THE IMPACT OF FINANCIAL LITERACY ON THE BEHAVIOURAL BIASES OF INDIVIDUAL INVESTORS' INVESTMENT DECISIONS

A THESIS SUBMITTED IN PARTIAL FULFILLMENT FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

In Commerce

Goa Business School

GOA UNIVERSITY

By

Ancy Fernandes

Goa University

Goa

August 2025

DECLARATION

I, Ancy Fernandes, 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 in full, to any other University or Institution for the award of any research degree.

Place: Taleigao Plateau.

Date: 20-08-2025 ANCY FERNANDES

CERTIFICATE

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

Prof. Dr. Juao C. Costa
Principal and Professor
Research Centre in Commerce
S.S.A. Government College and Research Centre,
Virnoda, Pernem, Goa.

ACKNOWLEDGMENT

'Let us not grow weary in doing good, for at the proper time we will reap a harvest if we do not give up' *- Galatians 6:9*

With a deep sense of humility and gratitude, I take this opportunity to acknowledge the many individuals whose support and guidance have made this research journey meaningful and possible.

First and foremost, I bow in gratitude to the Almighty, whose grace has guided me through every challenge, doubt, and turning point in this academic pursuit. Without divine strength and patience, this thesis would not have been completed.

I would like to express my sincere gratitude to my supervisor, Professor Juao Costa, Principal, S.S.A. Government College and Research Centre, Virnoda, Pernem, Goa, whose invaluable support made this research possible. His insightful guidance, unwavering encouragement, and expert advice have been instrumental at every stage of this study.

I am especially thankful to the Doctoral Research Committee, consisting of Prof. K. Subhash, who has also been my teacher and a source of inspiration to complete this research work. And Prof. Nilesh Borde for his support and assistance during various stages of my research.

I gratefully acknowledge the support of the librarian at Goa University and the non-teaching staff of the Academic Research section, whose cooperation made my work smoother.

I am thankful to the management, Principal Prof. Helic Baretto, the librarian and staff of Rosary College of Commerce & Arts for providing a supportive academic environment.

I extend my deepest appreciation to my family, my mother, my husband Franky, and my darling son Joshua for being a blessing in our lives.

A special tribute goes to my late father, whose memory continues to guide and inspire me. I fondly remember sitting on his cycle, he gently reminding me to study hard, words that motivated me throughout my academic journey.

Finally, I am sincerely thankful to the participants of my research study and to everyone who, in one way or another, contributed to the completion of this work.

Thank you.

Contents

List of Tables

List of Figures

List of Abbreviations

Short Form	Full Form
AB	Anchoring Bias
ALP	American Life Panel
ANN	Artificial Neural Networks
AvB	Availability Bias
AVE	Average Variance Extracted
CAPM	Capital Asset Pricing Model
CFA	Confirmatory Factor Analysis
CMV	Common Method Variance
COVID	Coronavirus Disease
CR	Composite Reliability
CVPAT	Cross-Validated Predictive Ability Test
EMH	Efficient Market Hypothesis
fsQCA	Fuzzy-set Qualitative Comparative Analysis
GFB	Gambler's Fallacy Bias
HB	Herding Bias
HCM	Hierarchical Component Model
HRS	Health and Retirement Study
HTMT	Heterotrait-Monotrait
IBM SPSS	International Business Machines-Statistical Package for Social Sciences
ID	Investment Decision
INFE	International Network on Financial Education
IPMA	Importance-Performance Map Analysis
IPO	Initial Public Offering
IRT	Item Response Theory
JSTOR	Journal Storage
LaB	Loss aversion Bias
MaB	Mental accounting Bias
MAE	Mean Absolute Error

MFB	Market Forces Bias
MGA	Multi-Group Analysis
MPT	Modern Portfolio Theory
MTMM	Multi-trait-Multimethod
NCA	Necessary Condition Analysis
NFCS	National Financial Capability Study
NN	Not Necessary
NSFE	National Strategy for Financial Education
OCB	Overconfidence Bias
OECD	Organisation for Economic Co-operation and Development
RaB	Regret aversion Bias
RAND	Research and New Development
RB	Representativeness Bias
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
SEM	Structural Equation Modelling
SMART PLS	Partial Least Square
SSRN	Social Science Research Network
UAE	United Arab Emirates
VIF	Variance Inflation Factor

ABSTRACT

Investment decisions are central to individuals' financial security and the macroeconomic development of nations. As financial markets become more accessible, the participation of individual equity investors increases. With this growth, investors exhibit behaviours driven by psychological biases rather than objective financial analysis. While traditional finance theories assume rationality in investor behaviour and symmetry in information among market participants, yet, investor inconsistencies in their investment decisions have shown these assumptions to be untrue.

Behavioural finance emerged to address these assumptions by integrating psychological and cognitive factors into financial decision-making. It recognises that individual investors often diverge from rationality, owing to biases such as heuristics, prospects, herding, and market forces bias. These biases impact how investors evaluate risk, perceive value, and, eventually, make investment decisions. Investors may trail the crowd due to herding bias or hold onto losing stocks longer than necessary due to loss aversion bias. Such behavioural biases challenge the outcome of investment decisions and the efficiency and overall predictability of financial markets.

With the confirmed presence of behavioural biases in the investor decisions scenario, financial literacy has surfaced as a potential saving factor in this relationship, connecting behavioural biases to investment decisions. Defined as the capability to understand and effectively use financial skills, including risk management, budgeting and investing. Individuals with a higher level of financial literacy are assumed to better manage biases and make sound investment decisions.

This study explores the impact of financial literacy on individual investors' behavioural biases. As retail participation in financial markets increases, the occurrence of investors' biases, such as herding, overconfidence, anchoring, gambler's fallacy, loss aversion, risk aversion, and mental accounting, among others, is displayed through suboptimal investment decisions. Recognising the importance of financial knowledge, behaviour and attitude in investor behaviour, this study examines how financial literacy moderates the link between behavioural biases and investment decisions of individual investors. Additionally, demographic variables are considered moderators to assess if investor characteristics influence the presence of these

biases. The research draws on data collected from a diverse sample of individual investors across three Indian states of Maharashtra, Goa and Karnataka, providing regional depth for the analysis.

The study provides a holistic understanding of individual investor behaviour by integrating the three dimensions of behavioural biases, financial literacy and investor demographics. In this regard, the study aims to:

I) To analyse the influence of behavioural biases on the investment decisions of individual investors by

   a. *Identifying the presence of Behavioural biases*: Determine which biases are prevalent among individual investors.
   b. *Assessing the Impact of the biases*: Analyse how these biases influence investment decisions.
   c. *Identifying the most prominent biases*: Establish which biases strongly influence investment decisions.
   d. *Examining the Necessary Conditions for Investment Decisions:* Since behavioural biases are present among investors, it is essential to determine the conditions that enable effective investment decisions despite these biases.

II) To examine the moderating effect of financial literacy on the relationship between behavioural biases and investment decisions by

   a. *Assessing the Level of Financial Literacy among Individual Investors*: Evaluating investors' financial knowledge, behaviour, and attitudes to determine their overall level of financial literacy.
   b. *Analysing the Moderating Role of Financial Literacy*: Investigating how financial literacy moderates the relationship between behavioural biases and investment decisions.

III) To study the moderating role of Investor demographics in the relationship between behavioural biases and investment decisions by

a. *Identifying key Demographics of Investors*: Examining variables such as age, gender, income, education, occupation, and investment experience to understand the demographic profile of individual investors.

b. *Analysing the Moderating Role of Demographics*: Investigating how different demographic factors moderate the impact of behavioural biases on investment decisions.

Methodologically, the study employs a robust analytical framework combining Structural Equation Modelling (SEM), Importance-Performance Map Analysis (IPMA), and Necessary Condition Analysis (NCA). SEM is used to determine the direct effects of behavioural biases on investment decisions. IPMA helps identify the relative importance and performance of biases. NCA complements this by placing the minimum presence of bias required as a necessary condition for an individual's investment decisions to identify variables that are not just influential but essential. The moderation analysis further identifies if financial literacy can significantly weaken the adverse effects of behavioural biases and if demographic factors like gender, marital status, age, occupation, education, and investment experience help determine whether significant differences exist in investor behaviour through Multi-Group Analysis (MGA).

The findings are:

Objective I

The findings of the first objective highlight the dual role of behavioural biases; they influence investor behaviour and act as essential precursors to investment decisions, suggesting that some investment decisions may rely on a minimum level of bias to be initiated.

Objective II

The financial literacy of the individual investors in this study is low. Financial literacy negatively moderates the relationship between heuristic bias and investment decisions and positively moderates the relationship between prospect bias and investment decisions of individual investors. Financial literacy does not significantly moderate the relationship between herding bias, market forces bias, and investment decisions. Financial literacy alone does not directly impact the investment decisions of individual investors. This crucial finding indicates that financial knowledge, behaviour, and attitudes influence investment decisions primarily by interacting with behavioural biases rather than as an independent factor.

Objective III

Females are more influenced by heuristic bias, while males exhibit more substantial prospect bias in investment decisions. Married investors exhibit a more substantial herding bias compared to unmarried investors. All age groups moderate the biases and investment decisions, indicating that age interacts with behavioural tendencies. Graduates exhibit stronger herding behaviour than postgraduates. Heuristic bias appears stronger among graduates compared to professionally qualified investors, with postgraduates also showing a higher reliance on heuristics than professionally qualified investors. Prospect bias is more pronounced among professional investors than among graduates. Private sector employees exhibit stronger herding behaviour than business/self-employed, followed by government employees. Low-income investors are more influenced by prospect bias than higher-income investors. Investors with 3 to 5 years of experience are more influenced by herding bias than those with less than 3 years of experience.

The study concludes by highlighting the dual role of behavioural biases; they influence investor behaviour and act as essential precursors to certain investment decisions, suggesting that some financial actions rely on a minimum level of bias to be initiated. Secondly, the study finds that financial literacy alone does not directly impact investment decisions. It highlights that its role is more indirect, shaping investors' reactions to behavioural biases rather than driving investment decisions independently. Finally, investor demographics affect the relationship between behavioural biases and investment decisions.

Financial literacy emerged as a critical factor in moderating the influence of behavioural biases on investment decisions. However, the results were mixed, and overall levels of financial literacy among investors were found to be low. Notably, financial literacy did not have a direct impact on investment decisions.

A substantial contribution of this study lies in its integrated approach that measures the influence of behavioural biases on investment behaviour and uncovers the critical role of

financial literacy and demographic factors in shaping these relationships. By combining SEM, IPMA, and NCA, the study offers a comprehensive understanding of investor behaviour.

The study significantly adds to behavioural finance literature by reporting negative moderation of financial literacy between prospect bias and investment decisions, and no impact of financial literacy on the investment decisions of individual investors.

Keywords: Financial Literacy, Behavioural Bias, Investment Decisions, Individual Investors, Necessary Condition Analysis.

CHAPTER 1

INTRODUCTION

Investment is a fundamental economic activity crucial to wealth creation and financial stability. It involves allocating funds with the expectation of future gains, whether through capital appreciation, interest earnings, or dividend income. In simple terms, investment refers to utilising savings to generate returns. From an economic perspective, it contributes to capital formation by channelling resources into productive assets that drive economic growth. Investment allocates money to different assets, such as stocks, bonds, real estate, or mutual funds, expecting to earn a return over time. Bodie et al. (2013) define investment as "the use of funds to achieve extra rewards from the investor's perspective". People invest for various reasons, whether to grow wealth, secure their future, or achieve financial independence. Investment decisions are not made in isolation. Risk tolerance, expected returns, market conditions, and personal financial goals influence them.

With financial markets becoming more complex, understanding how investors behave has never been more critical. Traditionally, theories like Markowitz's Modern Portfolio Theory (1952) and Fama's Efficient Market Hypothesis (1970) assumed that investors are rational beings who make logical decisions based on available information. However, real-world investment behaviour often deviates from traditional financial theories. Empirical evidence suggests that investors are influenced by emotions, cognitive biases, and heuristic-driven decision-making, leading to choices that may not align with rational financial models. This highlights the significance of behavioural finance, which makes a research-driven framework available to understand the psychological factors that shape investment decisions and contribute to deviations from expected utility theory.

1.1 Background to the Study

Investment plays a significant role in the financial system by efficiently allocating capital between surplus and deficit. This capital flow is essential for economic growth, allowing businesses to expand, enhancing productivity, and contributing to overall financial stability.

From a theoretical perspective, investment represents a trade-off between present consumption and future financial security, with the primary objective of generating returns while effectively managing risk. Beyond wealth accumulation, investment decisions are influenced by liquidity constraints, inflation hedging, and portfolio diversification. Different asset classes exhibit varying risk-return trade-offs; for instance, government bonds offer stability and predictable yields, whereas equities present higher volatility but the potential for superior long-term gains. Given the inherent uncertainty of financial markets, investment decision-making requires a structured approach to risk assessment, time horizon considerations, and portfolio optimisation to achieve financial objectives.

Making investment decisions is not as simple as picking an asset and expecting it to grow. It is a complex process that requires evaluating multiple options and considering various factors. Investors are influenced by their personal background, education, age, financial goals, and even emotions. While traditional financial theories suggest that investors make rational choices to maximise their returns, modern research in behavioural finance provides a different picture. It shows investors are not always logical; psychological biases, emotional reactions, and cognitive limitations often shape their investment decisions.

Overconfidence can lead investors to take excessive risks, loss aversion can make them overly cautious, and herding behaviour can cause them to follow the other investors. External factors, such as past experiences, financial literacy, and broader market trends, also significantly shape investment decisions. Understanding these influences helps explain why investors sometimes make irrational decisions from a purely financial standpoint.

Investment decisions shape not only individual financial well-being but also the overall functioning of financial markets. Over the years, different theories have emerged to explain how investors make choices and what drives their behaviour. These theories fall into two categories: Traditional finance theories and Behavioural finance theories.

Traditional finance theories assume that investors are rational and consistently seek to maximise their returns while minimising risk. These models rely on the idea that markets are efficient, meaning that all available information is reflected in asset prices. However, real-world evidence suggests that investors do not always behave this way. Behavioural finance challenges the assumption of rational decision-making by highlighting how human emotions, biases, and mental shortcuts influence financial decisions.

1.2 Traditional Theories

1.2.1 Modern Portfolio Theory (MPT)

Modern Portfolio Theory (MPT), proposed by Harry Markowitz in 1952, introduced the concept of diversification, and this theory revolutionised investment management. The theory highlights the interaction of different assets within a portfolio rather than individual assets. By holding a mix of assets with varying risk levels, investors can achieve an efficient frontier, a set of portfolios that offer the highest expected return for a given level of risk. MPT highlights the importance of unsystematic risk and systematic risk. While this theory has been widely adopted in financial markets, critics argue that it assumes investors can access perfect information and behave rationally, which is often untrue.

1.2.2 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM), developed by William Sharpe in 1964, builds upon MPT by establishing a relationship between systematic risk and expected returns. The concept of ‘beta’ was introduced by this model, a measure of an asset’s volatility relative to the overall market. This theory assumes that investors are risk-averse and have a direct relationship between returns and risk. The model proposes that an asset’s expected return is influenced by the risk-free rate, the market return, and the asset's level of systematic risk. While CAPM is widely used in financial analysis, it has several limitations. The model presumes that markets are frictionless, which means that the financial markets operate without any barriers, inefficiencies, or costs that could hinder trading or investment decisions; investors have homogeneous expectations, and beta fully captures risk, making it difficult to adapt.

1.2.3 Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH), introduced by Eugene Fama in 1970, proposes that financial markets operate efficiently and that asset prices reflect all available information. As a result, it suggests that investors cannot consistently achieve returns that exceed the market average performance because prices adjust almost instantly to new information. The theory categorises market efficiency into three forms:

- Weak-form efficiency: Past stock prices and trading volumes do not provide helpful information for predicting future prices.
- Semi-strong form efficiency: Asset prices incorporate all publicly available information, rendering fundamental analysis ineffective.
- Strong-form efficiency: All information, including insider knowledge, is fully reflected in stock prices, making it impossible to gain an advantage.

While EMH is supported by empirical evidence, real-world market anomalies, such as speculative bubbles and irrational investor behaviour, challenge its validity. Behavioural finance research suggests that emotional biases and psychological factors often prevent markets from being perfectly efficient.

1.3 Investment Decision Behaviour

Investors exhibit diverse behaviours influenced by numerous factors, including culture, geography, age, income, gender, marital status, education, socio-economic status, occupation, religion, life cycle stage, family structure, personality traits, emotions, financial literacy, motives, learning ability, risk tolerance, and media exposure. However, the most critical determinant of investment behaviour is their decision-making strategy.

Empirical research has consistently explored the socio-economic, demographic, and psychological factors that shape investment decisions. Ahmed (2019) investigated how these factors influence investors' choices, while Geetha and Ramesh (2011) highlighted that variations in financial literacy and return expectations drive investors toward different investment avenues. Jain and Mandot (2012) further emphasised that an investor's understanding of financial systems significantly impacts decision-making. Similarly, Kotian and Aithal (2024) examined investment preferences, and Kartini and Nahada (2021) found that psychological biases and heuristics largely shape investor behaviour.

Recent studies report findings of the impact of technology, social media influence, real-time financial data, and global market events on investor decision-making. The rapid expansion of fintech platforms, robo-advisors, and algorithmic trading has also reshaped how individuals approach investments, reducing reliance on traditional decision-making methods (Onabowale 2024; Falsetti 2025).

1.3.1 Traditional Approach to Investment Decision Behaviour

The concept of utility, introduced during the classical period of economics, forms the foundation of traditional investment theories. John S. Mill (1844) proposed the concept of the rational economic man, also called the '*Homo Economicus*', who makes investment decisions by maximising economic well-being under given constraints. This model is based on three key assumptions.

Investors exhibit perfect rationality, meaning they always make logical and optimal decisions. They are also believed to act with ideal self-interest, focusing solely on maximising their financial gains. Additionally, the assumption of perfect information suggests complete access to all relevant data and the ability to process it accurately. Based on this rational framework, investors are categorised as risk-averse, risk-neutral, or risk-seeking individuals, depending on their approach to risk and expected utility. However, real-world financial markets often deviate from these assumptions, leading to the rise of alternative theories.

1.3.2 Behavioural Finance Approach to Investor Decision Behaviour

Over time, researchers have observed that traditional finance theories fail to fully explain actual investor behaviour. Behavioural finance emerged as a response, challenging the classical rationality and market efficiency assumptions. According to Statman (1999) and subsequent studies, behavioural finance proposes an alternative perspective for key financial principles:

- Investors are not always rational - Cognitive biases and emotions significantly influence decision-making.
- Markets are not fully efficient - Price movements often reflect psychological factors and herd behaviour rather than pure fundamentals.
- Portfolio choices do not always follow Mean-Variance Theory - Investors may rely on heuristics, framing effects, or mental accounting rather than optimising risk-return trade-offs.
- Expected returns depend on more than just risk and return. Elements such as sentiment, market trends, and overconfidence affect asset pricing.

1.4 Theoretical Perspective on Behavioural Biases

1.4.1 Behavioural Finance

By the early 1990s, the dominance of the Efficient Market Hypothesis (EMH) started to decline as researchers and financial professionals began to see its limitations. The idea that investors always act rationally and that markets are perfectly efficient is no longer held up in the face of real-world evidence. This shift gave rise to Behavioural Finance, which combines insights from psychology to explain how investors make decisions. Unlike traditional finance theories that assume people always act logically to maximise returns, Behavioural finance acknowledges that emotions, cognitive biases, and psychological tendencies often drive financial decisions, leading to irrational behaviour. Markets are inherently unpredictable, and investor decisions are not always based purely on facts or logic; they are shaped by fear, overconfidence, herd mentality, and other psychological factors.

