. International Journal of Advertising, 30(1), 47–75. https://doi.org/10.2501/IJA-30-1-047-075

Conner, M., & Armitage, C. J. (1998). Extending the theory of planned behavior: A review and avenues for further research. Journal of Applied Social Psychology, 28(15), 1429–1464. https://doi.org/10.1111/j.1559-1816.1998.tb01685.x

Coakes, S. J., & Steed, L. (2009). *SPSS: Analysis without anguish: Version 14.0 for Windows* (3rd ed.). Willey

Cyr, D., Kindra, G., & Head, M. (2006). The influence of website structure on perceived trust in online information. Information & Management, 43(2), 196–207. https://doi.org/10.1016/j.im.2005.01.002

Dahlberg, T., Mallat, N., & Öörni, A. (2008). Consumer acceptance of mobile payment solutions: A literature review. *Electronic Commerce Research and Applications, 7*(2), 165–181.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. Management Science, 35(8), 982-1003.

Deshmukh, N., & Patel, R. (2022). The impact of mobile promotional strategies on consumer behaviour in m-commerce. Journal of Consumer Marketing, 39(4), 394–406. https://doi.org/10.1108/JCM-10-2021-491

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., (2020). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management, 102168*.

Eagly, A. H., & Chaiken, S. (1993). The psychology of attitudes. Harcourt Brace Jovanovich College Publishers.

Fogg, B. J., Soohoo, C., Danielson, D. R., Marable, L., Stanford, J., & Tauber, E. R. (2001). *How do users evaluate the credibility of Web sites? A study with over 2,500 participants*. *Proceedings of the 2001 Conference on Designing for User Experiences*, 1–15.

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. Addison-Wesley.

Fishbein, M., & Ajzen, I. (2010). Predicting and changing behavior: The reasoned action approach. Psychology Press.

Fowler, F. J. (2013). Survey research methods (5th ed.). Sage Publications.

Gao, L., & Bai, X. (2014). A unified perspective on the factors influencing consumer acceptance of internet of things technology. Asia Pacific Journal of Marketing and Logistics, 26(2), 211-231.

Gao, L., Waechter, K. A., & Bai, X. (2015). Understanding consumers' continuance intention towards mobile purchase: A theoretical framework and empirical study – A case of China. Computers in Human Behavior, 53, 249-262.

Gefen, D. (2003). TAM or just plain habit: A look at experienced online shoppers. Journal of End User Computing, 15(3), 1-13.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90. https://doi.org/10.2307/30036519

George, A., & Kumar, G. G. (2014). Antecedents of customer satisfaction in online shopping: An integrated framework and research propositions. Journal of Internet Commerce, 13(3-4), 281–305. https://doi.org/10.1080/15332861.2014.961346

George, J. F. (2004). The theory of planned behavior and Internet purchasing. Internet Research, 14(3), 198–212. https://doi.org/10.1108/10662240410542634

Ghazali, E. M., Zolkepli, I. A., & Ramayah, T. (2018).Do consumers want mobile commerce? A closer look at m-shopping and technology adoption in Malaysia. *Computers in Human Behavior, 84*, 1–13.

Hajli, M. N. (2014). *A study of the impact of social media on consumers*. *International Journal of Market Research, 56*(3), 387–404.

Hanafizadeh, P., Keating, B. W., & Khedmatgozar, H. R. (2014). *A systematic review of Internet banking adoption*. *Telematics and Informatics, 31*(3), 492–510.

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations* (2nd ed.). Sage Publications.

Hsieh, Y. H., Rai, A., & Keil, M. (2012). *Understanding digital inequality: Comparing continued use behavioral models of the 'digital haves' and 'have-nots'*. *Information Systems Research, 23*(3), 542–559.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (1998). *Multivariate data analysis* (5th ed.). Prentice Hall.

Hamzah, M. I., Othman, A. K., & Hassan, F. (2020). Mediating effects of individual market orientation on the link between learning orientation and job performance. Journal of Business & Industrial Marketing, 35(4), 655-668.

Hernandez, B., Jimenez, J., & Martin, M. J. (2009). Adoption vs acceptance of e-commerce: Two different decisions. European Journal of Marketing, 43(9/10), 1232-1245.

Huang, Z., Huang, S., & Zhang, C. (2015). Trust in m-commerce: The impact of consumer's trust in supply chain management and service quality. Industrial Management & Data Systems, 115(2), 231-252.

IAMAI. (2023). Internet and Mobile Association of India.

Karjaluoto, H., Mattila, M., & Pento, T. (2007). *Factors underlying attitude formation towards online banking in Finland*. *International Journal of Bank Marketing, 25*(2), 105–121.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10.

Kumar, A., & Mukherjee, A. (2018). *Understanding the role of millennials in mobile commerce adoption*. *Journal of Retailing and Consumer Services, 45*, 1–10.

Kanchan, U., Kumar, R., & Gupta, A. (2015). A study of online purchase behaviour of consumers in India. International Journal of Advanced Research in Computer Science and Management

Studies, 3(6), 79–85.

Kaplan, D., & Graziano, W. G. (2009). The subjective norm as a mediator of the attitude-behavior relationship: A meta-analysis review. Journal of Social Psychology, 149(3), 231-244.

Kapoor, A. P., & Vij, M. (2021). Following you wherever you go: Mobile shopping 'cart-checkout'abandonment. Journal of Retailing and Consumer Services, 61, 102553.

Kapoor, K. K., Dwivedi, Y. K., & Williams, M. D. (2014). Examining the role of three sets of innovation attributes for determining adoption of the interbank mobile payment service. Information Systems Frontiers, 16(5), 1039-1056.

Kasuma, J., Razak, F. L. A., Omar, N., Naim, A. S. A., Naimullah, B. S. S., & Darma, D. C. (2020). Attitude, Perceived Usefulness and Perceived Ease of Use towards Intention to Use M-Commerce: A Case of Grocery Shoppers in Kuching, Sarawak. Journal of Entrepreneurship & Business, 8(1).

Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. Computers in Human Behavior, 26(3), 310-322.

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems, 44(2), 544-564.

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2009). Trust and satisfaction, two stepping stones for successful e-commerce relationships: A longitudinal exploration. Information Systems Research, 20(2), 237-257.

Kim, H.-W., Chan, H. C., & Gupta, S. (2007). Value-based adoption of mobile internet: An empirical investigation. Decision Support Systems, 43(1), 111–126. https://doi.org/10.1016/j.dss.2005.05.009

Kim, J., & Lennon, S. J. (2013). Effects of reputation and website quality on online consumers' emotion, perceived risk, and purchase intention. Journal of Research in Interactive Marketing, 7(1), 33-56.

Kim, S. H., Kim, H. W., & Wang, H. (2010). Understanding key drivers of m-commerce adoption in South Korea. International Journal of Mobile Communications, 8(3), 298-315.

Kim, S. J., Wang, R. J. H., Maslowska, E., & Malthouse, E. C. (2016). "Understanding a fury in your words": The effects of posting and viewing electronic negative word-of-mouth on purchase behaviors. Computers in Human Behavior, 54, 511-521.

Kim, Y. G., Shin, D. H., & Lee, J. H. (2008). Understanding dynamics between initial trust and usage intentions of mobile banking. Information Systems Journal, 18(6), 545-580.

Kotler, P., & Armstrong, G. (2016). Principles of marketing (16th ed.). Pearson.

Kumar, V., & Roy, S. (2019). Lifestyle and demographic factors influencing m-commerce usage: Evidence from Indian consumers. Journal of Retailing and Consumer Services, 50, 8–17. https://doi.org/10.1016/j.jretconser.2019.04.010

Lee, M. C. (2011). *Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation-confirmation model*. *Computers & Education, 57*(2), 1362–1376.

Lim, W. M., Tan, G. W. H., & Lee, S. H. (2016).*Online shopping: A review of the literature. International Journal of Economics and Management, 10*(2), 1–20.

Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2014). The moderating effect of experience in the adoption of mobile payment tools in virtual social networks: The m-payment acceptance model in a virtual social network context. International Journal of Information Management, 34(2), 151-166.

Lim, H., & Dubinsky, A. J. (2004). Consumers' perceptions of e-shopping characteristics: An expectancy-value approach. Journal of Services Marketing, 18(7), 500-513.

Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How habit limits the predictive power of intention: The case of information systems continuance. MIS Quarterly, 31(4), 705-737.