Various scholars have defined behavioural finance over the years, reflecting its evolution as a discipline. Some notable definitions are given below in chronological order:

- Meir Statman (1999): Statman describes behavioural finance as the study that "*substitutes normal people for the rational people in standard finance*," highlighting the incorporation of actual human behaviour into financial models.
- Hersh Shefrin (2000): Shefrin defines behavioural finance as "*a rapidly growing area that deals with the influence of psychology on the behaviour of financial agents*," emphasising on the psychological factors affecting financial decision-making.
- Victor Ricciardi and Helen K. Simon (2000): Describe behavioural finance as an area that "*studies the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets*," focusing on the psychological aspects affecting market dynamics.
- Shefrin (2001) is *"the study of how psychology affects financial decision-making and financial markets."*
- Martin Sewell (2011) defines it as *"the study of the influence of psychology on financial practitioners' behaviour and its impact on markets, helping to explain inefficiencies."*

- Bikas et al. (2013) state that behavioural finance "*is the result of the structure of various sciences,*" highlighting its interdisciplinary nature, combining psychology and finance.
- David Hirshleifer (2015) defines behavioural finance as the study of "*the application of psychology to finance, with a focus on individual-level cognitive biases*," highlighting how personal biases influence financial decisions.

The foundations of Behavioural Finance were laid by psychologists Daniel Kahneman and Amos Tversky, who introduced the concept of heuristics and biases in decision-making under uncertainty (1974). Their groundbreaking work, *Prospect Theory: An Analysis of Decision under Risk (1979)*, demonstrated how investors often make decisions based on perceived gains and losses rather than objective probabilities. Richard Thaler further expanded on these ideas through his work on mental accounting and investment behaviour, showing how individuals categorise money in ways that lead to inconsistent investment decisions.

The discipline challenges the notion that individuals always act rationally in financial decisions, acknowledging that anchoring, gambler's fallacy, loss aversion, and herd biases impact investment choices and financial outcomes. By recognising these psychological influences, behavioural finance provides a more comprehensive understanding of financial markets, helping investors develop strategies that account for emotional and cognitive pitfalls.

Psychologists and financial researchers have long studied the systematic biases that shape human judgment and decision-making. Their findings reveal that even when investors can access accurate and reliable information, their investment decisions are affected by emotions, unconscious tendencies, and deep-seated fears. These factors create behavioural biases, which can be grouped into three broad categories:

1. Heuristics – Mental shortcuts that simplify decisions but can sometimes lead to errors.
2. Prospect theory– The perceived gains and losses affect their investment decisions.
3. Other behavioural biases – Other psychological tendencies that impact investment decisions.

The biases are not limited to inexperienced investors; even seasoned professionals are affected by them. Even when individuals can access accurate and reliable information, their decisions are not always rational. Emotional factors, subconscious tendencies, and deep-seated fears influence investment decisions. Investors are susceptible to various behavioural biases, leading to errors in judgment. In uncertain or complex situations, people often rely on heuristic mental shortcuts that simplify decision-making. While these shortcuts can be helpful, they also increase the risk of systematic mistakes, leading to sub-optimal investment choices (Chen et al., 2007).

Over the years, researchers have identified over fifty biases that influence investor behaviour, and new ones continue to be discovered. Scholars have attempted to categorise these biases into meaningful frameworks, often classifying them into heuristics (rules of thumb), beliefs, judgments, or preferences. Another standard classification divides biases into cognitive and emotional categories. However, no single theory thoroughly explains why people consistently make biased decisions. Instead of a universal model of investor behaviour, behavioural finance relies on empirical evidence to highlight the limits of human decision-making in financial contexts (Pompian, 2009).

1.4.2 Investors' Behavioural Biases

Knowing the impact of behavioural biases on an individual's investment decisions is essential, as these biases often lead investors away from rational decisions. By examining these tendencies, a more profound insight can be gained into why investors sometimes make choices that move away from logic and objective financial analysis.

The shift from the Efficient Market Hypothesis (EMH) to behavioural finance has placed greater emphasis on investor psychology, acknowledging that biases significantly influence financial decisions. Behavioural finance emphasises the need to recognise and address irrational financial behaviours, ultimately helping investors to adopt informed and strategic investment decisions.

1.4.2.1 Overconfidence Bias

Overconfidence bias occurs when individuals place excessive trust in their judgment, leading them to overestimate their knowledge, underestimate risks, and believe they have greater control over outcomes than they do (Ising, 2007; Pompian, 2006). In investing, this bias manifests in overconfident stock selection and market timing, often resulting in excessive trading and lower returns (Odean 1998). Studies indicate that men trade 45% more frequently than women due to the presence of this bias, leading to more significant financial losses (Barber and Odean 2001). Similarly, research on market analysts has highlighted how overconfidence and optimism can distort financial forecasting (Fagerström 2008). Overconfidence bias has a notably adverse effect on investment decision-making (Ainia and Lutfi 2019).

1.4.2.2 Representativeness Bias

Representativeness bias occurs when individuals evaluate probabilities based on similarity rather than objective data (Tversky & Kahneman, 1983). This bias can lead investors to make assumptions based on past experiences, sometimes resulting in flawed decisions. The belief that a stock performing well in the past will continue to do so, even when there is no fundamental basis for this assumption (Shefrin, 2001). As a result, they may overvalue companies with strong reputations, assuming that their stocks will always generate high returns despite evidence to the contrary. This bias is also observed in IPOs, where investors often focus on short-term excitement rather than long-term viability, leading to post-IPO underperformance (Loughran & Ritter, 1995).

1.4.2.3 Availability Bias

Availability bias is the tendency to judge probabilities based on how easily an event comes to mind rather than through logical analysis or statistical reasoning. People perceive events as more likely simply because they are easier to remember, even rare ones. This bias distorts financial decision-making, as judgments are shaped by personal experiences and emotional impact rather than objective facts. In investing, availability bias can lead people to overemphasise recent or widely publicised market events, making investment decisions based on headlines rather than sound financial analysis. It drives excessive trading, market overreactions, and asset mispricing (Hirshleifer, 2001), often amplified by media coverage (Li & Wu, 2018). This bias also promotes familiarity, limiting diversification (Huberman, 2001).

1.4.2.4 Anchoring Bias

Anchoring bias is relying too heavily on an initial reference point when making decisions, even when new information suggests a different conclusion (Tversky & Kahneman, 1974; Kahneman, 2011). Investors often anchor to past stock prices, avoiding adjustments despite an inflow of new information (Kaustia et al., 2008). This bias influences earnings forecasts and price expectations, leading to suboptimal investment choices (Russo & Carlson, 2002). Market inefficiencies arise when investors anchor to historical highs or lows, affecting asset pricing and portfolio diversification (Kundu & Banerjee, 2024).

1.4.2.5 Gambler's Fallacy

Gambler's fallacy is the mistaken belief that past random events influence future outcomes**,** even when no actual pattern exists. In financial markets, this bias leads investors to expect price reversals based on previous trends rather than analysing actual market fundamentals. (Tversky & Kahneman, (1974). Investors misinterpret random price movements as predictable cycles, leading to market inefficiencies (Barberis et al., 1998; Rashes, 2001). Additionally, sector-specific biases cause investors to assume that underperforming industries will recover without fundamental justification (Huber et al., 2010).

1.4.2.6 Regret Aversion Bias

Regret aversion bias leads investors to avoid investment decisions that might result in future regret, often leading to them holding onto losing stocks or avoiding risky but potentially profitable investments (Bell, 1982; Loomes & Sugden, 1982). This bias fosters conservative investment behaviour, limiting portfolio diversification and long-term wealth accumulation. It contributes to investors' hesitation to realise losses, assuming market reversals (Imas et al., 2016; Odean, 1998). Regret aversion often interacts with other biases, further distorting investment choices (Shefrin & Statman, 1985). Regret aversion bias has been shown to cause deviations from rational investment decisions, suggesting regret can lead to holding onto losing stocks to avoid the feeling of regret, and can impact their investment behaviour.

1.4.2.7 Loss Aversion Bias

Investors weighing potential losses more heavily than equivalent gains, causing risk-averse behaviour in financial decision-making (Kahneman, 1979). Investors who avoid selling losing investments to prevent the realisation of losses contribute to the disposition effect and suboptimal portfolio management (Odean, 1998; Shefrin & Statman, 1985). Loss aversion influences trading frequency and asset allocation, as investors often forgo opportunities for gains to minimise potential losses (Barberis et al., 2001). Empirical studies on loss aversion bias confirm market anomalies, as overemphasising avoiding losses can distort market prices and exacerbate volatility (Thaler, 1999). Loss aversion is critical in shaping investment decisions.

1.4.2.8 Mental Accounting Bias

The tendency of individual investors to compartmentalise funds into distinct "mental accounts" based on subjective criteria, such as the source or intended use of money, rather than treating money as a fully fungible resource (Thaler, 1999), is mental accounting bias. This makes investors take suboptimal investment decisions by segregating resources and refraining from reallocating funds even when more attractive opportunities are available (Shefrin & Thaler, 1988). Such compartmentalisation may result in poor portfolio diversification and inefficient asset allocation, as investors often prioritise the emotional satisfaction derived from these mental accounts over objective economic benefits (Nofsinger, 2017). Further, mental accounting can reinforce other behavioural biases by causing investors to rely on heuristic-driven decisions rather than thorough, data-driven analysis. This can adversely affect risk management and trading behaviour, as investors might become overly attached to specific mental accounts and underreact to new market information (Baker et al., 2019; Dhar & Zhu, 2006).

1.4.2.9 Herding Bias

A social bias wherein individual investors mimic the investment behaviour of other investors rather than relying on their own analysis, which often leads to suboptimal investment decisions. This behaviour is confirmed during the periods of market uncertainty, where the desire to conform can override objective assessment of available information. Herding bias contributes to market inefficiencies, as investors collectively drive prices away from fundamental values, potentially creating bubbles or intensifying market downturns (Hayat & Anwar, 2016; Rahayu et al., 2021). Individual investors are especially prone to herding behaviour due to limited access to comprehensive financial data and heightened reliance on social cues, unlike institutional investors, who typically have more resources for independent analysis (Goodfellow & Gebka, 2009). Additionally, herding bias has been linked to reputational concerns and to the fear of missing out, further compounding its effect on investment decision-making (Bikhchandani & Sharma, 2000). Herd mentality influences individual investment decisions in bull and bear markets, amplifying market volatility and trading volume. Even though investors may spend considerable time analysing available information, they often ignore their expertise and follow the majority, even when the herd's choices are misguided. (Ahn & Kim, 2024). This blind conformity can lead individuals to make faulty investment decisions as they align with the group's actions, sharing in the mistakes of the collective rather than trusting their analysis (Mahmood et al., 2024).

1.4.2.10 Market Forces Bias

Market forces bias influences individual investors to base their investment decisions predominantly on macroeconomic trends and overall market sentiment rather than firm-specific fundamentals. This bias leads investors to overreact to external market conditions like economic downturns, geopolitical events, or widespread market optimism. It may result in suboptimal asset allocation and increased portfolio volatility. Jain et al. (2022) found that investors often misprice assets by overemphasising short-term market trends, which can distort long-term investment strategies. Similarly, Shi et al. (2024) and Tan et al. (2023) observed that during the periods of heightened market volatility, investors are increasingly prone to be affected by prevailing market sentiments, thereby reducing diversification and amplifying risk. Market forces bias can trigger herd-like behaviours, where investors collectively respond to macro-level cues at the expense of detailed fundamental analysis. The failure to adopt systematic investment strategies prioritising rigorous, firm-specific evaluations over broad market trends is ignored, leading to irrational investment decisions.

1.5 Financial Literacy

Financial markets are complex, making it challenging for investors to navigate decision-making in real-world scenarios. With increasing global integration and financial sophistication, investment decisions have become more intricate and often carry irreversible consequences (Haidari, 2023). The growing variety of financial products, coupled with frequent changes in economic policies, adds another layer of difficulty. Financial literacy is crucial in shaping an investor's ability to assess risks and make informed decisions in this economic environment (Lusardi & Mitchell, 2014). While a sound understanding of financial markets empowers investors, limited financial knowledge could be a barrier.

Investor competence significantly influences financial decision-making, particularly in high-stakes situations. A well-informed investor can better interpret market signals, assess the impact of policy changes, and manage investment risks effectively. In contrast, individual investors with lower financial literacy may struggle to evaluate market trends, often relying on intuition or external influences instead of systematic analysis. Given the rapid growth of financial markets, understanding the task of financial literacy in shaping investment behaviour is essential, as uninformed decisions can lead to significant financial losses.

The Organisation for Economic Co-operation and Development (OECD) International Network on Financial Education (INFE) defines financial literacy as "a combination of awareness, knowledge, skill, attitude, and behaviour necessary to make sound financial decisions and ultimately achieve individual financial well-being." Lusardi & Mitchell (2011) further highlight that financial literacy enhances individuals' awareness regarding investment and retirement planning, enabling a prudent usage of financial resources.

Global research indicates a widespread lack of financial literacy, affecting developed and developing nations. Lusardi & Mitchell (2011) found that knowledge about stock markets remains particularly low worldwide. A study by Finnovate's August 2024 financial fitness survey reported an average financial fitness score of 5.29 out of 20, indicating very low literacy levels across personal finance domains (Business Standard, 2025).

A 2022 survey by Streak, a teenage-focused neobank, revealed that just 16.7% of Indian teenagers demonstrated financial literacy, with significant gaps in understanding investments, risk-reward dynamics, and the time value of money (Monteiro, 2022). The Reserve Bank of India's 2023 field survey assessed financial literacy across knowledge, behaviour, and attitude. Findings suggested that individuals with relatively strong financial knowledge often lacked appropriate financial behaviour or attitudes, highlighting the need for targeted financial education programs (Business Standard, 2022).

Within this context, financial literacy is crucial in mitigating the adverse effects of these biases. A lack of financial literacy exacerbates poor decision-making, increasing investors' susceptibility to psychological distortions and misjudgements of risk (Lusardi & Mitchell, 2014; Barberis & Thaler, 2003). Financial literacy has become vital for making reliable investment decisions as financial markets and products become increasingly complex. Defined as a combination of financial awareness, knowledge, skills, attitudes, and behaviours, financial literacy enables informed financial choices and secured long-term financial stability. Given the established impact of behavioural biases on investment decisions, this chapter examines the moderating role of financial literacy in mitigating these biases. By exploring this relationship, the study provides deeper insights into how investors navigate financial markets, balancing rational financial knowledge with psychological tendencies.

1.5.1 Financial Literacy and Behavioural Finance

Behavioural finance posits that investors, when making financial decisions, do not always act rationally. Instead, they rely on heuristics, simplified decision-making strategies that can result in irrational financial choices. The prevalence of financial illiteracy exacerbates these tendencies, preventing individuals from making informed decisions that maximise their financial well-being. A number of studies have highlighted the relevance of financial literacy in shaping investment behaviours and decision-making relating to financial products and services.

Alessie et al. (2011) and Arrondel et al. (2015) emphasised that investors with low financial literacy, particularly those lacking knowledge about stocks and bonds, are less likely to participate in stock markets. Similarly, Calvet et al. (2016) concluded that financially sophisticated individuals are more inclined to invest in risky assets and make efficient investment decisions. Allgood et al. (2016) examined the combined effect of actual and perceived financial literacy on household financial behaviour in the United States. Their findings indicate that both dimensions of financial literacy significantly influence investment decisions.

Financial literacy affects investor knowledge (Takeda et al., 2013), but there is a limited exploration of its interaction with behavioural biases in investment decision-making. Dhar and Zhu (2006) observed that highly educated and professional investors exhibit lower levels of disposition bias. Takeda et al. (2013) analysed Japanese stock investors and found that individuals with greater investment literacy are less prone to overconfidence.

Ates et al. (2016) reported a positive association between financial literacy and biases such as over-optimism, confirmation bias, and representativeness bias and a negative association between financial literacy and biases like overconfidence, cognitive dissonance, framing effects, and loss aversion. These findings highlight the growing interest in understanding how financial literacy influences behavioural biases and investment decision-making, necessitating further research in this domain (Lusardi, 2008).

1.5.2 Financial Literacy and Investment Decisions

Various factors, including personal preferences, motivation, available funds, time horizons, and financial goals, shape investment decisions. Investors often exhibit behavioural biases due to inexperience, limited knowledge, disinterest, and time constraints. Such biases can lead to irrational financial decisions, potentially contributing to market inefficiencies by disregarding fundamental financial principles.

Individuals need a comprehensive knowledge of financial concepts to make sound investment decisions. Financial stability requires broad knowledge of financial products and the ability to apply and communicate this knowledge effectively. Financially literate investors are better equipped to assess investment opportunities, mitigate risks, and make strategic financial choices. (Hassan et al., 2009; Abdeldayem, 2016).

1.5.3 Measurement of Financial Literacy

Financial literacy is typically assessed at the individual level and aggregated across demographic groups to offer a broader perspective on financial competence (Remund, 2010). The literature categorises financial literacy as: financial knowledge, personal financial management skills, financial decision-making ability, and confidence in financial planning. These elements collectively determine an individual's capacity to navigate financial challenges, make informed investment choices, and achieve long-term financial security.

For this study, financial literacy is "the degree to which an individual understands key financial concepts and possesses the ability and confidence to manage personal finances through appropriate short-term decision-making and long-term financial planning while adapting to economic changes" (Remund, 2010).

In the context of stock market investments, this definition is "the degree to which an individual understands stock market concepts, possesses knowledge and skills in investment decision-making, and effectively manages personal finances through various life stages."

Financial literacy is evaluated based on three core components: financial knowledge, financial behaviour, and financial attitude. Financial knowledge refers to an individual's understanding of fundamental concepts such as budgeting, saving, and financial management. Financial behaviour encompasses actions related to managing finances, including budgeting, saving, and responsible credit use. Financial attitude reflects an individual's beliefs and perspectives regarding money management and planning, influencing long-term financial decisions (Chowa et al., 2012).

1.6 Investor Demographics

The degree to which investors are affected by demographic factors, gender, income and education while making investment decisions is relevant. They act as predecessors while seeking investment opportunities. Earlier studies demonstrate that demographic factors, specifically gender, income, and education, play a moderating role in the relationship between behavioural biases and investment decisions. Male investors generally show high levels of overconfidence and risk-taking, while female investors tend to be more risk-averse and more dependent on herding bias (Baker et al., 2019; Lin, 2011). Income also appears to moderate these effects, although findings are mixed: some studies suggest that higher-income investors, benefiting from greater financial literacy, are less susceptible to biases, whereas others report minimal differences across income levels (Shusha & Touny, 2016; Lin, 2011). In addition, education enhances investors' capacity to process financial information and mitigate biases such as mental accounting and overconfidence, with higher education levels associated with more rational decision-making (Kumar & Goyal, 2016; Pushpa et al., 2023; Srivastav & Pandey, 2023). Cognitive psychology highlights that ageing is accompanied by changes in cognitive functions such as memory, attention, and decision-making (Salthouse, 2019). These mental shifts may influence how individuals engage in investment decisions, potentially affecting the allocation of financial resources and investment decisions.

1.7 Need and Purpose for the Research

Behavioural biases, financial literacy, and demographic characteristics shape investor behaviour. Biases such as overconfidence, anchoring, loss aversion, herding, and mental accounting influence individual investors into irrational decisions, deviating from the benefits of optimal investment decisions. Although these biases are inherent to human cognition, their impact on investment decisions can result in inefficient market behaviour and personal financial losses if left unaddressed.

Financial literacy affects investors' outlook, determining their understanding of financial concepts, assessing risk, and interpreting market signals. Investors with low financial literacy are more vulnerable to behavioural biases, often relying on heuristics and emotions rather than essential evaluations when making investment decisions. An investor with limited knowledge of market fundamentals may follow social cues and herd instead of conducting independent analysis, leading to suboptimal investment decisions. Similarly, a lack of understanding of diversification principles may reinforce loss aversion, causing investors to hold onto underperforming assets for too long.