Lu, J. (2014). Are personal innovativeness and social influence critical to continue with mobile commerce? Internet Research, 24(2), 134-159.

Lu, J., & Su, P. (2009). Factors affecting purchase intention on mobile shopping web. International Journal of Business and Management, 4(1), 87–95. https://doi.org/10.5539/ijbm.v4n1p87

Lu, J., Yao, J. E., & Yu, C. S. (2005). Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. Journal of Strategic Information Systems, 14(3), 245-268.

Luarn, P., & Lin, H. H. (2005). Toward an understanding of the behavioral intention to use mobile banking. Computers in Human Behavior, 21(6), 873-891.

Mallat, N. (2007). Exploring consumer adoption of mobile payments – A qualitative study. *The Journal of Strategic Information Systems, 16*(4), 413–432.

Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.

Miniard, P. W., & Cohen, J. B. (1981). *Modeling personal and normative influences on behavior. Journal of Consumer Research, 8*(2), 169–177.

Mital, M., Chang, V., Choudhary, P., Papa, A., & Pani, A. K. (2021). Adoption of Internet of Things in India: A test of competing models using a structured equation modeling approach. *Technological Forecasting and Social Change, 173*, 121073.

Molla, A., & Licker, P. S. (2005). *E-commerce adoption in developing countries: A model and instrument*. *Information & Management, 42*(6), 877–899.

Moon, J. W., & Kim, Y. G. (2001). *Extending the TAM for a World-Wide-Web context*. *Information & Management, 38*(4), 217–230.

Morosan, C., & DeFranco, A. (2016). It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *International Journal of Hospitality Management, 53*, 17–29.

Mathieson, K. (1991). Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. Information Systems Research, 2(3), 173-191.

Mclean, G., Al-Nabhani, K., & Wilson, A. (2020). Developing a mobile applications customer experience model (MACE) – Implications for retailers. Journal of Business Research, 109, 104-115.

Mehta, P., & Chatterjee, R. (2022). Green consumer behaviour in India: A study of eco-conscious purchase intentions. Journal of Cleaner Production, 367, 132823.

Mehta, R., & Shah, S. (2021). Promotional strategies and consumer impulsive buying behaviour: Evidence from Indian e-commerce platforms. Indian Journal of Marketing, 51(3), 15–27. https://doi.org/10.17010/ijom/2021/v51/i3/157394

Mitchell, A. A., & Olson, J. C. (1981). Are product attribute beliefs the only mediator of advertising effects on brand attitude? Journal of Marketing Research, 18(3), 318–332. https://doi.org/10.2307/3150973

Mortimer, G., Fazal e Hasan, S. M., Andrews, L., & Martin, J. (2016). Online grocery shopping: The impact of shopping frequency on perceived risk. The International Review of Retail, Distribution and Consumer Research, 26(2), 202-223.

Nguyen, T. D., Ngo, L. V., & Ruël, H. (2020). Social capital, knowledge sharing, and innovation: Evidence from Vietnam's information technology industry. *Journal of Innovation & Knowledge, 5*(4), 282–290.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Nysveen, H., Pedersen, P. E., & Thorbjørnsen, H. (2005).Intentions to use mobile services: Antecedents and cross-service comparisons. *Journal of the Academy of Marketing Science, 33*(3), 330–346.

Ooi, K. B., & Tan, G. W. H. (2016). Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card. Expert Systems with Applications, 59, 33-46.

Pallant, J. (2020). *SPSS survival manual: A step-by-step guide to data analysis using IBM SPSS* (7th ed.). McGraw-Hill Education

Pappas, I. O. (2016). Marketing strategies and tactics in the age of digital transformation. *Journal of Strategic and International Studies, 12*(2), 1–11.

Park, C., & Kim, Y. (2003). Identifying key factors affecting consumer purchase behavior in an online shopping context. International Journal of Retail & Distribution Management, 31(1), 16-29.