While behavioural biases have been widely studied, the moderating role of financial literacy is overlooked. While studies analyse biases and financial literacy in isolation, the potential interaction exists as a gap. This is particularly present in emerging economies, where financial literacy is low and access to reliable financial information is limited. As a result, individual investors may be more prone to biased investment decisions.

The thesis looks at the role of financial literacy in moderating the impact of behavioural biases on individual investors' investment decisions; by providing relevant insights for developing targeted education programs based on segmentation analysis, thereby contributing to better financial outcomes through informed investment decisions.

1.8 Statement of the Problem

The availability of information, reflected in securities pricing, determines the degree of market efficiency (Fama, 1970; Beaver, 1981). However, markets are rarely fully efficient or entirely inefficient (Rau, 2010). Gilson and Kraakman (1984) suggest that market efficiency is achieved when asset prices accurately reflect the actual value of investments.

In the modern financial landscape, finance is pivotal in everyday life. To safeguard against financial instability, individuals must allocate their resources wisely across various investment options. India's monetary system facilitates savings and channels them toward productive ventures. Amid abundant investment avenues, investors naturally gravitate toward opportunities offering high returns with minimal risks. A range of factors, like strategies, frequency, time horizon, goals, role of media, technology, and external influences, shape investment decisions. Behavioural biases are particularly influential (Hirshleifer, 2015; Gabhane et al., 2023).

Contrary to traditional finance assumptions, which view investors as rational agents, investors often make irrational decisions due to misinterpretations, flawed judgments, and cognitive distortions. (Polychronakis, 2023; Obeng, 2020). Emotions and psychological influences significantly shape financial behaviour. Behavioural finance, which questions conventional theories such as EMH, portfolio theory, and risk-return trade-offs, highlights these human elements (Maria, 2019). The classical model of a utility-maximising rational individual, as proposed by Modigliani and Miller, is increasingly criticised due to limited empirical support (Stern, 2022; Kaczynski & Juniper, 2022). While the efficient market theory suggests that irrational traders distort prices and rational investors profit through arbitrage, behavioural insights point to the substantial role of human biases in decision-making (Tsoukis et al., 2025; Umapathy, 2024).

Multiple variables affect investor behaviour in the stock market, including investment duration, peer actions, performance benchmarks, and prevailing speculation and volatility (Xia & Madni, 2024). Investment approaches vary significantly, while some investors conduct careful analysis, others invest impulsively, often driven by expectations of high returns. Huang (2018) argues that investors usually fall prey to behavioural biases, such as herding, disposition effect, and overconfidence, due to inadequate technical knowledge and misplaced confidence in their decision-making capabilities. These biases hinder rational decision-making and ultimately influence investment outcomes. (Polychronakis, 2023; Jain & Kesari, 2022).

The behaviour of investors has been widely studied, revealing significant implications for asset pricing. Therefore, understanding the drivers of investment decision behaviour is a critical concern in financial research. Different investor characteristics reflect varying levels of behavioural biases. Investor personality also influences financial decision-making. (Sattar et al., 2020; Sadi et al., 2011). Pompian (2012) emphasise the impact of individual traits on investment choices. Behavioural and psychological factors are central to investment behaviour, noting significant cultural differences, such as the tendency for Asian investors to exhibit more substantial biases compared to European investors (Chang et al., 2004).

Given these complexities, studying individual investor behaviour in greater depth is vital. Such research can inform the development of personalised advisory services and contribute to more stable and secure financial systems. Many investors lack the technical expertise and often rely on brokers or seasoned investors for effective market participation. However, generalised advisory frameworks fail to account for diverse personal characteristics. Therefore, understanding investor profiles and behaviours is essential to support sound decision-making in increasingly complex financial markets.

1.9 Research Gap

Extensive research on financial literacy and investment behaviour exists; however, the interaction between financial literacy and behavioural biases in investment decision-making remains insufficiently explored. Several key gaps exist in the literature that warrant further investigation:

1.9.1 Limited Research on how Financial Literacy influences Behavioural Biases in Investment Decisions

Financial literacy is widely recognised as an essential factor in enhancing investment decisions; its role in mitigating or reinforcing behavioural biases remains debatable. Studies of Van Rooij et al. (2011), Lusardi and Mitchell (2014), Özen and Ersoy (2019), Suresh (2024), and Tansuchat and Thaicharo (2025) state that higher financial literacy mitigates biases leading to more rational investment choices. However, research indicates that even financially literate investors are not entirely immune to psychological distortions such as overconfidence and herding, which continue to influence their decisions (Mouna & Jarboui, 2015).

Recent studies continue to investigate this complex relationship. A survey by Adil and Ansari (2022) and Mahmood et al. (2024) examined individual investors in the Pakistan Stock Exchange, reporting that financial literacy moderates biases such as anchoring, overconfidence, and herding, thereby shaping investment decisions. Similarly, a review by Zahera and Bansal (2018) identified key biases affecting investors, including overconfidence, anchoring, herding, and loss aversion, emphasising the use of enhanced financial education to counteract these tendencies. Many existing studies assume that financial literacy naturally results in rational investment behaviour, yet recent evidence challenges this notion, suggesting that financially knowledgeable investors may still exhibit biases (Athota et al., 2023). This contradiction highlights the need for a deeper exploration of how financial literacy interacts and moderates behavioural biases in investment decision-making.

While financial literacy mitigates certain biases, its effectiveness varies across different behavioural biases. The need to understand how financial literacy impacts the presence of biases to encourage more rational investment decisions is emphasised. This suggests that while financial literacy may help investors make sensible choices, it does not eliminate biases and, in some cases, may even reinforce them.

This gap necessitates further targeted research to understand the extent to which financial literacy influences specific biases and, in totality, the biases of individual investors ultimately shaping investment behaviour.

1.9.2 Need for Advanced Analytical Techniques in Financial Literacy and Behavioural Bias Research

Recent studies have increasingly employed advanced analytical techniques to explore financial literacy, behavioural biases, and investment decisions of individual investors. A study focusing on Generation Z investors in India utilised Structural Equation Modelling (SEM) to examine how financial literacy, risk attitude, herding behaviour, and information search collectively influence investment choices. The findings indicated that these behavioural factors significantly impact the decision-making processes of young investors.

Similarly, research conducted among households in Kerman, Iran, applied SEM to investigate the effects of behavioural biases and financial literacy on investment decisions. The study revealed that financial literacy and certain behavioural biases substantially affect investment choices of households, highlighting the intricate interplay between knowledge and psychological factors.

In another study, SEM was employed to analyse the influence of behavioural finance factors on investment decisions within the Saudi equity markets, incorporating risk perception and financial literacy as mediating variables. The results demonstrated that biases such as herding, disposition effect, blue-chip bias, and overconfidence significantly impact both risk perception and financial literacy, affecting investment decisions.

These studies underscore the value of employing sophisticated modelling techniques like SEM to uncover the multifaceted links between financial literacy and behavioural biases. However, this domain remains limited in applying other advanced methods, such as Importance-

Performance Map Analysis (IPMA) and Necessary Condition Analysis (NCA). Expanding diverse analytical tools could provide deeper insights into which biases most significantly influence investment behaviour and how financial literacy interventions can be tailored to address them effectively.

1.9.3 Use of Demographics as Moderators

While research has explored the impact of behavioural biases on investment decision-making, the moderating role of demographic factors such as gender, age, marital status, education, occupation, and income remains understudied. Existing studies often analyse these demographic variables as independent predictors of investment behaviour rather than examining their potential to moderate the relationship between biases and decision-making (Nga & Yien, 2013).

Gender-based differences in risk aversion and overconfidence are well-documented, but limited research investigates how gender influences the strength of these biases in shaping investment decisions. While age is recognised as a determinant, there is a want of empirical evidence on how younger and older investors differ in their susceptibility to biases such as herding and loss aversion (Fong et al., 2021). Marital status, which can impact financial risk-taking due to family responsibilities and financial security concerns, is rarely examined as a moderating factor.

Education and financial literacy are critical in shaping investment rationality, yet few studies assess whether higher educational attainment mitigates or amplifies specific biases. Moreover, occupation and income levels influence financial decision-making, but how they moderate behavioural biases remains unclear, especially in diverse economic contexts. Given these gaps, research is needed to systematically examine the moderating effects of demographic variables between behavioural biases and investment decisions. Understanding these moderating effects can provide valuable insights into investor behaviour and contribute to developing targeted financial policy interventions.

1.9.4 Limited Focus on Emerging Markets and Individual Investors

The field of behavioural finance has gained significant attention over the past two decades, much of the empirical work continues to be concentrated in developed economies, where markets are more mature and investors generally have greater access to financial education (Lusardi & Mitchell, 2023). This creates a knowledge gap in understanding how behavioural biases operate in emerging markets, wherein financial literacy levels are often lower and investor behaviour patterns are shaped by unique cultural, informational, and infrastructural factors (Agarwal, 2020). Studies such as those by Waweru et al. (2008) and Tekçe et al. (2016) reveal that in an emerging market, individual investors are significantly influenced by biases such as overconfidence, herding, and loss aversion, which often lead to irrational decision-making. However, these studies remain limited in scope and usually overlook the associative role of financial literacy. Although Baker et al. (2019) and Dureha and Jain (2022) have highlighted how psychological factors influence investment decisions. There remains a need for comprehensive research that investigates how financial literacy may mitigate the effects of these biases, especially among Indian individual investors. This study attempts to analyse the interplay between behavioural biases and financial literacy of individual investors in the Indian context.

1.10 Research Questions

Understanding individual investor behaviour is essential in today's dynamic financial markets, especially in emerging economies, where retail participation is rapidly increasing. While behavioural finance has uncovered a range of cognitive biases that influence investment decisions, whether financial literacy can mitigate or amplify these biases remains unclear. Additionally, demographic factors and advanced analytical tools are underexplored in this context. In light of these gaps, the following research questions have been developed to guide this study:

1. How do behavioural biases such as heuristic bias, prospect bias, herding bias and market forces bias affect investment decisions of individual investors?
2. To what extent does financial literacy moderate the relationship between heuristic bias, prospect bias, herding bias and market forces bias and investment decisions of individual investors?
3. What is the function of investor demographics (gender, marital status, age, education, occupation, income, investment experience) in moderating the relationship between behavioural biases and investment decisions of individual investors?

1.11 Research Objectives

The following objectives are framed to fill the research gaps:

Objective 1: To analyse the influence of behavioural biases on the investment decisions of individual investors.

The first objective examines the impact of behavioural biases on investment decisions among individual investors through:

a. *Identifying the presence of Behavioural biases*: Determine which biases are prevalent among individual investors.
b. *Assess the Impact of the biases*: Analyse how these biases influence investment decisions.
c. *Identify the most prominent biases*: Establish which biases strongly influence investment decisions.
d. *Examine the Necessary Conditions for Investment Decisions***:** Since behavioural biases are present among investors, it is essential to determine the conditions that enable effective investment decisions despite these biases.

Objective 2: To examine the moderating effect of financial literacy on the relationship between behavioural biases and investment decisions.

This objective is achieved through the following:

a. *Assessing the Level of Financial Literacy among Individual Investors*: Evaluating investors' financial knowledge, behaviour, and attitudes to determine their overall level of financial literacy.
b. *Analysing the Moderating Role of Financial Literacy*: Investigating how financial literacy moderates the relationship between behavioural biases and investment decisions.

Objective 3: To study the moderating role of Investor demographics in the relationship between behavioural biases and investment decisions.

This objective is achieved through the following:

a. *Identifying key Demographics of Investors*: Examining variables such as age, gender, income, education, occupation, and investment experience to understand the demographic profile of individual investors.

b. *Analysing the Moderating Role of Demographics*: Investigating how different demographic factors moderate the impact of behavioural biases on investment decisions.

1.12 Significance of the Study

This study offers both theoretical enrichment and practical utility in behavioural finance, in the context of individual investors in emerging markets like India. It aims to bridge crucial gaps in understanding how behavioural biases affect investment decisions and how financial literacy and demographic factors shape this relationship.

Aligned with the first objective**,** the study investigates the prevalence and influence of relevant behavioural biases on investment decisions. By identifying the most prominent biases and the necessary conditions for rational investing, the research deepens the behavioural finance discourse and informs models of investor decisions.

Addressing the second objective**,** the study adds value by examining financial literacy not just as a standalone factor, but as a moderator that can potentially weaken or neutralise the adverse effects of behavioural biases. This is particularly important as previous literature has shown mixed evidence regarding whether financial literacy can effectively counteract cognitive distortions. The empirical evidence provided here helps clarify this relationship, which can contribute to the design of financial education initiatives.

With the third objective, the study extends its significance by exploring how demographic factors moderate the influence of behavioural biases. Understanding these dynamics is critical for developing tailored financial literacy interventions and regulatory policies that consider diverse investor profiles when making investment decisions.

By employing advanced analytical tools such as Structural Equation Modelling (SEM), Importance-Performance Map Analysis (IPMA), and Necessary Condition Analysis (NCA), this study provides a methodologically robust understanding of investor behaviour. The insights generated will be valuable to investors, financial advisors, policy makers, and educators who aim to improve financial decision-making and promote more stable and efficient financial markets in India and similar emerging economies.

1.13 Scope of the Study

The following dimensions define the scope of the present study:

The study focuses on examining the influence of behavioural biases on the investment decisions of individual investors, with a particular emphasis on the moderating role of financial literacy. The geographical scope of the research is limited to three Indian states, Maharashtra, Goa, and Karnataka, chosen for their active retail investor base and varied socio-economic profiles. The study targets individual investors participating in financial markets.

Behavioural biases include heuristic bias, prospect bias, herding and market factor bias. This study treats Heuristic and prospect biases as second-order constructs, each comprising specific behavioural biases directly influencing investment decisions. The research also investigates how financial literacy moderates these biases and investment decisions. Furthermore, demographic variables such as age, gender, marital status, education, occupation, income, and investment experience are examined as potential moderators in the relationship between behavioural biases and investment decisions.

The study uses a cross-sectional research design and employs Structural Equation Modelling (SEM) along with Importance-Performance Map Analysis (IPMA) and Necessary Condition Analysis (NCA) to analyse responses collected through a structured questionnaire.

1.14 Summary

A well-functioning financial system is vital for economic growth, facilitating capital formation and the efficient allocation of resources. Investment decision-making is a key component of this system, with individual investors playing a significant role in channelling savings into productive financial assets. However, with the assumed presence of behavioural biases among individual investors, which influence investment decisions, leading to irrational financial behaviour, poor asset allocation, and market inefficiencies.

This chapter provides a theoretical background on the relevant theories on behavioural finance, introducing the various behavioural biases that investors exhibit and their impact on investment decisions.

CHAPTER 2
REVIEW OF LITERATURE

The sub-sections of the literature review chapter discuss how individual investors' biases influence their investment decisions. It also explores the connection between behavioural biases, financial literacy and investor demographics in forming investment decisions. Accordingly, the conceptual model is presented, and hypotheses are developed and articulated to assume a significant relationship between them.

2.1 Behavioural Biases

As neo-classical financial theories suggest, investors are not always rational and do not act predictably. When faced with complex decisions and uncertainty, they often exhibit irrational behaviour. Various unobservable factors, including emotions, personal beliefs, cognitive biases, and individual competence, influence this behaviour. Understanding these psychological and behavioural tendencies is essential for gaining deeper insights into investors' decision-making processes. Identifying these unknown variables, such as investors' preferences and beliefs, can provide valuable explanations for their investment decisions.

Behavioural finance explores how cognitive and emotional biases shape investor behaviour, leading to market anomalies in prices and returns (Baker & Nofsinger, 2002). It also examines investors' interpretation and response to financial information when making investment decisions. Unlike traditional finance, which assumes rationality, behavioural finance acknowledges that biases and heuristics often drive investment behaviour. These biases can cause investors to deviate from expected utility-maximising decisions, sometimes leading to inefficiencies in financial markets.

Investors may exhibit a range of behavioural biases when making financial decisions. Some may be influenced by psychological factors such as personal preferences, emotions, or subjective judgments, which shape their investment choices. Others may rely on social influence and follow the actions of their peers, a phenomenon known as herding. Investors influenced by overconfidence bias overestimate their knowledge and make riskier decisions. In contrast, availability bias causes them to give excessive weight to recent or easily accessible information, even when irrelevant. Investors also use heuristics or mental shortcuts to simplify decisions, which may lead to systematic errors. Additionally, market-related factors, including sentiment and perceived arbitrage opportunities, can further influence investor behaviour, sometimes leading to deviations from fundamental valuations and principles.

The effect of behavioural biases in shaping investor decisions has been widely studied. Early research identified key biases such as overconfidence (De Bondt & Thaler, 1985), mental accounting (Thaler, 1985), loss aversion (Kahneman, 1979) and herding. Subsequent studies have examined how collective biases influence investor behaviour under different theoretical frameworks (Shefrin & Statman, 2000; Grinblatt & Han, 2005; Waweru et al., 2008; Kourtidis et al., 2011; Hon-Snir et al., 2012; Kudryavtsev et al., 2013). These studies provide empirical evidence that psychological and social factors significantly impact decisions in financial markets.

The following sections of the literature review explore the impact of individual and collective behavioural biases on investor behaviour.

2.1.1 Heuristics Biases

'Heuristics,' known as the rule of thumb, is a behavioural bias of investors under conditions of uncertainty (Ritter, 2003). Heuristic biases comprise representativeness, availability bias, anchoring (Kahneman, 1974), gambler's fallacy, and overconfidence (Waweru et al., 2008). Heuristic biases significantly influence investor behaviour (Kahneman, 1974; Ritter, 2003).

2.1.1.1 Overconfidence

This well-researched psychological bias arises when individuals overvalue their knowledge, skills, and decision-making abilities (Shiller, 2000). Investors exhibiting overconfidence tend to be excessively optimistic about their abilities, often relying more on personal judgment than publicly available data, leading to increased risk-taking and frequent trading (De Bondt & Thaler, 1995; Hvide, 2002; Daniel et al., 1998). The studies following these prominent works have consistently linked overconfidence to unwarranted trading, market volatility, and mispricing.

Recent research further explores how overconfidence bias impacts investment decisions. Studies by Adil et al. (2022) and Das and Panja (2022) indicate overconfident investors engage in high-risk speculative trading, believing they can constantly outperform the market, often resulting in higher transaction costs and reduced returns. Bakar and Yi (2016) and Madaan and Singh (2019) highlight the presence of overconfidence among investors; Gonzalez-Igual et al. (2021); Van Hoeserlande (2023) found demographic influences, showing that younger and female investors exhibit greater overconfidence wherein this finding is in contrast to the findings of Barber and Odean (2001); they found that men exhibit higher levels of overconfidence compared to women. Van Hoeserlande (2023) found overconfidence bias leading to aggressive investment behaviours and a tendency to underestimate market uncertainties.

Market conditions also play a crucial role. Overconfidence is amplified during bullish phases, where investors overestimate their predictive abilities, while in bearish markets, they fail to recognise misjudgements, adding to further inefficiencies. The market shocks are more pronounced among investors with overconfidence bias (Statman et al., 2006). Additionally, Metawa et al. (2019) suggest that overconfident investors positively impact investment decisions. Still, excess trading makes them more vulnerable to market fluctuations. Barber and Odean (2011) and Van Hoeserlande, C. (2023) found that overconfident investors tend to hold undiversified portfolios. Seraj et al. (2022) emphasise the role of financial literacy in mitigating overconfidence, as less knowledgeable investors are more prone to overestimating their abilities, reinforcing the need for education programs. Barber and Odean (2013) examined Taiwanese investors and found that overconfidence contributed to financial losses due to frequent trading. Similarly, Grinblatt and Keloharju (2009) found that overconfident Finnish investors exhibited a strong correlation between frequent trading and sensation-seeking behaviour.

Survey-based studies complement these findings by exploring psychological and demographic factors influencing overconfidence. Glaser and Weber (2007) surveyed 3,000 online investors and found that self-perceived superior investment skills led to frequent trading. Deaves et al. (2010) found that market experience often heightened overconfidence due to knowledge deterioration through a survey of 350 market participants. Menkhoff (2010) surveyed 692 fund managers across multiple countries and found that experienced, educated, and successful managers displayed overconfidence and trend-following behaviour. Menkhoff et al. (2013)

conducted an online study with 496 European capital market participants, showing that investment experience and age influenced overconfidence in opposite directions. Gloede & Menkhoff (2014) surveyed 105 German financial professionals, revealing that overconfidence was more driven by self-perception than actual expertise. Parveen et al. (2020) investigated the overconfidence bias of individuals trading at the Pakistan Stock Exchange and found that investors overreact to any new information that arrives in the market, thereby affecting their decisions.

Empirical research consistently demonstrates that overconfidence distorts investment behaviour, leading to excessive trading, mispricing, and increased market volatility. Market-based studies highlight how overconfidence affects trading patterns and financial performance, while survey-based research identifies key demographic and psychological factors contributing to this bias.

2.1.1.2 Representativeness Bias

Representativeness bias is an individual's tendency to base decisions on stereotypes, prior knowledge, or limited experiences rather than considering all relevant information (Baker et al., 2001). When individual investors depend on a small set of observations from their environment while disregarding broader data, it leads to systematic errors in judgment. In investment decision-making, representativeness bias often causes investors to overreact to information, assuming that past trends will continue indefinitely.

Marsden et al. (2008) highlight that representativeness bias contributes to stock market overreactions, resulting in price volatility. Investors fail to consider significant future risks, instead relying on limited past experiences to guide their decisions (Sumantri et al., 2024). Individual investors are driven to make flawed assumptions, such as associating higher stock prices with better quality or viewing consistently high-performing stocks as perpetual winners, even when fundamentals suggest otherwise (Chen et al., 2007; Khan et al., 2021).

Empirical research provides mixed evidence regarding the impact of representativeness bias. Jain et al. (2020) and Shah et al. (2018) found an insignificant effect, suggesting that while investors may initially be impelled by patterns, financial literacy can moderate this bias. Similarly, Yasmin and Ferdaous (2023) reported no significant impact, indicating that investors in specific markets do not always rely on past trends when making decisions.

Conversely, Parveen et al. (2020) found a significant impact of representativeness bias, particularly among retail investors with limited financial knowledge. Their findings align with those of Kartini and Nahada (2021), who describe how investors frequently assume that past performance reliably predicts future returns. This tendency leads investors to categorise stocks based on historical returns rather than fundamental analysis, reinforcing speculative behaviour. Wong et al. (2018) further emphasise that such heuristic-driven decision-making often results in momentum trading, where investors believe recent trends will continue and neglect undervalued opportunities.

2.1.1.3 Availability Bias

Individual investors, when they excessively rely on readily available information, form mental shortcuts based on correlations between seemingly similar objects or scenarios, are affected by availability bias (Tversky & Kahneman, 1974). Rather than seeking comprehensive data, investors make decisions based on easily recalled or recently encountered information, often leading to distorted risk perceptions and suboptimal financial choices. Investors influenced by availability bias prefer local stocks over international ones because of familiarity and accessibility to information (Waweru, 2008).

Empirical research presents mixed findings regarding availability bias in investment decision-making. Madaan and Singh (2019) found a significant impact, suggesting that investors frequently rely on easily accessible information when evaluating stocks, leading to impulsive trading and an overemphasis on short-term trends.

Conversely, Bakar and Yi (2016), Gurung et al. (2024), and Khan et al. (2021) found a low or an insignificant impact of availability bias on investment decisions. Their findings suggest that while investors may initially be influenced by readily available information, factors such as financial literacy, professional guidance, and market experience can mitigate this bias. Similarly, Jain et al. (2020) reported no significant relationship, indicating that investors may not necessarily rely on the most recent information in certain market conditions.

These mixed results suggest the availability bias may vary based on external moderating factors such as market efficiency, financial education, and investor experience. While some investors may be highly susceptible to easily recalled information, others may consider a more analytical approach, reducing the presence of this cognitive bias in their decision-making process.

2.1.1.4 Anchoring Bias

When considering investment decisions, the reliance on initial reference points, such as past stock prices or historical performance, is an anchoring bias (Tversky & Kahneman, 1974). Individuals make insufficient adjustments to this reference point even when new information is available, resulting in sub-optimal decisions. Investors affected by anchoring bias retain losing stocks for too long, expecting prices to return to their initial reference points, or they may be overly influenced by historically sampled information from memory, setting their expectations for future gains (Berg and Moss, 2022).

Tversky and Kahneman (1974) describe anchoring bias as dependence on pre-existing or initial information (the "anchor"). Individuals adjust their perceptions based on this reference point, making biased judgments. In investing, individuals influenced by anchoring bias base their decisions on a particular piece of information, whether the first information they acquire or the only information available, causing them to place undue importance on it. The initial value allocated creates a blinding effect and irrational judgments over time (Aren & Hamamci, 2021). Despite the availability of new or more relevant information, investors often remain attached to their initial information.

Empirical research on anchoring bias presents mixed findings regarding its impact on investment decisions. Falah and Haryono (2023) found an insignificant effect, with only a moderate and low impact of anchoring bias on investors' choices. Their study suggests that while investors may initially rely on reference points, other factors, such as market trends and financial knowledge, lessen the influence of anchoring bias. Similarly, Jain et al. (2020) reported no significant impact, implying that investors in specific markets may not strongly influence historical price points when making investment decisions. Madaan and Singh (2019) also found no substantial evidence linking anchoring bias to investment behaviour, suggesting that individual investors may use additional decision-making frameworks beyond their initial reference points.

In capital markets, anchoring bias is commonly observed among investors who fixate on the purchase price of stocks in their portfolios. Many investors base their selling decisions on this reference point, often choosing to sell when the stock price rises above their purchase price. Additionally, some investors use the highest historical price of a stock as a benchmark, which influences their reluctance to sell at a loss. This tendency prevents them from making rational decisions, as they retain declining stocks, anticipating reaching past values instead of objectively evaluating current market scenarios (Gurung et al., 2024).

The variation in findings suggests that the effect of anchoring bias may depend on external moderating factors, such as financial literacy, investor experience, and the availability of market information.

2.1.1.5 Gambler's Fallacy Bias

Gambler's fallacy bias is particularly evident in financial decision-making, where investors mistakenly assume that a prolonged upward or downward trend is bound to reverse. An investor may predict that a stock experiencing continuous gains will soon decline or that a losing stock is "due" for a rebound, despite lacking supporting financial fundamentals (Tversky & Kahneman, 1974).

Waweru et al. (2008) found that investors influenced by the gambler's fallacy tend to become pessimistic after bull markets and optimistic after bear markets, often making investment decisions that contradict rational market analysis.

Similarly, Zielonka (2004) conducted an experimental study on stock market professionals and discovered that their responses to market signals were shaped by multiple behavioural biases, including the gambler's fallacy. Despite their expertise, these professionals tended to forecast stock price movements based on perceived market reversals rather than objective analysis.

Kirera and Mburugu (2019), among the many biases studied, found a low presence of the gambler's fallacy in their study at the Nairobi stock market, indicating an absence of false belief that the past stock performance would necessarily reverse.

Gambler's fallacy may play a limited or situational role in investment decisions. It must be studied in combination with other biases to understand its actual impact on individual investors' investment decisions.

2.1.2 Prospect Bias

Prospect theory, a widely studied concept in behavioural finance, was introduced by Kahneman and Tversky (1979). The theory suggests that individuals tend to underweight probable outcomes compared to certain ones. According to Kahneman and Tversky (1979), people perceive specific outcomes as equivalent and establish a reference point. Subsequent outcomes are then evaluated in relation to this reference point. Investors assess gains and losses based on this reference, exhibiting risk-seeking behaviour when gains exceed the reference point and risk aversion when losses fall below it. This implies that losses have a greater psychological impact than equivalent gains, making the value function steeper for losses. Individuals are risk-averse with gains and risk-acceptant with losses. Therefore, decisions are framed around a reference point. As a result, investors focus more on gains and losses than on overall wealth accumulation (Levy, 1992). Prospect theory incorporates several behavioural biases, including regret aversion, loss aversion, and mental accounting (Waweru et al., 2008).

2.1.2.1 Regret Aversion Bias

Regret aversion bias occurs when investors avoid making decisions that could potentially lead to feelings of regret, often resulting in suboptimal financial choices. Regret is a negative emotion that arises when a different choice is recognised or imagined that could have led to a better outcome than our current situation. (Zeelenberg, 1999). Investors with this bias hold onto losing investments for too long just to avoid realising the negative return, or they may avoid new investment opportunities due to fear of making a wrong choice (Shefrin & Statman, 1985).

Regret occurs when individuals recognise that they have made mistakes in decision-making. When making investment decisions, the bias manifests in holding onto losing stocks for extended periods while quickly selling winning stocks (Baker et al., 2017; Lehenkari & Perttunen, 2004). Investors do this to avoid the psychological discomfort of admitting a bad investment decision, often leading to long-term financial underperformance.

Several studies have examined the role of regret aversion in investment decision-making. (Jain et al, 2020), Yasmin & Ferdaous, 2023) found that regret aversion bias affects investors' willingness to take risks, leading to overly cautious investment behaviours. Their findings suggest that investors who have previously experienced losses may hesitate to invest in volatile assets, even when potential returns are high.

2.1.2.2 Loss Aversion Bias

This bias is evident when individuals prefer taking risks over accepting a guaranteed loss in an investment scenario (Shefrin, 2000). Investors tend to be more sensitive to losses than to gains, meaning the same magnitude of loss has a greater psychological impact than an equivalent gain. Unlike regret aversion, which stems from past decisions, loss aversion is more about anticipating losses. Research also suggests that losses following prior losses have a more significant effect on investor behaviour than losses occurring after prior gains (Barberis & Thaler, 2003; Barberis & Huang, 2001).

Several studies have examined the impact of loss aversion bias on investment decision-making, yielding mixed findings. Kartini and Nahada (2021) and Jain et al. (2020) found a significant negative impact, indicating that loss-averse investors tend to be overly cautious, avoiding high-risk investments even when potential returns are favourable. Similarly, Yasmin and Ferdaous (2023), Areiqat et al. (2019) highlighted that loss aversion strongly influences investment behaviour, leading to conservative decision-making and suboptimal portfolio diversification. Hossain and Siddiqua (2022) reported a significant impact of loss aversion on investment decisions, implying that loss aversion does play a decisive role in certain market conditions or investor segments.

However, other studies suggest a weaker or insignificant relationship. Zeif and Yechiam (2022) found that individuals did not show loss aversion for small, equal-sized gains and losses; instead, participants often chose riskier options, indicating gain-seeking behaviour. This challenges the idea that loss aversion is a universal bias. Rawat (2023) and Shrestha et al. (2025) found that loss aversion had a statistically insignificant direct effect on investment decisions, implying that loss aversion does not play a decisive role in certain market conditions or investment segments. These variations in findings suggest external factors such as financial literacy, risk tolerance, the size of potential losses, and market dynamics may determine their influence.

2.1.2.3 Mental Accounting Bias

Mental accounting refers to individuals' cognitive processes to categorise, evaluate, and track financial activities (Thaler, 1999). Investors mentally separate their portfolios into different accounts and treat them differently (Ritter, 2003). This can lead to variations in risk-taking behaviour across different investments (Shefrin & Statman, 1985). Mental accounting bias influences investor decisions and contributes to the tendency to sell winning stocks too quickly while holding on to losing stocks and focusing on individual gains and losses rather than overall portfolio performance (Thaler, 1999) and also investment evaluation and choice (Ranyard & Abdel-Nabi, 1993)

Jain et al. (2020) and Umeaduma (2024) examined the impact of mental accounting on investment decision-making and found that individuals rely on psychological budgeting rather than rational financial analysis. Their study suggests that investors influenced by mental accounting are more likely to retain underperforming assets in one account while engaging in riskier investments in another, demonstrating a lack of holistic financial planning.

Investors may treat dividends and capital gains differently, opting to spend dividend income while preserving their initial capital, even when reinvesting might yield higher long-term returns (Thaler, 1999; Khalili et al., 2025). Additionally, mental accounting can lead to risk-seeking behaviour in one financial account while maintaining excessive risk aversion in another. Mahapatra and Mishra (2020) highlight that investors often create separate mental accounts for different investment goals, such as retirement savings and speculative trading, resulting in inconsistent risk preferences across accounts.

Shefrin and Statman (1985) suggest that mental accounting contributes to selling winning investments too early to "lock in" gains while holding onto losing investments in the hope of future recovery. This reinforces irrational decision-making, as individuals fail to evaluate their portfolios based on overall performance.

2.1.3 Herding Bias

Herding behaviour occurs when individuals rely on others in various social and economic situations to make decisions. In stock markets, herding is characterised by investors imitating others instead of analysing their private information to make independent choices (Banerjee, 1992). This behaviour tends to be correlated among individuals (Devenow & Welch, 1996), particularly when social interactions influence stock market investments (Hong et al., 2004). Investors often follow fund managers and financial analysts, perceived as high-ability peers, and replicate their investment decisions (Economou et al., 2018).

Hasan et al. (2023) suggested that herding behaviour can drive stock trading activity and further market momentum. Herding can be identified by observing investors' buying and selling decisions, their selection of stocks, the volume of trades, and the speed at which they follow others (Merli & Roger, 2013)

Research on herding behaviour can be broadly classified into empirical studies focusing on stock market returns (Hwang & Salmon, 2004; Chiang et al., 2013; Litimi, 2017; Lao & Singh, 2011; Ouarda et al., 2013; Fransiska et al., 2018; Zhou & Lai, 2009) and those relying on survey-based evidence.

Survey-based studies have provided evidence of herding behaviour. Khare and Kapoor (2024) surveyed Indian institutional investors, portfolio managers, investment advisors and financial analysts and found that they engaged in herding based on trend-following strategies. Similarly, Lütje (2009) surveyed German asset managers and confirmed that institutional herding existed due to risk aversion and loss aversion biases.

Herding bias stems from the need for information, with investors often looking to friends and family for guidance (Abideen et al., 2023). Herding bias affects investment decisions positively, with investors adjusting their choices based on others' actions (Rahayu et al., 2021; Ainul, 2024; Madaan & Singh, 2019). Metawa et al. (2019) found that herding motivates investors to align their prices with those of others, disregarding their information. Herding is more prevalent during market turmoil (Jain & Kesari, 2023).

2.1.4 Market Forces Bias

Behavioural finance theories suggest that stock market price changes and news events can influence investors, leading to either overreaction or underreaction to new information (De Bondt et al., 1985). Additionally, past price trends often cause investors to follow historical movements beyond a rational level (Rubinstein, 2001). Investor behaviour is also shaped by trends in popular stocks and seasonal market patterns (Bhanu, 2023), sometimes leading them to overlook fundamental stock valuations (Lowenstein, 2006). Key market factors such as price fluctuations, seasonal trends, popular stock movements, and company fundamentals significantly shape investor decision-making. The most relevant market influences include price changes, market information, historical stock trends, investor preferences, overreaction to price fluctuations, and seasonal patterns (Caporale & Plastun, 2019).

Survey-based research explored the market factors on investor behaviour. Lai et al. (2010) surveyed investors from 621 Malaysian listed companies in 1999, revealing that market fundamentals played a crucial role in investors' underreaction to price changes. Shabgou and Mousavi (2016) analysed investors in the Tehran Stock Exchange and found that market forces significantly guide investment decisions. Their study revealed that investors base investment decisions on prevailing market sentiment rather than rational financial analysis.

Similarly, Ngoc (2014) explored investment decisions and market conditions to find that market fluctuations directly affect investor psychology. His research suggests that in bullish markets, investors tend to exhibit overconfidence and take excessive risks, whereas in bearish markets, they become excessively cautious, often leading to suboptimal decision-making.

Market forces bias involves letting external market factors, such as trends, news, or macroeconomic pressures, excessively influence investment decisions. Investors deviate from their original strategies or goals due to this bias. It is similarly known as market sentiment bias and reflects how market trends and customer sentiments affect investment decisions.

2.2 Behavioural Biases and Investment Decisions of Individual Investors

Investors adopt diverse criteria rather than a single, integrated approach when making investment decisions. They often rely on others, past outcomes, shortcuts, or strategies to minimise losses in complex decision-making situations. These behavioural biases significantly guide their investment decisions. Several studies have investigated the impact of behavioural biases on investor behaviour by examining a few key biases or grouping them into relevant categories.

Shefrin (2000) introduced a conceptual framework that classified behavioural biases into heuristic-driven biases, frame dependence, and market inefficiencies. Waweru et al. (2008) further categorised behavioural biases into four major groups: Prospect theory biases, Heuristic-driven biases, Herding biases, and Market factors. They also incorporated additional biases within the heuristics category, namely, the gambler's fallacy and overconfidence. Market factors included price changes, market information, past stock trends, customer preferences, overreaction to price movements, and fundamental stock attributes influencing investment decisions. Waweru et al (2008) examined institutional investors in the Nairobi Stock Exchange, finding that multiple behavioural biases influenced investment decisions, with heuristics being the most dominant, followed by prospect theory biases. Among heuristic biases, availability bias, anchoring, and gambler's fallacy were particularly prominent.

Kourtidis and Chatzoglou (2011) surveyed 345 investors in Greece and applied cluster analysis to classify investors into three groups: high-profile, moderate-profile, and low-profile. The classification was based on overconfidence bias, risk tolerance, self-monitoring, and social influence. They found that investors' high overconfidence, risk tolerance, and social influence achieved better trading performance, placing them in the high-profile investor category.

Kudryavtsev et al (2013) examined the impact of five behavioural biases: disposition effect, herd behaviour, availability heuristic, gambler's fallacy, and hot-hand fallacy on investor decision-making. An online survey of 305 professional and non-professional investors in Israeli investment firms found that active traders exhibited moderate behavioural biases, professional investors were less susceptible to biases, and all five biases more strongly influenced female investors.

Several studies have examined behavioural biases among Indian investors. Subash (2012) investigated the influence of biases such as overconfidence, representativeness, herding, anchoring, cognitive dissonance, regret aversion, gambler's fallacy, mental accounting, and hindsight bias on Indian stock market investors using a sample of 92 respondents. The study concluded that young investors were significantly more affected by gambler's fallacy, anchoring, and hindsight bias than experienced investors. Khan et al. (2021) used the moderation role of long-term orientation of investors by analysing data from 374 stock market participants. They found that investors are primarily influenced by availability and representativeness bias.

Mehta & Chaudhari (2016) surveyed the individual investors of the Indian stock market and identified correlations between various behavioural biases, such as gambler's fallacy, representativeness, regret aversion, overconfidence, hot-hand fallacy, anchoring, cognitive biases, and herding and their investment strategies. Haritha and Ochil (2024) found that Indian equity individual investors are strongly influenced by social and market behavioural factors in their investment decision process.

Agarwal and Rao (2023) examined the demographics and investor sophistication on behavioural biases, finding that overconfidence, disposition effect, herding bias, and representativeness bias. These studies highlight the impact behavioural biases have on investment decisions in developed and emerging markets. Bekaert and Harvey (2002) noted that many emerging markets operate differently from developed ones due to infrequent trading, slow information assimilation, and relative inefficiency.