Park, D. H., Lee, J., & Han, I. (2007). The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement. International Journal of Electronic Commerce, 11(4), 125–148. https://doi.org/10.2753/JEC1086-4415110405

Patil, D., & Bansal, A. (2018). Understanding rural consumer behaviour in India. International Journal of Rural Management, 14(1), 62–78. https://doi.org/10.1177/0973005218763507

Patil, P., & Rani, S. (2021). Factors affecting intention to adopt mobile wallets in India: An application of TPB. International Journal of Management Studies, 8(2), 112–125. https://doi.org/10.18843/ijms/v8i2/12

Paul, J., Modi, A., & Patel, J. (2016). Predicting green product consumption using theory of planned behavior and reasoned action. Journal of Retailing and Consumer Services, 29, 123–134. https://doi.org/10.1016/j.jretconser.2015.11.006

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce, 7(3), 101-134.

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. MIS Quarterly, 30(1), 115-143.

Petty, R. E., Cacioppo, J. T., & Schumann, D. (1983). Central and peripheral routes to advertising effectiveness: The mediating role of involvement. Journal of Consumer Research, 10(2), 135-146.

Rogers, E. M. (1962). *Diffusion of innovations* (1st ed.). New York: Free Press of Glencoe.

Ryan, E. H., & Bonfield, E. H. (1980). *The Fishbein-Ajzen model of attitude-behavior relations: A meta-analysis. Journal of Consumer Research, 7*(3), 307–316.

Rana, R., & Singh, J. (2021). App quality, user satisfaction and m-commerce engagement: An empirical investigation. International Journal of Information Management, 58, 102321. https://doi.org/10.1016/j.ijinfomgt.2020.102321

Rao, K., & Sinha, M. (2020). Online consumer behaviour in tier II and III cities in India: A study on emerging digital markets. Journal of Business and Retail ManagementResearch,14(3),120130.https://doi.org/10.24052/JBRMR/V14IS03/ART-11

Riquelme, H. E., & Rios, R. E. (2010). The mediating effect of gender in the adoption of mobile banking. International Journal of Bank Marketing, 28(5), 328-341.

Rogers, E. M. (2003). Diffusion of Innovations (5th ed.). Free Press.

Russo, I., Confente, I., Gligor, D. M., & Cobelli, N. (2017). The combined effect of product returns experience and switching costs on B2B customer re-purchase intent. Journal of Business & Industrial Marketing, 32(5), 664-676.

Schiffman, L. G., & Wisenblit, J. (2019). *Consumer behavior* (12th ed.). Pearson Education.

Shareef, M. A., Baabdullah, A. M., Dutta, S., Kumar, V., & Dwivedi, Y. K. (2021). Consumer adoption of mobile banking services: An empirical examination of factors according to adoption stages. *Journal of Retailing and Consumer Services, 61*, 102554.

Sheth, J. N. (2021). Impact of demographic factors on consumer behavior in digital markets. *Journal of Business Research, 124*, 1–9.

Shin, D. H. (2010). The effects of trust, risk, and privacy concern on users' acceptance of location-based services. *International Journal of Mobile Communications, 8*(4), 393–411.

Shin, D., & Kang, M. (2016). Understanding the role of cultural differences in the adoption of mobile commerce: A cross-national study. *Information & Management, 53*(4), 499–510.

Simon, H. A. (1955). A behavioral model of rational choice. The Quarterly Journal of Economics, 69(1), 99–118.

Sadi, A. S. (2012). Modeling the Factors Affecting the Adoption of Mobile Commerce in Malaysia Higher Institutions (Doctoral dissertation, Kulliyyah of Information and Communication Technology, International Islamic University Malaysia).

Saxena, S., & Khanna, M. (2019). Influence of website quality on consumer online purchase

behaviour: Evidence from Indian fashion e-commerce. Indian Journal of Marketing, 49(5), 37–49. https://doi.org/10.17010/ijom/2019/v49/i5/143363

Saxena, S., & Yadav, R. (2019). Investigating the role of subjective norm and brand consciousness in brand loyalty: Evidence from Indian fashion retail. Journal of Retailing and Consumer Services, 51, 234–240. https://doi.org/10.1016/j.jretconser.2019.06.010

Sharma, R., & Kapoor, S. (2021). Impact of digital media on youth consumer behaviour in India. Journal of Retailing and Consumer Services, 59, 102400. https://doi.org/10.1016/j.jretconser.2020.102400

Sharma, S., & Gupta, V. (2020). Influence of subjective norms and attitude on online shopping behaviour in India: An extension of the TPB model. Indian Journal of Marketing, 50(7), 8–20. https://doi.org/10.17010/ijom/2020/v50/i7/155026

Singh, A., & Kaur, G. (2019). Cultural values and consumer behaviour: A study of Indian consumers. Asian Journal of Business Research, 9(2), 78–90. https://doi.org/10.14707/ajbr.190065

Sivathanu, B. (2019). Adoption of digital payment systems in the era of demonetization in India: An empirical study. Journal of Science and Technology Policy Management, 10(1), 143-171.