Le Luong and Thi Thu Ha (2011) investigated the individual investors' investment decisions in the Vietnam Stock Exchange and noted that market factors had the most significant influence, with other factors playing a moderate role. Ngoc (2014) also examined Vietnamese stock market investors and identified five key factors influencing investment decisions: Herding, Market, Prospect, Overconfidence-gamble's fallacy, and Anchoring-ability bias.

L. Kengatharan and N. Kengatharan (2014) analysed the behavioural factors affecting individual investors in the Colombo Stock Exchange, identifying anchoring (a heuristic bias) as having the strongest influence on investment decisions, while herding-related stock choices had the least impact. Their study also found that investment performance was negatively influenced by overconfidence and herding behaviour, while anchoring had a high positive influence.

Abul (2019) examined the overconfidence bias, herd behaviour bias, and risk appetite of investors at the Kuwait Stock Exchange. Herd behaviour and risk appetite played a role in investor decision-making.

Saleem et al. (2023) studied multiple behavioural biases among investors in the Pakistan Stock Exchange. They concluded anchoring, optimism bias, and loss aversion significantly affected investment decisions.

These studies illustrate the profound role of behavioural biases in shaping investor decision-making, particularly in emerging markets. While investors may consider fundamental financial indicators such as return on equity, profit margins, and future growth before investing (Zahera & Bansal, 2018), underlying psychological and emotional biases affect individual investors.

2.3 Financial Literacy and Investment Decisions of Individual Investors

Within this context, financial literacy is crucial in mitigating the adverse effects of these biases. A lack of financial literacy exacerbates poor decision-making, increasing investors' susceptibility to psychological distortions and misjudgements of risk (Lusardi & Mitchell, 2014; Barberis & Thaler, 2003). Financial literacy has become essential for making sound investment decisions as financial markets and products become increasingly complex. Defined as an amalgamation of financial awareness, knowledge, skills, attitudes, and behaviours, financial literacy enables individuals to make informed financial choices and secure long-term financial stability.

2.3.1 Financial Literacy, Behavioural Biases and Investment Decisions

Various factors, including personal preferences, motivation, available funds, time horizons, and financial goals, shape investment decisions. Investors often exhibit behavioural biases due to inexperience, limited knowledge, disinterest, and time constraints. These can lead to irrational financial decisions, potentially contributing to market inefficiencies by disregarding fundamental financial principles (Arianti, 2018; Baihaqqy et al., 2020)

Individuals with a comprehensive understanding of financial concepts and instruments to make sound investment decisions. Financial stability requires broad knowledge of financial products and the ability to apply and communicate this knowledge effectively. Financially literate investors are better equipped to assess investment opportunities, mitigate risks, and make strategic financial choices. (Abdeldayem, (2016).

The impact of financial literacy on investor behaviour has been examined through various constructs related to financial knowledge and behavioural biases.

Hassan Al-Tamimi and Anood Bin Kalli (2009) studied the financial literacy of UAE investors, revealing that income level, education, and workplace activity influenced their behaviour. They also found a significant relationship between financial literacy and investment decisions.

Rasheed et al. (2021) found that behavioural biases significantly influence investors' decision-making. The moderation analysis further revealed that financial literacy is crucial in mitigating these biases, leading to more rational investment decisions.

Chandra et al. (2023) studied young adults in Surabaya to examine how financial literacy and risk perception influence their investment decisions. The findings indicate that both financial literacy and risk perception significantly positively impact investment decisions, both individually and when considered together.

Mouna and Anis (2017) investigated the determinants of financial literacy and investment behaviour. First, individuals with a low level of financial literacy are less likely to invest in the stock market. Second, the financial literacy level is affected by age, education level, and annual income; third, investors with low financial knowledge and skills are more prone to behavioural biases.

Poor investment choices and bad financial behaviour have been attributed to financial illiteracy. Individual investors can maximise their earnings and allocate resources more wisely by being financially literate. Financial literacy influences investment decisions favourably and moderates the relationship between risk aversion and risk investment. People get the most out of their assets (Aren and Aydemir, 2015).

Abdulridha (2024) examined the relationship between determinants of investor behaviour and individual investors' investment decisions, considering the moderating effect of financial literacy and found that financial literacy encourages dependence on accounting information, neutral information, and personal financial needs, which affect investment decisions of Iraqi investors. Financial literacy was a significant moderator in these relationships while taking investment decisions.

Financial literacy enhances investors' ability to recognise their financial needs and make informed investment decisions, such as buying or selling stocks, that align with their goals of maximising returns and minimising risks (Kishan & Alfan, 2019).

Raut (2020) conducted a study across four Indian states, Bihar, West Bengal, Delhi, and Assam and found that Indian investors were significantly influenced by social pressure. However, this influence could be mitigated through enhanced financial literacy.

Mahmood et al. (2024) found a strong positive relationship between overconfidence bias and investment decisions. Financial literacy independently enhances the rational investment behaviour and moderates this relationship by mitigating the risks associated with overconfidence.

Agarwal et al (2015) analysed the investment behaviour, liability choices, risk tolerance, and insurance usage of a select group of Indian investors. Their findings indicated that most respondents were financially literate at a basic level, though financial literacy varied across demographic and socio-economic groups. Risk tolerance, investment preferences, and financial goals were closely linked to financial literacy.

Poudel et al. (2024) found that financial literacy significantly affects investment decisions. With lower financial literacy, the effect of herding and overconfidence bias on investment decisions was high; financial literacy moderates overconfidence bias and investment decisions of Nepalese investors.

However, a negative association between financial literacy and behavioural biases of individual investors was found, implying that with an increase in financial literacy, the likelihood of investors facing behavioural biases reduces. (Rasool & Ullah, 2020)

Sivaramakrishnan et al (2017) studied the financial literacy of individual investors in Mumbai, Delhi, Coimbatore, and Ranchi. They analysed key factors such as attitude toward investing, subjective and objective financial literacy levels, investment intentions, and actual investment behaviour. Their study revealed that investment intention strongly predicted actual investment behaviour. Both subjective and objective financial literacy influenced investment intentions, though only objective financial literacy significantly impacted investment behaviour.

Financial literacy significantly affected investment decisions for both genders. Financial literacy moderated the effect of overconfidence only for males, while for females, it significantly moderated the effects of all four biases—overconfidence, risk aversion, herding, and disposition. (Adil et al., 2022).

Empirical research treats financial literacy and behavioural biases as independent constructs. There is a lack of an integrated model that examines how financial literacy moderates the relationship between multiple behavioural biases and the investment decisions of individual investors in emerging economies.

2.4 Behavioural Biases and Investor Demographics

Investor behaviour tends to vary based on individual characteristics. Stock market participants come from diverse backgrounds, differing in gender, age, education, employment, and income. These variations can influence investment behaviour and decisions. Several studies have examined how investor biases are shaped by their demographic and characteristics. The following section presents a review of relevant literature on investor demographics.

2.4.1 Gender

Gender differences are crucial in manifesting behavioural biases, influencing how men and women approach investment decisions. Research consistently shows, men exhibit higher levels of overconfidence bias, often overestimating their knowledge, predictive abilities, which leads to unwarranted trading and riskier investment strategies (Mishra & Metilda, 2015; Bushra et al., 2024; Kansal & Singh, 2018; Katper et al., 2019; Rahman & Gan, 2020; Raj, 2025). Similarly, herding bias is more prevalent among men, as they tend to follow market trends and peer influence rather than relying on independent analysis, whereas women demonstrate a more cautious and research-based approach (Kumar & Goyal, 2016; Rahman & Gan, 2020; Jamil & Khan, 2016; Prosad et al., 2015; Raj, 2025). In contrast, women are more prone to mental accounting bias**,** categorising financial decisions into separate accounts, which results in structured financial management and lower impulsive trading (Rzeszutek et al., 2015; Yalcin et al., 2016; Sharma & Firoz, 2020; Beatrice et al., 2021). Additionally, anchoring bias tends to affect men more, as they heavily depend on past stock prices or reference points, whereas women exhibit a more flexible decision-making process (Baker et al., 2019). However, (Owusu & Laryea, 2023) observed that females anchor more than their male counterparts.

A similar pattern emerges with representativeness bias**,** where men are more likely to stereotype investments based on past trends, leading to overreactions and misjudgements, while women take a more analytical and data-driven approach (Yalcin et al., 2016; Baker et al., 2019; Katper et al., 2019). These findings highlight that while men are more susceptible to biases that drive aggressive and risk-seeking behaviours, women demonstrate greater caution, structure, and confidence on analytical reasoning in their investment decisions. Understanding these gender-specific tendencies is essential for developing tailored financial strategies and improving investment decisions.

2.4.2 Marital Status

Extensive research has investigated how demographic characteristics such as gender, age, education, occupation, and income influence behavioural biases in investment decision. However, the use of marital status as a moderating factor in this context remains underexplored. While some studies have considered marital status among other demographic variables, they often focus on direct relationships rather than their potential moderating effects. Katper et al. (2019) examined the how behavioural biases affect investment decisions, proposing hypotheses about marital status as a moderator among other demographic factors. This gap suggests a need for focused studies to determine whether and how marital status influences the relationship between behavioural biases and investment decision-making

2.4.3 Age

An individual investor's age determines how behavioural biases affect investment decisions. Studies have consistently found that overconfidence bias is more prevalent among younger investors, driving them to riskier and frequent trades. (Trejos et al., 2019; Kumar & Goyal, 2016; Siraji, 2019). In contrast, older investors tend to be more cautious and demonstrate lower overconfidence (Lin, 2011), unlike in the case of anchoring (Bushra et al., 2024). Mental accounting bias appears to be stronger among older investors, as they categorise and allocate their financial resources more rigidly (Rzeszutek et al., 2015; Yalcin et al., 2016; Sharma & Firoz, 2020; Bushra et al., 2024). This suggests that individuals develop a structured approach to managing investments as they age, possibly due to increased financial experience.

Herding bias is more pronounced among younger investors who follow market trends and investment decisions of others (Sharma & Firoz, 2020; Reka & Sasirekha, 2019; Kumar & Goyal, 2016). Older investors rely more on their judgment and experience, making them less susceptible to herding behaviour (Kudryavtsev et al., 2013). Availability bias, which relies on recent or easily accessible information, is also more dominant among younger investors (Baker et al., 2019; Kudryavtsev et al., 2013). This could be attributed to their reliance on digital news and social media updates.

Similarly, representativeness bias, where investors make decisions based on stereotypes or past patterns, is more common among younger individuals (Yalcin et al., 2016). Older investors, in contrast, are less likely to generalise past trends to future investment outcomes, reflecting a more rational decision-making process. The literature suggests that younger investors are more prone to biases such as overconfidence, herding, availability, and representativeness. In comparison, older investors exhibit stronger mental accounting tendencies but demonstrate greater caution and rationality in their investment choices.

2.4.4 Income

Investors' susceptibility to behavioural biases is strongly shaped by their level of income. Overconfidence bias is more prevalent among high-income investors, as they tend to overestimate their financial knowledge and ability to predict market trends, leading to excessive trading and risk-taking (Khilar & Singh, 2019; Isidore, 2019; Kansal & Singh, 2018; Kumar & Goyal, 2016; Mushinada & Veluri, 2019). Similarly, herding bias is influenced by income levels, with lower-income investors following market trends due to limited access to financial information, while high-income investors may exhibit herding behaviour during periods of market uncertainty (Kumar & Goyal, 2016; Baker et al., 2019; Prosad et al., 2015). Availability bias is also shaped by income disparities, as lower-income investors tend to base decisions on recent news or easily accessible information rather than comprehensive market analysis (Baker et al., 2019; Srivastav & Pandey, 2023; Mouna & Jarboui, 2017). Representativeness bias, where investors judge stocks based on past trends, is observed in both income groups. High-income investors may assume that previously successful investments will continue performing well, while lower-income individuals rely on simplified heuristics due to limited financial literacy (Yalcin et al., 2016; Baker et al., 2019). Additionally, anchoring bias, where investors fixate on initial information when making investment choices, is more pronounced among lower-income individuals who rely on past prices or outdated financial data to guide their decisions (Baker, H. K., Kumar, S., Goyal, N., & Gaur, V. (2019; Srivastav, S., & Pandey, A. (2023)). Overall, income level significantly affects the extent to which investors exhibit behavioural biases, influencing their decision patterns in financial markets.

2.4.5 Education

Education significantly influences the extent investors exhibit behavioural biases in financial decision-making. Representativeness bias, which leads investors to make decisions based on past patterns rather than rational analysis, is more prevalent among individuals with lower financial education, as they tend to rely on heuristics and simplified decision-making strategies (Baker et al., 2019; Srivastav & Pandey, 2023; Dhungana et al., 2022). Overconfidence bias, where investors overestimate their knowledge and predictive abilities, is also affected by education levels. Highly educated investors may display overconfidence due to their exposure to financial theories and market trends, leading to excessive trading and risk-taking behaviour. (Bushra et al., 2024; Baker et al., 2019). Herding bias, where investors follow the majority's actions rather than relying on independent analysis, is commonly observed among those with limited financial education, as they may lack the expertise to assess market conditions critically (Sabir et al., 2019; Trejos et al., 2019; Mushinada & Veluri, 2018; Mushinada, 2020; Baker et al., 2019; Kansal & Singh, 2018; Prosad et al., 2015). However, even highly educated investors are not immune to herding, particularly during volatile market conditions, when they may follow institutional investors' or financial analysts' recommendations instead of conducting their evaluations (Baker et al., 2019; Prosad et al., 2015). Thus, while education can help mitigate certain biases by enhancing financial literacy and critical thinking, it does not eliminate irrational decision-making tendencies in investment behaviour.

2.4.6 Occupation

The nature of an investor's occupation can shape behavioural biases and influence how financial and investment decisions are made. Herding bias varies across occupations. Gunathilaka (2021) found that professionals in specific fields are more prone to following the crowd rather than relying on independent analysis, while Prosad et al. (2015) observed that finance and business professionals exhibit greater susceptibility to market trends. Overconfidence bias is particularly evident among financial professionals, as Kansal and Singh (2018) reported that investment managers tend to take excessive risks due to their overconfidence, while Isidore (2019) found that business executives and entrepreneurs exhibit more overconfidence compared to salaried employees. Similarly, availability bias affects professionals differently, with Mushinada and Veluri (2018) noting that finance professionals rely heavily on recent market events, leading to biased judgments. Baker et al. (2019) highlight that doctors and engineers often recall personal financial experiences rather than market fundamentals when making investment decisions. Representativeness bias is also occupation-dependent, as self-employed individuals and business professionals are more likely to make investment decisions based on stereotypes rather than thorough analysis. At the same time, Dhungana and Sharma (2022) found that professionals in high-risk fields like finance and real estate rely on past patterns rather than objective evaluation. Lastly, anchoring bias is prevalent among investment bankers and financial analysts, who rely on initial price levels when making investment choices. At the same time, Baker et al. (2019) reported that legal and healthcare professionals also anchor their decisions based on initial price cues rather than comprehensive market data. These findings highlight how different professions influence behavioural biases, shaping financial decisions in distinct ways.

2.4.7 Investment Experience

Investment experience significantly influences how individuals process financial information and respond to market situations. Taylor (1975) was among the first to explore how age and experience affect investment judgments, suggesting that with experience, individuals acquire better decision-making skills through increased knowledge and exposure to market patterns.

Several studies support the view that experience enhances rationality and reduces susceptibility to biases. Kumar and Goyal (2015) found that experienced investors are generally less prone to heuristics such as representativeness and availability bias, as they draw upon historical knowledge and analytical reasoning. Similarly, Waweru et al. (2008) observed that more seasoned investors exhibited lower presence of herding bias and overconfidence bias as compared to less experienced counterparts.

Barber and Odean (2001) highlighted that frequent traders, often those with more experience, can become overconfident, attributing past successes to skill rather than luck, leading to frequent trading and suboptimal returns. This shows that experience does not uniformly reduce biases and may even exacerbate some, such as overconfidence. Similarly, Aziz et al. (2024) found that investment experience does not moderate investment decisions.

Ritter (2003) emphasised that while experienced investors may interpret market signals more effectively, they are still vulnerable to biases like mental accounting and loss aversion rooted in deep psychological tendencies. Similarly, Bikas (2016) concluded that although experience improves certain aspects of investment behaviour, emotional biases such as regret aversion and anchoring remain influential.

Investment experience reduces behavioural biases by promoting rational and informed decision-making. Experienced investors rely more on systematic analysis, showing less overconfidence, loss aversion, and herding tendencies compared to novices (Barber & Odean, 2001; Baker et al., 2019; Alrabadi et al., 2018).

Investment experience as a moderating factor in the relationship between behavioural biases and decision-making generally reduces the influence of cognitive biases and enhances rationality; it may not fully shield investors from emotional or psychological influences and, sometimes, may even amplify them.

2.5 Conceptual model

A conceptual model has been developed to present the impact of various behavioural biases on investment decisions while considering the moderating role of financial literacy and investor demographics. This model categorises ten major behavioural biases into heuristic-driven biases, prospect biases, herding bias, and market forces bias.

The first two classifications align with Shefrin (2001) framework, while herding and market forces bias are grouped separately. Heuristic-driven biases include overconfidence bias, representativeness bias, anchoring bias, availability bias, and gamblers' fallacy bias, which stem from investors' cognitive shortcuts in processing financial information. Prospect Biases, comprising regret aversion bias, loss aversion bias, and mental accounting bias, influence investment decisions based on how financial outcomes are framed and affect investment decisions. The other behavioural biases include herding bias and market forces bias, which arise from social influences and macroeconomic factors affecting individual investors' decisions.

In this study, behavioural biases serve as independent variables, and investment decisions act as a dependent variable. Additionally, financial literacy and demographic variables, namely gender, marital status, age, education, occupation, income and investment experience, are considered moderating variables that may influence the strength and direction between biases and investment decisions. Financial literacy, in particular, plays a crucial role in determining whether financial literacy can mitigate biases and whether even financially literate investors remain susceptible to behavioural biases. Similarly, investor demographics may influence how different groups of investors process financial information and make decisions. By systematically evaluating behavioural biases alongside financial literacy and demographic factors, this study aims to uncover how psychological and informational biases impact investor behaviour. In doing so, it seeks to bridge gaps in the behavioural finance literature and provide deeper insights into the investment decisions of individual investors. A comprehensive discussion on the measurement of constructs used in this study is presented in Chapter Four.