Slade, E. L., Williams, M. D., Dwivedi, Y. K., & Piercy, N. C. (2015). Exploring consumer adoption of proximity mobile payments. Journal of Strategic Marketing, 23(3), 209-223.

Smith, J. (2019). *Marketing to Gen Z: Understanding the preferences and behaviors of the next generation*. ResearchGate.

Sunita, C. (2023). Consumer Perception Towards Sustainable Packaging in E-Commerce Industry: A Factor Analytic Approach. Quing: International Journal of Commerce and Management, 3(2), 177-185.

Tan, G. W. H., Ooi, K. B., & Lin, B. (2014). Predicting the drivers of behavioral intention to use mobile learning. *Computers in Human Behavior, 35*, 1–10.

Tarkiainen, A., & Sundqvist, S. (2005). Subjective norms, attitudes and intentions of Finnish consumers in buying organic food. British Food Journal, 107(11), 808-822.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144-176.

Thakur, R. (2013). Customer adoption of mobile payment services by professionals across two cities in India: An empirical study using modified technology acceptance model. Business Perspectives and Research, 1(2), 17-29.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2012). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.

Venkatesh, V., Thong, J.Y.L., & Xu, X. (2012). Consumer acceptance and use of information

technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157-178.

Vermeir, I., & Verbeke, W. (2006). Sustainable food consumption: Exploring the consumer "attitude–behavioral intention" gap. Journal of Agricultural and Environmental Ethics, 19(2), 169–194. https://doi.org/10.1007/s10806-005-5485-3

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. MIS Quarterly, 26(2), iii–xiii.

Wedel, M., & Kamakura, W. A. (2012). *Market segmentation: Conceptual and methodological foundations* (2nd ed.). Springer Science & Business Media.

Wang, R. J. H., Malthouse, E. C., & Krishnamurthi, L. (2015). On the go: How mobile shopping affects customer purchase behavior. Journal of retailing, 91(2), 217-234.

Wang, Y., & Lin, C. A. (2009). Consumer attitudes toward marketing and consumerism in China and the United States. International Journal of Advertising, 28(1), 125–146. https://doi.org/10.2501/S026504870920014X

Wang, Y.-S., & Lin, H.-H. (2012). Determinants of user acceptance of mobile banking: An empirical study. International Journal of Mobile Communications, 10(6), 578–597. https://doi.org/10.1504/IJMC.2012.049238

Wei, K. K., Teo, H. H., Chan, H. C., & Tan, B. C. Y. (2011). Conceptualizing and testing a social cognitive model of the digital divide. Information Systems Research, 22(1), 170-187.

Wei, R., Lo, V. H., & Wang, H. Y. (2011). The antecedents of mobile shopping behavior: An empirical study in China. Journal of Information Technology Management, 22(1), 1-12.

Xu, H., & Gupta, S. (2009). The effects of privacy concerns and personal innovativeness on potential and experienced customers' adoption of location-based services. Electronic Markets, 19(2-3), 137-149.

Yadav, R., & Pathak, G. S. (2016). Intention to purchase organic food among young consumers: Evidences from a developing nation. Appetite, 96, 122–128. https://doi.org/10.1016/j.appet.2015.09.017

Yadav, R., & Pathak, G. S. (2016). Young consumers' intention towards buying green products in a developing nation: Extending the theory of planned behavior. Journal of Cleaner Production, 135, 732–739. https://doi.org/10.1016/j.jclepro.2016.06.120

Yang, K. (2010). Determinants of US consumer mobile shopping services adoption: Implications for designing mobile shopping services. Journal of Consumer Marketing, 27(3), 262–270. https://doi.org/10.1108/07363761011038338

Yang, K. C. (2005). Exploring factors affecting the adoption of mobile commerce in Taiwan. Journal of CyberPsychology & Behavior, 8(2), 222–231. https://doi.org/10.1089/cpb.2005.8.222

Yang, K., & Forney, J. C. (2013). The moderating role of consumer technology anxiety in mobile shopping adoption: Differential effects of facilitating conditions and social influences. Journal of Electronic Commerce Research, 14(4), 334-347.

Yousafzai, S. Y., Foxall, G. R., & Pallister, J. G. (2010). Explaining Internet banking behavior: Theory of Reasoned Action, Theory of Planned Behavior, or Technology Acceptance Model? Journal of Applied Social Psychology, 40(5), 1172–1202.

https://doi.org/10.1111/j.1559-1816.2010.00615.x

Zeithaml, V. A. (1985). *Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence*. *Journal of Marketing*, 52(3), 2–22.

Zhou, T. (2011). *An empirical examination of users' post-adoption behavior of mobile services*. *Behaviour & Information Technology, 30*(4), 319–330.

Zhang, L., Zhu, J., & Liu, Q. (2012). A meta-analysis of mobile commerce adoption and the moderating effect of culture. Computers in Human Behavior, 28(5), 1902–1911. https://doi.org/10.1016/j.chb.2012.05.008

Zhou, T. (2011). An empirical examination of initial trust in mobile banking. Internet Research, 21(5), 527–540. https://doi.org/10.1108/10662241111176353

Zhou, T. (2011). Understanding mobile internet continuance usage from the perspectives of UTAUT and flow. Information Development, 27(3), 207-218.

Zhou, T. (2012). Examining mobile banking user adoption from the perspectives of trust and flow experience. Information Technology and Management, 13(1), 27–37. https://doi.org/10.1007/s10799-011-0111-8

Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. Decision Support Systems, 54(2), 1085-1091.

QUESTIONNAIRE FOR STUDY

Greetings Sir/Madam,

I am Roopa Acharya alias Pooja Prabhudesai, Assistant Professor, C.E.S. College of Arts & Commerce, Cuncolim, Goa. I am conducting a survey on Consumer behaviour towards use of Mobile Commerce for shopping, as a part of my Ph.D. study.

The title of my Study is **"Antecedents to Consumer Behaviour towards M-Commerce: An Empirical Study"**

M-commerce which is also termed as mobile commerce is the buying and selling of goods and services through mobile devices like smartphone and tablets

Kindly answer all the questions given below. Information provided by you will be kept confidential and will be used only for academic purpose.

Please co-operate and spare 15 minutes of your valuable time to respond to this survey.

Thank you for your precious time.

PART 1

This part of the questionnaire deals with **"Demographic" and "Socio-Economic Factors" of the respondents**.

Kindly answer the following questions.

Q.1 Name----------

Q.2 Gender:

- Male
- Female

Q.3 Age:

- Less than 20 years
- 21 to 40 years
- 41 to 60 years
- 61 years and above

Q.4 Education:

- Up to HSSC
- Graduation
- Post-Graduation and above
- Professional
- Other

Q.5 Area of location

- Municipal Area
- Panchayat Area

Q.6 Marital Status

- Married
- Unmarried

Q.7 Occupation

- Unemployed
- Service
- Business
- Home Maker
- Retired

Q.8 Monthly family income

- Less than Rs 25,000
- Rs 25,000 to Rs 50,000

- Rs 50,000 to Rs.75.000
- Rs 75,000 to Rs 1,00,000
- More than Rs 1,00.000

PART-2

This part of the questionnaire is to collect information on **"Attitude towards mobile commerce"**. Your responses to this part of the questionnaire will help to understand your views about benefits and limitations of using M-commerce for shopping.

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	Opinion	1	2	3	4	5
1	I think there is wide choice of products at reasonable prices on mobile commerce shopping platforms					
2	I feel M-commerce shopping platforms offer quick customer care service					
3	I think M-commerce lacks physical shopping experience					
4	I feel M-commerce is very convenient(Useful) for shopping from anywhere, anytime					
5	I think M-commerce transactions are not safe & secure					

6	I feel using mobile commerce without good knowledge and understanding of mobile technology is not safe					
7	I think customer reviews and ratings on M-commerce shopping portals are not reliable to make shopping decisions					
8	I think user friendly M-commerce apps make shopping simple and enjoyable					
9	I think use of M-commerce leads to shopping addiction					
10	I think M-commerce gives privacy in shopping personal products					

PART-3

This part of the questionnaire is to collect information on **"Perceived Behavioural Control Towards M-Commerce"**. Your responses to this part of the questionnaire will tell whether you need to take permission before using m-commerce for shopping.