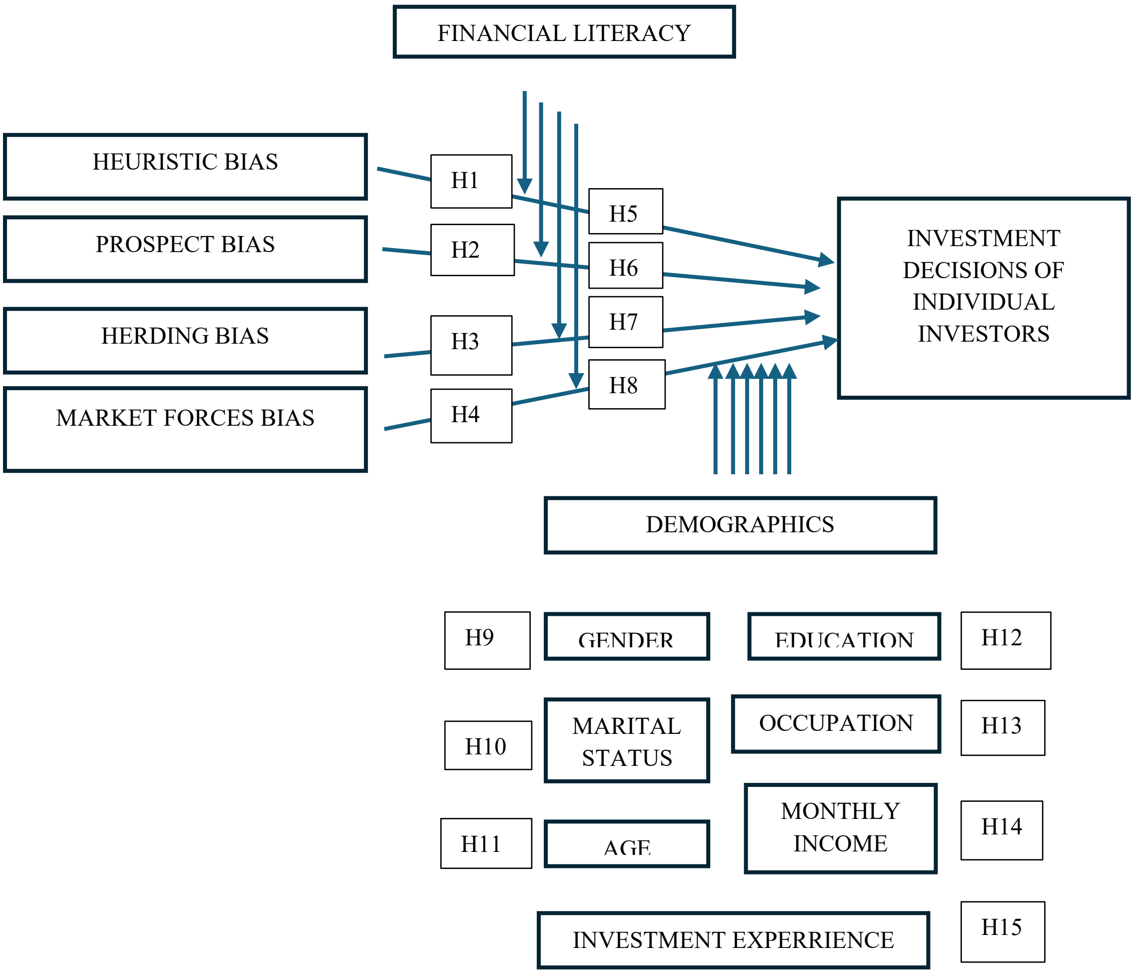

Figure 2.1: Proposed Conceptual Model
Compiled by the Researcher

2.6 Hypotheses of the study

The study proposes the following hypotheses:

1. Hypotheses examining the influence of Behavioural Biases on Investment Decisions of individual investors.

   H1: Heuristic Bias significantly influences the investment decisions of individual investors.

   H2: Prospect Bias significantly influences the investment decisions of individual investors.

   H3: Herding Bias significantly influences the investment decisions of individual investors.

   H4: Market Forces Bias significantly influences the investment decisions of individual investors.

2. Hypotheses examining the moderating role of Financial Literacy on the relationship between Behavioural biases and investment decisions.

   H5: Financial literacy significantly moderates the relationship between heuristic bias and investment decisions of individual investors.

   H6: Financial literacy significantly moderates the relationship between prospect bias and investment decisions of individual investors.

   H7: Financial literacy significantly moderates the relationship between herding bias and investment decisions of individual investors.

   H8: Financial literacy significantly moderates the relationship between market forces bias and investment decisions of individual investors.

3. Hypotheses examining the moderating role of investor demographics in the relationship between Behavioural biases and investment decisions.

   H9: Gender significantly moderates the relationship between the behavioural biases and investment decisions of individual investors

H9a: Gender significantly moderates the relationship between heuristic bias and investment decisions of individual investors.

H9b: Gender significantly moderates the relationship between prospect bias and investment decisions of individual investors.

H9c: Gender significantly moderates the relationship between herding bias and investment decisions of individual investors.

H9d: Gender significantly moderates the relationship between market forces bias and investment decisions of individual investors.

H10: Marital status of the investors significantly moderates the relationship between the behavioural biases and investment decisions of individual investors

H10a: Marital status significantly moderates the relationship between heuristic bias and investment decisions of individual investors.

H10b: Marital status significantly moderates the relationship between prospect bias and investment decisions of individual investors

H10c: Marital Status significantly moderates the relationship between herding bias and investment decisions of individual investors

H10d: Marital Status significantly moderates the relationship between market forces bias and investment decisions of individual investors

H11: Age significantly moderates the relationship between the behavioural biases and investment decisions of individual investors

H11a: Age significantly moderates the relationship between heuristic bias and investment decisions of individual investors.

H11b: Age significantly moderates the relationship between prospect bias and investment decisions of individual investors.

H11c: Age significantly moderates the relationship between herding bias and investment decisions of individual investors.

H11d: Age significantly moderates the relationship between market forces bias and investment decisions of individual investors.

H12: Education significantly moderates the relationship between the behavioural biases and investment decisions of individual investors

H12a: Education level significantly moderates the relationship between heuristic bias and investment decisions of individual investors.

H12b: Education level significantly moderates the relationship between prospect bias and investment decisions of individual investors.

H12c: Education level significantly moderates the relationship between herding bias and investment decisions of individual investors.

H12d: Education level significantly moderates the relationship between market forces bias and investment decisions of individual investors.

H13: Occupation significantly moderates the relationship between the behavioural biases and investment decisions of individual investors

H13a: Occupation significantly moderates the relationship between the heuristics bias and investment decisions of individual investors

H13b: Occupation significantly moderates the relationship between the prospect bias and investment decisions of individual investors

H13c: Occupation significantly moderates the relationship between the herding bias and investment decisions of individual investors

H13d: Occupation significantly moderates the relationship between the market forces bias and investment decisions of individual investors

H14: Income significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors

H14a: Income significantly moderates the relationship between the heuristic bias and investment decisions of individual investors

H14b: Income significantly moderates the relationship between the prospect bias and investment decisions of individual investors

H14c: Income significantly moderates the relationship between the herding bias and investment decisions of individual investors.

H14d: Income significantly moderates the relationship between the market forces bias and investment decisions of individual investors.

H15: Investment experience significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors

H15a: Investment experience significantly moderates the relationship between the heuristic bias and investment decisions of individual investors.

H15b: Investment experience significantly moderates the relationship between the prospect bias and investment decisions of individual investors.

H15c: Investment experience significantly moderates the relationship between the herding bias and investment decisions of individual investors.

H15d: Investment experience significantly moderates the relationship between the market forces bias and investment decisions of individual investors.

2.7 Summary

A comprehensive review of the relevant literature on behavioural finance, emphasising the various behavioural biases investors exhibit and their impact on investment decisions, is provided in this chapter. The literature review highlighted variations and differing perspectives in existing research. These insights guided the research objectives, the conceptual model's development, and the framing of relevant hypotheses. The subsequent chapter delves into the design, sample, and data analysis approach adopted to evaluate the impact of financial literacy on the behavioural biases of individual investors' investment decisions.

CHAPTER 3
RESEARCH METHODOLOGY

The research methodology establishes a structured approach and an operational framework for conducting the study. Research methodology provides a comprehensive approach to research practice. Kothari (2004) asserts that research methodology extends beyond research methods to ensure a valid and reliable research outcome.

The previous chapters have explored the theoretical foundations and contributed to understanding investor decision-making behaviour. This chapter focuses on the research methodology adopted to achieve the study's objective and begins with the specific research design implemented in this study.

Additionally, this chapter details the study's target population, selected sample size, sampling elements, and techniques used. The remaining sections discuss the data collection process, research instrument development, pilot study, measurement of research constructs, and adherence to ethical guidelines.

3.1 Research Design for the Present Study

A research design is a comprehensive blueprint outlining the methods and procedures for data collection and analysis. According to Zikmund et al. (2014), "A research design is a master plan that specifies the methods and procedures for collecting and analysing the needed information". Similarly, Kothari (2004) describes research design as "an arrangement of conditions for collecting and analysing data in a manner that aims to combine relevance to the research purpose with economy in procedure".

The research design for this study establishes the conceptual framework guiding the overall research process. Based on an extensive literature review, key research gaps were identified, leading to the formulation of research objectives. A conceptual model was then developed, followed by formulating research hypotheses.

A structured questionnaire was designed to collect empirical data, drawing insights from existing literature. Data was collected using an online survey method, ensuring a comprehensive and diverse sample representation.

Table 3.1: Summary of the Research Design

Research Philosophy	Objectivist and Critical Realism
Research Paradigm	Positivist
Research Approach	Deductive
Research Type	Descriptive
Research Method	Quantitative
Research Strategy	Survey
Type of Survey	Sample Survey
Research Design	Cross Sectional
Sampling Frame	Individual investors based on Maharashtra, Goa and Karnataka
Sampling Unit	Individual investors
Sampling Technique	Convenience and snowball sampling
Data Collection Tool	Questionnaire
Source of Data	Primary
Statistical Techniques	CFA, SEM

Compiled by the Researcher

3.1.1 Population

The population or universe refers to the complete set of units or entities that share a common set of characteristics, forming the basis from which samples are drawn for generalising study findings. Identifying the study population is a fundamental step in the research process. Bell and Bryman. (2007) defines population as "the universe of units from which the sample is to be selected." The population is "the entire set of objects or group of people that is the focus of research and about which the researcher seeks to determine specific characteristics" (Rwegoshora, 2016).

For this study, the population comprises retail individual investors residing in Maharashtra, Goa and Karnataka who have invested in the securities market. The focus is exclusively on individual or retail investors because they are more susceptible to behavioural biases, often lacking awareness of the psychological factors influencing their investment decisions.

Once the population is identified, the next step involves defining the sampling frame, which consists of a comprehensive list of all units within the population from which the sample is drawn (Sekaran, 2016; Zikmund et al., 2014). However, the study could not establish a formal sampling frame due to the absence of an official database of retail investors in the selected geographical regions. This limitation influenced the choice of sampling techniques and sample size determination, which are discussed in the subsequent sections.

3.1.2 Sampling Design

A sampling design is a structured approach to selecting an appropriate sample from the defined population. It outlines the strategies and processes for ensuring the sample accurately represents the population, covering aspects such as the sampling frame, sampling unit, sample size, sampling techniques, and estimation methods.

Although testing the entire population would yield the most accurate results, time, cost, and resource constraints make it impractical. As a result, a subset of the population is selected to represent the overall group.

The sample was selected for this study to ensure a broad representation of the target population, allowing for reliable analysis and meaningful findings.

3.1.3 Sampling Element

This study examines the influence of various behavioural biases on individual investors' investment decisions in Maharashtra, Goa, and Karnataka. Consequently, the sampling elements consist of active individual equity investors who reside in different cities across these states and independently make buy or sell decisions based on their judgment rather than for the benefit of any organisation. Specifically, the study targets a diverse group of active individual equity investors, varying in gender, age above 18 years, geographical location, educational background, investment experience, income levels, and professional occupations.

3.1.4 Sampling Technique

The choice of sampling strategy significantly impacts the research quality and the reliability of its findings. Given the absence of a publicly available individual equity investors database, this study employs a non-probabilistic sampling approach. However, non-probability sampling methods have inherent limitations in terms of generalising findings to the entire population (Vehovar et al., 2016; Buelens et al., 2018). The nature of this research necessitated the use of such an approach. The convenience and snowball sampling techniques have been utilised within the non-probabilistic framework.

According to Vogt et al. (2012), snowball sampling involves an initial respondent providing the name of another potential participant, who then refers additional respondents, forming a chain. This technique, also known as chain sampling, is justified in cases where a comprehensive sampling frame is unavailable and the initial sample is drawn from diverse sources (Frank & Snijders, 1994). Meanwhile, convenience sampling involves selecting respondents who are easily accessible to the researcher, making it a widely used method for obtaining first-hand data due to its simplicity, speed, and cost-effectiveness.

Initially, convenience sampling was used to identify brokerage firms, depository participant branches, and bank desks dealing with capital market products to compile a list of active retail investors. Once an initial group of respondents was identified from various sources, the snowball sampling technique was applied, wherein the initial participants were requested to refer other investors with similar profiles. These referred individuals were then contacted and invited to participate in the survey.

3.1.5 Sample Size

An appropriate sample size is crucial for drawing meaningful inferences about the target population. Henry (1990) emphasises that selecting an accurate sample size is fundamental to obtaining reliable results. Hair et al. (2014) further argue that an insufficient sample size may lead to convergence failure, suboptimal outputs, and inaccurate parameter estimates.

The adequacy of a sample size depends on multiple factors, including its representativeness, the statistical techniques used, as different methods require varying minimum sample thresholds, benchmarks from similar studies, and constraints related to time and resources (Saunders, 2012).

Given the absence of a structured sampling frame, the sample size for this study was determined using widely accepted rules of thumb aligned with the chosen data analysis techniques. The study employs Structural Equation Modelling (SEM). Hair et al (2012) recommend having at least 10–15 respondents per variable and corresponding items. Bentler and Chou (1987) suggest that five cases per construct are sufficient if the data is normalised and free of missing or outlying cases. Hair et al. (2010) advise that a minimum of 100 respondents is necessary for statistical analysis in quantitative research.

Kyriazos (2018) categorises sample sizes as follows: 50 (very poor), 100 (poor), 200 (fair), 300 (good), 500 (very good), and 1,000 (excellent). Reinartz et al. (2009) advocate for a sample size of at least 200 when using SEM.

Following the variable-to-case ratio Bentler et al. (1987) recommended, this study analyses 10 constructs comprising 66 items. Based on the formula, $66 \times 10 = 660$, the minimum required sample size is 660 respondents. However, the sample size for this study is 685, which meets and exceeds the suggested benchmarks, ensuring adequacy for analysis.

3.1.6 Time Frame and Geographical Scope

The study focused on individual retail equity investors residing in Maharashtra, Goa, and Karnataka. The research was conducted from May 2019 to April 2025. To ensure the reliability and validity of the survey tool, a pilot study was conducted from January to September 2023. After organising and validating the data, the primary research phase began in January 2024 and was completed by October 2024.

3.2 Data Collection

Data collection involves a structured approach to locating information sources and obtaining relevant details to explore the research topic thoroughly. Choosing an appropriate method for data collection plays a pivotal role in shaping the overall research design (Sekaran, 2016; Zikmund et al., 2014). As Saunders (2012) emphasises, the method chosen should be consistent with the research goals and questions.

This study incorporates both primary and secondary data collection methods. Primary data refers to original information gathered directly by the researcher to explore specific research questions (Collis & Hussey, 2014). The study places significant emphasis on primary data, as it draws extensively from survey responses collected from participants.

Secondary data provides supplementary material to gain a broader perspective and understanding of the research problem. The researcher referred to various sources, including books on behavioural finance, research papers, articles published in national and international journals, theses, both published and unpublished, and online sources. Additionally, online resources such as Google Scholar, ResearchGate, SpringerLink, ScienceDirect, JSTOR, Wiley Online Library, Taylor & Francis Online, SSRN, and Emerald Insight were utilised to access relevant literature and academic publications.

3.2.1 Data Collection Procedure

An online survey technique was employed to collect data for this study. During the preliminary phase, the researcher personally visited several licensed brokerage firms, branches of depository participants, and banks that provide capital market services across different locations in Goa.

The researcher sought permission from brokerage firms to access their investor databases for survey participation. However, this approach was unsuccessful due to privacy concerns and the requirement for formal approval from corporate headquarters. Nonetheless, some brokerage firm heads agreed to informally approach their clients to request their participation in the survey.

An online survey was conducted to enhance the response rate and reach a broader audience more conveniently and cost-effectively. Several factors motivated the researcher to adopt an online data collection approach. Firstly, it was observed that new-generation investors rarely visit brokerage offices, preferring online trading over in-person transactions. Secondly, post-COVID-19 pandemic, in-person interactions were significantly limited, making physical data collection challenging.

As a result, an online survey was conducted using Google Forms, generating a link that was shared across multiple social media platforms, such as Gmail, WhatsApp, and Instagram. These survey links were also distributed to identified stockbrokers, who were requested to forward them to investors at random. A higher response rate was anticipated given the strong relationship between brokers/bankers and investors. Additionally, the researcher compiled a list of online contacts and invited them to participate in the survey. Participants were encouraged to share the survey link within their networks. Follow-up emails and online reminders were sent to boost the response rate further.

Although online surveys offer convenient data collection, they have well-documented limitations. Deutskens et al. (2004) note that response rates for electronic surveys tend to be low due to people's busy schedules and concerns regarding data privacy. Kaplowitz et al. (2012) argue that the lack of direct interaction between the researcher and respondents can lead to data collection challenges. Furthermore, online surveys restrict the sample to individuals with internet access and basic digital literacy, excluding certain investor groups.

3.2.2 Research Instrument

A research instrument is a structured tool to collect primary data from selected respondents. A well-structured instrument minimises errors and facilitates accurate participant responses (Sreejesh at al., 2014). A structured questionnaire was chosen as the primary research instrument to capture investor behaviour and achieve the research objectives. The questionnaire is included in Appendix C of this study.

Dillman (2011) emphasises that a well-designed questionnaire, combined with an appropriate data collection method, enhances response rates. The study adopted a self-administered approach, wherein respondents completed the questionnaire independently, without researcher assistance. This approach was deemed appropriate as the survey statements were clearly defined, reducing the potential for interviewer bias (Bell & Bryman, 2007).

Questionnaires are widely used in quantitative research due to their efficiency and reliability. They allow for standardised data collection, making analysis straightforward. Moreover, questionnaires are cost-effective and time-efficient compared to other data collection techniques (Bell & Bryman, 2007). Respondents also feel more comfortable answering surveys independently, as they can respond at their convenience without external pressure (Kriauciunas et al., 2011).

3.2.3 Questionnaire Design and Layout

A questionnaire's overall design and presentation significantly influence response rates. This study ensured that the questionnaire's content, structure, and layout were relevant, explicit, and concise to maximise response rates. Edwards et al. (2002) suggest that excessively long or short questionnaires can deter participation. Research indicates that questionnaires spanning three to four pages tend to achieve higher response rates than those that are either too brief or excessively lengthy (Adams & Gale, 1982). The questionnaire was designed with a compact structure to maintain brevity while covering essential topics, focusing only on critical research items.

The questionnaire consists of four sections, each addressing a specific aspect of the study:

- Section A: Collects respondents' demographic information, including gender, age, education, income, occupation, and investment experience.
- Section B: Assesses three components of financial literacy namely financial knowledge, financial behaviour, and financial attitude.
- Section C: Examines psychological biases affecting investment decisions through statements designed to capture various behavioural biases. The statements were carefully phrased to prevent respondents from easily identifying the biases being assessed.
- Section D: Uses statements that assess investment decision-making of individual investors in the stock market.

A five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was employed to measure responses. Likert scales are widely used for assessing attitudes, beliefs, and opinions (Rogelberg et al., 2001). Finally, the cover letter also assured respondents of data confidentiality, emphasising that the information provided would be used solely for academic purposes while adhering to ethical research standards.

3.2.4 Pilot Study

The questionnaire used in this research was assessed for both face and content validity. Prior to the primary survey, an essential pre-test was done, using a questionnaire on a small sample to help identify any potential issues in the study design. As recommended by Lancaster et al. (2004), a pilot survey should include at least 30 participants. The primary objective of the pilot testing was to refine the questionnaire by evaluating its practicality, identifying any design or instrumentation flaws, and making necessary adjustments. This process enables the researcher to establish a structured framework and ensures that the data collected effectively addresses the research questions, thereby enhancing the overall quality of the study.

Additionally, the pilot survey aids in evaluating the validity of the questionnaire and the reliability of the collected data. Validity refers to the extent to which an instrument accurately measures what it is intended to measure. The primary goal of assessing questionnaire validity is to confirm whether the instrument is appropriate regarding content, structure, and expected outcomes.