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	**Opinion**	**1**	**2**	**3**	**4**	**5**
1	I need to take permission from family members to buy products on mobile commerce sites					
2	I have full freedom to spend any amount of money while shopping on m-commerce sites					

3	I can make my decision to shop anytime on mobile commerce shopping sites whenever I feel like shopping					
4	I don't need to take permission from anyone to shop using mobile commerce sites					

PART-4

This part of the questionnaire is to collect information on **'Subjective Norm'.** Your responses to this part of the questionnaire will tell whether, you give importance to other people's opinion for taking decisions to use or not to use mobile commerce for shopping

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	**Opinion**	**1**	**2**	**3**	**4**	**5**
1	I use mobile commerce for shopping since, most people who are important to me prefer mobile commerce for shopping					
2	I use mobile commerce for shopping since, most people who are important to me have recommended it to me					
3	I don't use mobile commerce for shopping since, most people who are important to me think that using mobile commerce for shopping is not safe					
4	I use mobile commerce for shopping since, most of my followers on social networking sites encourage me to use mobile commerce for shopping					
5	I use mobile commerce for shopping, even when people who are close to me are not in favour of it					

6	I always depend on other people's opinion for shopping on mobile commerce sites					

PART-5

This part of the questionnaire is to collect information on '**Mobile Commerce Intention'.**

Your responses to this part of the questionnaire, will make your intentions clear whether you will give preference to mobile commerce while shopping in future or not.

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	**Opinion**	**1**	**2**	**3**	**4**	**5**
1	I intend to use mobile commerce to keep my shopping private and confidential					
2	I intend to use mobile commerce as I believe that it is convenient (Useful)					
3	I intend to use mobile commerce as I believe that it is safe to use					
4	I intend to use mobile commerce as it is cheaper than offline shopping					
5	I don't intend to use mobile commerce due to my past experience with it					
6	I intend to use mobile commerce since people who are important to me have recommended it to me					
7	I intend to use mobile commerce since I believe that it is easy to use					
8	I don't intend to use mobile commerce due to lack of knowledge of using mobile commerce					

Q.9. Please share at least one good/ bad experience of yours with mobile commerce, if you have used it for shopping

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Q.10. What are your expectations from mobile commerce shopping platforms, for improving future shopping experiences with mobile commerce?

PART-6

This part of the questionnaire is to collect information on **'Mobile Commerce Purchase Behaviour'.**

Your response to this part of the questionnaire will tell your actual use of mobile commerce for the purchase of different categories of products listed in the statements below.

You are requested to rate the following statements on a scale of 1 to 5, where 1=Strongly Disagree (SDA) 2= Disagree (DA) 3= Neither Agree Nor Disagree(N) 4 = Agree (A) 5=Strongly Agree (SA)

Sr. No	Opinion	1	2	3	4	5
1	In the past few years, I have been using mobile commerce for shopping electronic products					
2	In the past few years, I have been using mobile commerce for shopping sports products.					
3	In the past few years, I have been using mobile commerce for shopping clothing, shoes and Jewellery items					

4	In the past few years, I have been using mobile commerce for shopping beauty and personal care products					
5	In the past few years, I have been using mobile commerce for shopping home and kitchen appliances					
6	I have never used mobile commerce for shopping					
7	In the past few years, I have been using mobile commerce for shopping for Books, Magazines and Newspapers					
8	In the past few years, I have been using mobile commerce for shopping for healthcare and medicines					
9	In the past few years, I have been using mobile commerce for shopping for stationary items and games					
10	In the past few years, I have been using mobile commerce for shopping for groceries					

Q.11 Do you enjoy shopping on mobile commerce sites?

- Yes
- No

Q.12 Do you require other people's help while using mobile commerce for shopping?(e.g. while completing shopping transaction/ while using mobile commerce for shopping)

- Yes
- No

Q.13 If yes, please state the reason. ----------

----------THE END----------