Face validity ensures respondents find the questionnaire clear, unambiguous, reasonable, and easy to understand. This is the most straightforward validation technique, primarily focused on determining whether the instrument is suitable for the study. Content validity, on the other hand, ensures that the survey instrument comprehensively covers all aspects of the construct being measured. According to Saunders (2012), content validity examines whether the research instrument adequately covers the research questions.

The questionnaire was pre-tested on a small sample of 72 investors to confirm face validity. The draft questionnaire was shared with academicians, experts in behavioural finance, brokers, financial advisors, and senior doctoral candidates for their feedback and recommendations. The expert panel was asked to review the questionnaire’s content, wording, sequence, and length. All items were carefully examined throughout the pre-testing phase to enhance their content validity and ensure respondents could easily comprehend the questionnaire.

Several modifications were made based on the feedback, including reducing the questionnaire length and removing sections that sought sensitive personal information such as name, email ID, phone number, and location. The final version of the questionnaire was approved only after incorporating all recommendations and refinements suggested by subject matter experts, sample investors, and academicians specialising in behavioural finance.

3.2.5 Reliability of the Instrument

Following the validation process, the instrument's reliability was tested using Cronbach's Alpha (Cronbach, 1951), a widely used measure for assessing internal consistency. For an instrument to be considered reliable, Cronbach's Alpha coefficient for all constructs should exceed the recommended threshold of 0.70 (Hair et al., 2010; Ten Berge, 1995).

Chapter 4 presents the Cronbach's Alpha values for all the constructs used in the study. As indicated in the table, all constructs achieved a Cronbach's Alpha value above the 0.70 threshold, demonstrating a satisfactory and acceptable level of internal consistency.

3.2.6 Measurement of Constructs

This section provides a detailed overview of the survey instrument, outlining the variables and metrics used in the study. All study variables and scale items were adapted from various sources following an extensive review of the relevant literature. The key studies referenced in developing the research instrument include those examining various behavioural biases influencing investment decisions. The collected responses allowed quantification of biases and investment decision-making patterns, establishing a measurable link between biases as the independent variables and investment decisions as the dependent variable, with heuristic bias and prospect bias being the second-order constructs. The questionnaire mapped specific responses to different biases, providing insights into how these biases influence investment decisions. The key studies referenced in developing the research instrument include those examining various behavioural biases influencing investment decisions. Overconfidence bias was sourced from Jain et al. (2021) and Kengatharan and Navaneethakrishnan (2014). Representativeness bias was derived from Baker et al. (2017) and Boussaidi (2013). Items for Anchoring bias include Jahanmiri et al. (2018) and Zaiane (2015), while availability bias was adapted from Elhussein and Abdelgadir (2020) and Isidore (2019). Gambler's fallacy bias was examined in studies by Waweru et al. (2008). Regret aversion bias was referenced from Gazel (2015), and Mental accounting bias was sourced from Iram et al. (2021) and Shefrin & Statman (2000). Herding bias was drawn from Prosad et al. (2015), Bikhchandani and Sharma (2000). Market forces bias was included based on Jain et al. (2021), investment decision was referenced from Jain et al. (2021) and Mintzberg et al. (1974). The study ensures the reliability and validity of the instrument by drawing upon well-established scales from previous empirical research.

Chapter 4 presents a detailed table illustrating the operationalisation of the survey items, listing each item along with its respective source. While the scale items were adapted from prior research, slight modifications were made to the format and wording to better align with the study's objectives and requirements.

3.2.7 Response Distribution

Of the 729 investors who received the Google Forms survey, 685 submitted completed responses. However, 44 responses were excluded. As a result, the study's final dataset consisted of 685 valid responses.

3.2.8 Data Coding and Processing

Data coding and processing are critical steps in research to ensure a structured and meaningful analysis of respondents' perspectives. This process includes data verification, editing, coding, and transcription, transforming raw responses into a format suitable for statistical evaluation.

Since Google Forms automatically records responses in a structured format, the data collection was more streamlined than physical surveys. Responses were automatically stored in Google Sheets, eliminating the need for manual data entry. The dataset was exported in Excel (.xlsx) format to facilitate statistical analysis and transferred to IBM SPSS 21.0 for further study.

Pre-coding was applied to all structured questions, multiple-choice and Likert scale items, ensuring responses were numerically coded for easy processing. Special attention was given to categorising data into appropriate nominal, ordinal, ratio, and interval measurement scales, ensuring compatibility with statistical techniques.

3.2.9 Statistical Techniques

The study employed statistical tools and techniques to derive meaningful insights and draw valid conclusions. The selection of statistical methods was guided by the study's objectives, the nature of the data, the scales used, and the research design. Confirmatory Factor Analysis (CFA) was then utilised to assess the reliability and validity of these constructs.

Cronbach's alpha and Composite Reliability were calculated to evaluate internal consistency and reliability. Convergent validity was assessed using factor loadings (standardised estimates) and Average Variance Extracted (AVE), while discriminant validity was established by comparing the square root of the AVEs with their respective inter-construct correlations.

Data normality was examined using Skewness and Kurtosis measures, while Multicollinearity was assessed through the Variance Inflation Factor (VIF) and Pearson Correlation Matrix. Descriptive statistics, such as mean values, were used to identify prominent behavioural biases among retail investors.

For hypothesis testing and measuring the impact of behavioural biases on investment decision-making, Structural Equation Modelling (SEM) was employed. In the PLS-SEM framework, model evaluation was conducted using key indicators that assess predictive relevance and explanatory power rather than traditional model fit indices. The Q^2 test was employed to determine the model's out-of-sample predictive relevance, ensuring its robustness. Additionally, the R^2 value was examined to assess the explained variance of the dependent variable.

3.2.10 Software Used

The statistical analysis was conducted using IBM SPSS Statistics Version 21.0 and SMART PLS-SEM 4. SMART PLS-SEM 4, a specialised software for Partial Least Squares Structural Equation Modelling (PLS-SEM), was employed for model estimation. It enables researchers to analyse complex relationships between latent variables, making it particularly useful for exploratory research and theory development. The software offers advanced features such as bootstrapping for significance testing and blindfolding for predictive relevance (Q^2).

3.3 Ethical Considerations

Ethical considerations are crucial in research, especially when investigating human behaviour. The study adhered to ethical principles such as honesty, integrity, impartiality, privacy, anonymity, confidentiality, informed consent, openness, and transparency. To ensure informed consent, the research questionnaire was accompanied by a cover letter outlining the study's purpose and emphasising voluntary participation. Participants were also informed of their right to withdraw from the study at any stage.

To maintain openness, honesty, and accuracy, the researcher acknowledged previous scholarly contributions, transparently documented research procedures, and made findings accessible while ensuring that claims were justified by empirical evidence.

The collected data was solely used for research purposes and accurately reflected participants' responses. Confidentiality and privacy were strictly maintained throughout the study. The questionnaire did not request sensitive personal details such as names, locations, or mobile numbers, ensuring that respondents' identities remained anonymous.

3.4 Summary

This chapter provided a comprehensive overview of the research design and methodology adopted to meet the study's objectives. It justified the choice of research approach, philosophy, and strategy while detailing the sampling design, questionnaire development, measurement of constructs, and data collection procedures.

Additionally, the chapter elaborated on the statistical techniques employed, the software used for analysis, and the ethical considerations adhered to throughout the research. The following chapters present the data analysis and interpretation, aligning the findings with the study's objectives and hypotheses.

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION - INFLUENCE OF BEHAVIOURAL BIASES ON INVESTMENT DECISIONS

This chapter presents a comprehensive analysis aligned with the first research objective, which examines the presence, impact, and relevance of behavioural biases and their influence on investment decisions. The study is structured into four key sections, employing descriptive and inferential statistical techniques to derive meaningful insights.

The chapter begins with data screening and cleaning procedures to check the accuracy and reliability of the dataset. Various statistical tests are conducted to assess normality, multicollinearity, and Common Method Variance (CMV), ensuring the robustness of the subsequent analysis. Additionally, the demographic profile of the respondents is presented to offer insights into the characteristics of individual investors who participated in the study.

Following this, the first section investigates the presence of behavioural biases among individual investors using descriptive statistics, specifically mean values. This allows for assessing how much each bias influences investment behaviour, offering an initial understanding of their prevalence within the sample.

The second section examines the impact of behavioural biases on investment decisions using Partial Least Squares Structural Equation Modelling (PLS-SEM). This technique enables the evaluation of the strength and significance of relationships between biases and investment decisions, providing empirical validation for the hypothesised effects. The analysis includes Confirmatory Factor Analysis (CFA) to validate the measurement model, assessing internal consistency reliability, convergent validity, and discriminant validity. The structural model is then evaluated through collinearity diagnostics, path coefficients, the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2).

The third section expands the analysis through the Importance-Performance Map Analysis (IPMA), which offers more profound insights into the relative importance of each bias in shaping investment decisions while simultaneously evaluating their performance. This approach helps identify biases that exert a strong influence on investment behaviour but may be underperforming in terms of effectiveness, thereby aiding in prioritisation.

Finally, the chapter employs Necessary Condition Analysis (NCA) to determine whether certain biases are prerequisites for investment decisions. Unlike conventional impact assessments, NCA helps identify biases essential for effective decision-making, providing a complete understanding of their role.

This chapter provides a structured and empirical examination of behavioural biases in investment decisions through these analytical techniques, contributing to the broader understanding of investor behaviour.

4.1 Data Cleaning and Pre-Analysis Checks

Data cleaning ensures the quality and reliability of responses collected through Google Forms. The dataset contained no missing values since all survey questions were considered compulsory. The data were further examined for duplicate entries, unengaged responses and patterned answering behaviour. Additionally, the dataset was screened for potential outliers that could compromise the validity and reliability of the statistical analysis results.

4.2 Data Distribution

Normality is a key consideration in multivariate analysis as it influences data distribution, ideally forming a bell-shaped curve. Although PLS-SEM does not require strict normality assumptions, assessing skewness and kurtosis provides insights into data distribution, which can impact bootstrapping and model estimation.

Skewness measures the asymmetry of the data distribution, while kurtosis evaluates its peakness or flatness. Addressing skewness helps in managing potential outliers, which, as previously stated, were removed based on strong theoretical justifications. Therefore, this study primarily focuses on kurtosis to assess data normality.

In a perfectly normal distribution**,** both skewness and kurtosis values are zero. However, for psychometric properties, values within the range of -2 to +2 are considered acceptable (Field, 2009; Hair et al., 2014). The results confirm that all variables in this study fall within the acceptable kurtosis threshold**,** ensuring the suitability of the data for further analysis. Table 4.1 presents the skewness and kurtosis values for normality assessment**.**

Table 4.1: Test of Normality based on Kurtosis and Skewness

CONSTRUCT	Mean	Standard Deviation	Kurtosis	Skewness
Financial Knowledge	3.705	0.559	-0.214	-0.592
Financial Behaviour	4.098	0.993	0.858	-1.205
Financial Attitude	3.383	1.273	-0.446	-0.732
Overconfidence Bias	3.383	1.273	-0.959	-0.343
Representative bias	3.391	1.166	-0.759	-0.284
Anchoring Bias	3.433	1.225	-0.803	-0.378
Availability Bias	3.410	1.233	-0.895	-0.330
Gambler's Fallacy	3.481	1.202	-0.705	-0.437
Regret aversion Bias	3.408	1.217	-0.763	-0.355
Loss Aversion Bias	3.473	1.211	-0.852	-0.387
Mental Accounting Bias	3.400	1.176	-0.787	-0.355
Herding Bias	3.379	1.317	-1.082	-0.335
Market forces Bias	3.468	1.207	-0.880	-0.346
Investment Decisions	3.477	1.291	-0.933	-0.449

Source: Primary Data

4.2.1 Common Method Variance (CMV)

Given that data were collected through self-reported responses, Harman's Single-Factor Test and Full Collinearity Assessment were conducted to detect potential CMV issues. The results confirmed that CMV was not a significant concern.

Table 4.2: Harman's Single-Factor Test

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.347	17.561	17.561	13.347	17.561	17.561
2	8.053	10.597	28.158			
3	3.682	4.845	33.003			
4	3.109	4.091	37.094			
5	2.930	3.855	40.948			
6	2.648	3.484	44.433			
7	2.352	3.095	47.528			
8	2.112	2.779	50.307			
9	2.095	2.757	53.064			
10	1.939	2.552	55.616			
11	1.746	2.298	57.914			
12	1.530	2.013	59.927			
13	1.446	1.903	61.829			
14	1.338	1.761	63.590			
15	1.268	1.668	65.258			
16	1.135	1.493	66.752			
17	1.063	1.399	68.151			
18	1.004	1.321	69.472			
19	.949	1.248	70.720			
20	.884	1.164	71.884			

Source: Primary Data

Harman's Single-Factor Test was conducted by performing an exploratory factor analysis with a constrained one-factor solution. The results indicated that the single-factor solution accounted for 17.561% of the variance, as presented in Table 4.2.

4.3 Demographic Profile of Respondents

Data collection was conducted using a structured questionnaire. A total of 729 individual investors from Maharashtra, Goa and Karnataka who had invested in the stock market were contacted through online channels. Of the 729 investors who received the Google Forms survey, 685 submitted completed responses. However, 44 responses were excluded.

Table 4.3: Demographic Profile of Respondents

PROFILE	GROUP	FREQUENCY	PERCENTAGE
Gender	Male	300	43.8
	Female	**385**	56.2
	Total	**685**	100
Age	18-30 years	179	26.2
	31-45 years	**270**	39.4
	46-60 years	135	19.7
	61 years and above	101	14.7
	Total	**685**	100
Marital Status	Married	300	43.8
	Single	**385**	56.2
	Total	**685**	100
Education	Graduate	**364**	53.2
	Post Graduate	214	31.2
	Professional	107	15.6
	Total	**685**	100
Occupation	Private Sector	**244**	35.6
	Government Sector	223	32.6
	Business/Self Employed	218	31.8
	Total	**685**	100
Monthly Income	Less than Rs 50,000	**395**	57.7
	Rs 50,000 and above	290	42.3
	Total	**685**	100
Investment Experience	Less than 3 year	300	43.8
	3-5 years	**385**	56.2
	Total	**685**	100

Source: Primary Data

Table 4.3 presents a summary of the respondents' demographic characteristics. While traditionally, financial investment decisions in India have been dominated by male household members, recent trends indicate a growing participation of women in financial decision-making. This shift can be attributed to increasing financial literacy, economic empowerment, and greater access to investment opportunities. Additionally, this study's higher female response rate may be due to the outreach methods used or a greater willingness among female investors to participate in financial research.

According to a study by the State Bank of India (2024), one in every four new investors in the Indian stock market is a woman, highlighting a shift in investment behaviour. Similarly, a report by the National Stock Exchange (2024) states that 22% of Indian stock market investors are now women, reflecting a gradual but significant rise in female participation. Additionally, a survey conducted by Axis Mutual Fund (2024) found that 72% of women make the final decisions regarding their investments, suggesting that financial awareness and independence among women are increasing. These trends challenge the long-standing perception that men are the primary decision-makers in financial assets and justify the higher proportion of female respondents in this study.

The study categorised respondents into age groups: 18-30 years, 31-45 years, 46-60 years, and above 60 years. The results revealed that 39.4% (n=270) of respondents were between 31 and 45 years old, followed by 26.1% (n=179) in the 18-30 age group. The 46-60 age group comprised 19.7% (n=135), while 14.7% (n=101) were above 60 years. Regarding educational qualifications, the majority of respondents were graduates (53.1%, n=364), followed by postgraduates with 31.2% (n=214), while a smaller proportion (15.6%, n=104) held professional degrees. The monthly income levels of respondents were broadly divided into two categories: below 50k per month, with 57.7% (n=395), and above, with 42.3% (n=290). When analysing investment experience, the largest group of respondents had 3-5 years of experience (56.2%, n=385), followed by those with less than 3 years of experience (43.8%, n=300).

4.3.1 Presence of Behavioural Biases

Table 4.4 presents the ranking of behavioural biases based on their presence among individual investors. The results indicate that all ten biases examined have mean scores greater than 3, suggesting that respondents exhibit various behavioural biases in their investment decision-making. These findings align with previous studies (Sahi et al., 2013; Prosad et al., 2015). Among the identified biases, gambler's fallacy, market forces bias and anchoring bias stand out with the highest mean scores of 3.481, 3.468, and 3.433, respectively.

Table 4.4: Ranking of Biases in the order of presence

Bias	Mean	Rank
Overconfidence Bias	3.383	7
Representativeness Bias	3.391	6
Anchoring Bias	3.433	3
Availability Bias	3.411	5
Gambler's Fallacy Bias	3.481	1
Regret Aversion Bias	3.421	4
Loss Aversion Bias	3.406	8
Mental Accounting Bias	3.400	9
Herding Bias	3.379	10
Market Forces Bias	3.468	2

Source: Primary Data

4.4 Partial Least Squares-Structural Equation Modelling (PLS-SEM Analysis)

In this study, all the constructs are reflective and measured using multiple indicators. The evaluation of the measurement model includes checking for internal consistency, reliability, and discriminant validity. Convergent validity is assessed through Composite reliability and Average Variance Extracted (AVE). The analysis of the outer model (measurement model) ensures the robustness and accuracy of how the constructs are measured.

Since evaluating the measurement model is a prerequisite before analysing the structural model, this step was performed using the Partial Least Squares-Structural Equation Modelling (PLS-SEM) approach. The process focused on confirming that the constructs used were both reliable and valid.

4.4.1 Model Measurement

The researcher developed a comprehensive questionnaire designed to gather responses on 12 key variables: broadly heuristic bias, prospect bias, herding bias, market forces bias, financial literacy, and investment decisions. To enhance the analytical framework, two higher-order constructs were delineated: Heuristic Bias, encompassing overconfidence bias, representativeness bias, anchoring bias, availability bias, and the gambler's fallacy, and

Prospect Bias, which includes loss aversion, regret aversion, and mental accounting bias. The questionnaire comprised 40 observed items, capturing the complexity of these biases and their influence on decision-making.

Following the data collection phase, thorough data screening was conducted to cleanse and prepare the dataset for subsequent analysis. Confirmatory Factor Analysis (CFA) assessed the model's fit, ensuring it adhered to convergent and discriminant validity criteria. This analysis effectively illuminated the intricate relationships among the higher-order and lower-order constructs, providing a robust foundation for understanding the interplay of behavioural biases and financial literacy in investment decisions.

The data were analysed using the variance-based method, Partial Least Squares (PLS), with SmartPLS 4.0 software, following the two-stage analytical approach recommended by Anderson and Gerbing (1988). The measurement model was evaluated to check the convergent and discriminant validity. The structural model was tested in the second stage to evaluate the hypotheses. A bootstrapping procedure (5000 resamples) was employed to assess the significance of outer loadings and path coefficients, as suggested by Sarstedt et al. (2016).

Table 4.5: Cronbach's Alpha, Composite Reliability and Average Variance Extracted

DIMENSIONS AND INDICATORS	OUTER LOADING	CRONBACH ALPHA	COMPOSITE RELIABILITY (CR)	AVERAGE VARIANCE EXTRACTED (AVE)
OVERCONFIDENCE BIAS				
OCB1	0.83			
OCB2	0.807			
OCB3	0.822			
OCB4	0.84	0.895	0.895	0.68
REPRESENTATIVENESS BIAS				
RB1	0.811			
RB2	0.707			
RB3	0.709			
RB4	0.723			
RB5	0.763	0.86	0.861	0.553

ANCHORING BIAS				
AB1	0.8			
AB2	0.823			
AB3	0.744			
AB4	0.713	0.854	0.854	0.595
AVAILABILITY BIAS				
AvB1	0.872			
AvB2	0.83			
AvB3	0.756			
AvB4	0.853			
AvB5	0.756			
AvB6	0.785	0.919	0.919	0.656
GAMBLER'S FALALCY BIAS				
GFB1	0.83			
GFB2	0.79			
GFB3	0.825	0.855	0.856	0.664
REGRET AVERSION BIAS				
RaB1	0.779			
RaB2	0.81			
RaB3	0.718	0.812	0.813	0.593
LOSS AVERSION BIAS				
LaB1	0.763			
LaB2	0.81			
LaB3	0.744	0.816	0.817	0.598
MENTAL ACCOUNTING BIAS				
MaB1	0.81			
MaB2	0.737			
MaB3	0.848	0.841	0.841	0.639
HERDING BIAS				
HB1	0.813			
HB2	0.854			
HB3	0.755			
HB4	0.898	0.899	0.899	0.692
MARKET FORCES BIAS				
MFB1	0.836			
MFB2	0.906		0.89	0.672

MFB3	0.807			
MFB4	0.718	0.891		
INVESTMENT DECISIONS				
ID1	0.864			
ID2	0.793			
ID3	0.851			
ID4	0.753			
ID5	0.834			
ID6	0.796			
ID7	0.812	0.933	0.933	0.665

Source: Primary Data

4.4.2 Evaluation of the Measurement Model

The measurement model was evaluated to confirm the accuracy of the proposed relationships between indications and constructs. According to Hair et al. (2020), a measurement theory outlines how the observed variables systematically and logically reflect the theoretical concepts being studied.

4.4.2.1 Reliability Analysis

In this study, all constructs are reflective and measured using multiple items. This section presents the assessment of these reflective constructs for reliability (Wong, 2013; Sarstedt et al., 2016). The reliability analysis aimed to ensure consistency among the measured variables in representing their intended constructs. To evaluate reliability, composite reliability and Cronbach's alpha (α) were utilised. As shown in Table 4.5, Cronbach's alpha for all latent variables exceeded 0.7, and the composite reliability values were also greater than 0.7. These findings confirm the reliability of all constructs.

4.4.2.2 Construct Validity

Construct validity signifies the extent to which constructs and their respective measures align accurately. Construct validity ensures and addresses related measurement concerns, as its confirmation is essential for both theoretical development and empirical validation. Two key components of construct validity are convergent validity and discriminant validity (Sarstedt et al., 2016). Convergent validity measures the extent to which different indicators of the same construct correlate (Sarstedt et al., 2016). On the other hand, discriminant validity evaluates whether a construct is distinctly different from other constructs in the study (Sarstedt et al., 2016).

4.4.2.3 Convergent Validity

Convergent validity was assessed to determine whether the items within each construct exhibit a high degree of shared variance. It refers to the extent to which a measure of a construct aligns with other indicators of the same construct (Sarstedt et al., 2016). Convergent validity is established when the indicators of a reflective construct demonstrate significant agreement and share substantial variance (Sarstedt et al., 2016).

4.4.2.4 Average Variance Extracted (AVE)

Fornell and Larcker (1981) introduced Average Variance Extracted (AVE) as a key measure of convergent validity. AVE represents the mean of the squared standardised factor loadings for a construct's indicators. According to Sarstedt et al. (2016), AVE is calculated as the total of squared loadings divided by the number of indicators, reflecting the overall variance captured by a construct's measures. To confirm convergent validity, AVE should exceed 0.5 (Wong, 2013; Sarstedt et al., 2016). In this study, as shown in Table 4.6, the AVE values for all latent variables exceed the threshold of 0.5. Thus, convergent validity for the study's constructs is confirmed (Sarstedt et al., 2016).

4.4.3 Discriminant Validity

Discriminant validity refers to "the extent to which a measure is truly distinct and not merely a reflection of another variable". Establishing discriminant validity ensures that a construct is unique and captures phenomena not accounted for by other constructs within the model (Sarstedt et al., 2016). In this study, discriminant validity was assessed for the ten constructs to determine whether they are genuinely distinct from one another. Following Sarstedt et al. (2016), three approaches were utilised to evaluate discriminant validity:

1. Assessment of Cross-loadings
2. Fornell-Larcker Criterion
3. Heterotrait-Monotrait (HTMT) Ratio of Correlations

4.4.3.1 Cross-Loadings

Discriminant validity is considered established when an indicator's outer loading on its designated construct is higher than its cross-loadings on all other constructs within the model (Wong, 2013; Sarstedt et al., 2016). Table 4.6 presents the measurement model's outer loadings and cross-loadings for all indicators. As observed in the table, each indicator's loading on its respective construct consistently exceeds its cross-loadings on other constructs, thereby meeting the criteria for discriminant validity (Wong, 2013; Sarstedt et al., 2016).

Table 4.6: Cross Loadings

	AB	AvB	GFB	HB	ID	LaB	MaB	MFB	OCB	RB	RaB
AB1	0.800										
AB2	0.823										
AB3	0.744										
AB4	0.713										
AvB1		0.872									
AvB2		0.83									
AvB3		0.756									
AvB4		0.853									
AvB5		0.756									
AvB6		0.785									
GFB1			0.83								
GFB2			0.79								
GFB3			0.825								
HB1				0.813							
HB2				0.854							
HB3				0.755							

HB4				0.898							
ID1					0.864						
ID2					0.793						
ID3					0.851						
ID4					0.753						
ID5					0.834						
ID6					0.796						
ID7					0.812						
LaB1						0.763					
LaB2						0.81					
LaB3						0.744					
MFB1							0.836				
MFB2							0.906				
MFB3							0.807				
MFB4							0.718				
MaB1								0.81			
MaB2								0.737			
MaB3								0.848			
OCB1									0.83		
OCB2									0.807		
OCB3									0.822		
OCB4									0.84		
RB1										0.811	
RB2										0.707	
RB3										0.709	
RB4										0.723	

RB5										0.763	
RaB1											0.779
RaB2											0.81
RaB3											0.718

Note: AB-Anchoring Bias, AvB-Availability Bias, GFB-Gambler's Fallacy Bias, HB-Herding Bias, ID-Investment Decision, LaB-Loss Aversion Bias, MFB-Market Forces Bias, MaB-Mental accounting Bias, OCB-Overconfidence Bias, RB-Representativeness Bias, RaB- Regret Aversion Bias.

Source: Primary Data

4.4.3.2 Fornell-Larcker Criterion

The Fornell-Larcker criterion (Fornell & Larcker, 1981) states that the square root of the Average Variance Extracted (AVE) for each construct should be greater than its correlation with any other construct. This ensures that a construct shares more variance with its own indicators than with any other construct in the model (Sarstedt et al., 2016). Table 4.7 presents

CONSTRUCT	AB	AVB	GFB	HB	ID	LaB	MaB	MFB	OCB	RB	RaB
AB	0.771										
AVB	0.346	0.810									
GFB	0.299	0.335	0.815								
HB	0.177	0.197	0.162	0.832							
ID	0.306	0.387	0.325	0.407	0.816						
LaB	0.264	0.245	0.213	0.054	0.301	0.773					
MaB	0.326	0.269	0.257	0.276	0.380	0.341	0.800				
MFB	0.269	0.147	0.255	0.187	0.367	0.266	0.161	0.820			
OCB	0.478	0.300	0.452	0.225	0.320	0.202	0.300	0.214	0.825		
RB	0.402	0.419	0.431	0.316	0.400	0.154	0.376	0.217	0.418	0.744	
RaB	0.247	0.270	0.318	0.234	0.502	0.355	0.477	0.156	0.282	0.373	0.770

Note: AB-Anchoring Bias, AvB- Availability Bias, GFB-Gambler's Fallacy Bias, HB-Herding Bias,ID-Investment Decision, LaB-Loss Aversion Bias, MFB-Market Forces Bias, MaB-Mental accounting Bias, OCB-Overconfidence Bias, RB-Representativeness Bias, RaB- Regret Aversion Bias

Table 4.7: Fornell and Larcker Criterion

Source: Primary Data

the results of the Fornell-Larcker criterion analysis, where the diagonal values represent the square root of the AVE for each construct. The table indicates that for all constructs, the square root of the AVE is higher than their correlations with other constructs, confirming discriminant validity using this approach (Sarstedt et al., 2016).

The Fornell and Larcker (1981) test compares the correlation between constructs with the square root of AVE. To establish discriminant validity, the correlation values should be lower than the corresponding square root of AVE in the same row and column. This criterion ensures that a construct is more strongly related to its own indicators than to other constructs, thereby demonstrating its distinctiveness. The results presented in Table 4.7 confirm that all off-diagonal correlation values are lower than the square root of AVEs on the diagonal, further supporting discriminant validity.

4.4.3.3 Heterotrait-Monotrait Ratio (HTMT)

Henseler et al. (2015) introduced the Heterotrait-Monotrait Ratio (HTMT) as a method to assess discriminant validity by examining construct correlations. Derived from the Multi-Trait-Multimethod (MTMM) matrix proposed by Campbell and Fiske (1959). HTMT is calculated by comparing the average of heterotrait-hetero method correlations (i.e., correlations between indicators of different constructs) with the average of monotrait-hetero method correlations (i.e., correlations between indicators within the same construct).

Table 4.8 presents the HTMT correlations for all constructs, obtained using complete bootstrapping in PLS-SEM with 5000 sub-samples. The confidence interval method applied is the bias-corrected and accelerated (BCa) bootstrap at a significance level of 0.05, as Sarstedt et al. (2016) recommended. The results in Table 4.8 indicate that all HTMT values are below the threshold of 0.90, confirming the distinctiveness of the constructs (Henseler et al., 2015; Sarstedt et al., 2016).

In conclusion, the study employed three key approaches to assess discriminant validity: Cross-Loadings, Fornell-Larcker Criterion, and HTMT Ratio. Since all three methods meet the required thresholds, the discriminant validity of the constructs in the measurement model is confirmed.

Table 4.8: Heterotrait-Monotrait Ratio (HTMT)

	AB	GFB	HB	ID	LaB	MaB	MFB	OCB	RB	RaB
AB										
GFB	0.334									
HB	0.197	0.165								
ID	0.386	0.325	0.406							
LaB	0.247	0.214	0.071	0.301						
MaB	0.27	0.257	0.28	0.379	0.337					
MFB	0.145	0.254	0.19	0.365	0.265	0.16				
OCB	0.299	0.451	0.225	0.32	0.203	0.302	0.215			
RB	0.419	0.429	0.32	0.401	0.158	0.377	0.216	0.461		
RaB	0.268	0.316	0.234	0.503	0.355	0.476	0.156	0.282	0.374	

Note: AB-Anchoring Bias, AvB- Availability Bias, GFB-Gambler's Fallacy Bias, HB-Herding Bias,ID-Investment Decision, LaB-Loss Aversion Bias, MFB-Market Forces Bias, MaB-Mental accounting Bias,OCB-Overconfidence Bias, RB-Representativeness Bias, RaB- Regret Aversion Bias.

Source: Primary Data

4.4.4 Evaluation of the Structural Model

The Partial Least Squares-Structural Equation Modelling (PLS-SEM) analysis consists of two primary components: the measurement model and the structural model. The following section presents the evaluation of the structural model.

4.4.4.1 Structural Model

Once the reliability and validity of the measurement model (outer model) are established, the next step is to evaluate the hypothesised relationships within the structural model (inner model). This stage assesses the model's ability to predict relationships between endogenous and exogenous constructs. The assessment follows key criteria, including the significance of the path coefficients (β), coefficient of determination (R^2), predictive relevance (Q^2), and effect size. To test the significance of the path estimates, a bootstrap analysis with 5000 sub-samples was conducted. The findings from these analyses serve to validate the research hypotheses. Figure 4.1 illustrates the structural model analysis using PLS-SEM.

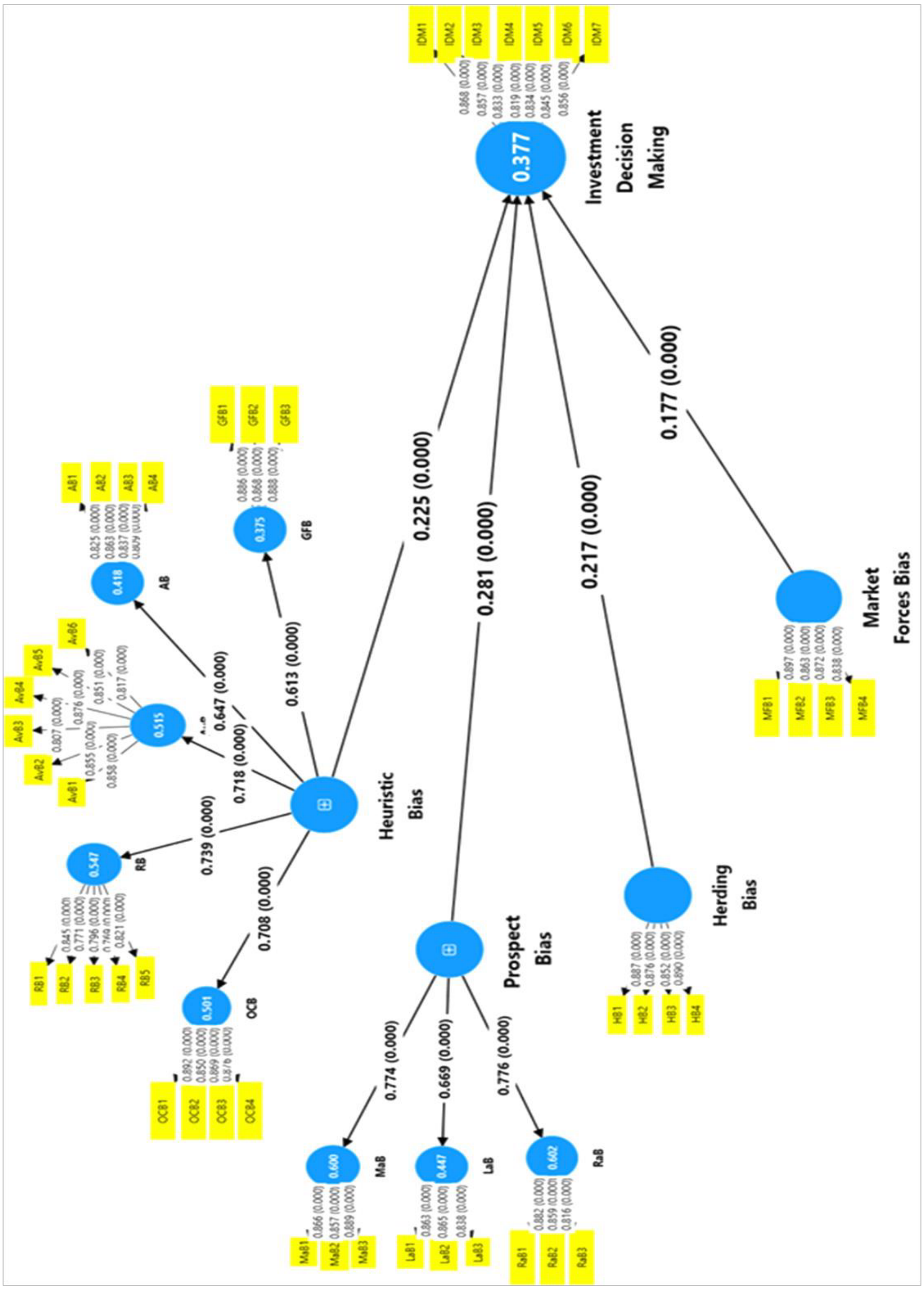

Figure 4.1: PLS SEM Path coefficient

The given model is a reflective-reflective Hierarchical Component Model (HCM) rather than a reflective-formative model. The higher-order constructs (e.g., "Heuristic Bias" and "Prospect Bias") and the lower-order constructs (namely Herding and Market forces biases) are depicted.

4.4.4.2 Collinearity Assessment

Collinearity among predictor variables was initially examined during data screening under multivariate analysis assumptions. No multicollinearity issues were identified, allowing for further model assessment. The collinearity check was performed using latent variable scores generated by Smart PLS software. These scores were used in multiple regression analyses, where a set of predictor constructs acted as independent variables, while any other latent variable that was not the dependent variable was assessed.

Table 4.9 presents the Variance Inflation Factor (VIF) results for higher-order constructs. Since all VIF values are below 5, collinearity concerns are not present. This indicates that the constructs capture distinct information and do not measure the same variables redundantly. As a result, all variables are deemed appropriate for inclusion in the study.

Table 4.9: Variance Inflation Factor

Item code	**VIF**		**Item code**	**VIF**
AB1	1.846		OCB1	2.799
AB2	2.389		OCB2	2.408
AB3	2.004		OCB3	2.405
AB4	1.849		OCB4	2.673
AvB1	2.892		RB1	2.272
AvB2	3.124		RB2	1.739
AvB3	2.39		RB3	1.862
AvB4	3.251		RB4	1.876
AvB5	3.091		RB5	2.114

AvB6	2.386		RaB1	2.122
GFB1	2.373		RaB2	2.006
GFB2	2.023		RaB3	1.636
GFB3	2.348		MFB1	2.996
ID1	2.942		MFB3	2.48
ID2	2.91		MFB4	2.323
ID3	2.464		MaB1	1.918
ID5	2.471		MaB2	1.966
ID6	2.747		MaB3	2.261
ID7	2.931		HB1	2.753
LaB1	1.897		HB2	2.456
LaB2	1.833		HB3	2.289
LaB3	1.719		HB4	2.662

Source: Primary Data

4.5 Hypothesis Testing Using PLS-SEM

After validating the measurement model through Confirmatory Factor Analysis (CFA), the study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) using version 4.0 to examine the hypothesised relationships between variables. Consequently, a conceptual model has been developed, identifying key behavioural biases, namely, heuristics bias, prospect bias, herding, and market forces bias that influence individual investors' investment decisions in the states of Maharashtra, Goa and Karnataka. The conceptual model that was proposed includes four postulates relating to direct linkages between "Heuristic bias" (H1), "Prospect bias" (H2), "Herding bias" (H3), "Market forces bias" (H4), and individual investment decisions. These hypotheses aim to predict the impact of behavioural biases on individual investors' investment decisions.

Table 4.10: Significance of the path coefficient (β) Results of PLS path analysis

Hypothesis	Path Analysis	Path Coefficient	Standard Error	T stats	P values
H1	Heuristic Bias → Investment Decisions	0.228	0.04	5.654	0.000
H2	Prospect Bias→ Investment Decision	0.282	0.038	7.324	0.000
H3	Herding Bias → Investment Decision	0.216	0.036	6.087	0.000
H4	Market Forces Bias→ Investment Decision	0.175	0.037	4.738	0.000
R^2		0.377			

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

4.5.1 Hypotheses Testing Results: Direct Relationships

Table 4.10 presents the results derived from structural equation modelling, confirming that all four hypotheses concerning direct relationships are supported at a 5% significance level (p-value < 0.05). The model demonstrates an explanatory power, with an R^2 value of 37.70% (0.3770), indicating that the predictors collectively account for 37.7 % of the variance in the outcome variable. The detailed findings and interpretations for each hypothesised direct relationship between the predictor and outcome variables are outlined below.

H1: Heuristic bias significantly influences the investment decisions of individual investors. As shown in Table 4.10, the standardised regression coefficient for the relationship between heuristic bias and investment decisions is 0.228, with a t-value of 5.654 (greater than 1.96). This indicates a significant impact of cognitive dissonance on investment decisions, supporting H1.

H2: Prospect bias significantly influences the investment decisions of individual investors. Table 4.10 reports a standardised regression coefficient of 0.282 for the relationship between prospect bias and investment decisions, with a t-value of 7.324 (greater than 1.96). These results confirm a significant influence of the prospect bias on investment decisions, supporting H2.

H3: Herding bias significantly influences the investment decisions of individual investors. According to Table 4.10, the standardised path coefficient for herding bias in relation to investment decisions is 0.216, with a t-value of 6.087 (greater than 1.96). This confirms a significant impact of herding bias on investment decisions, supporting H3.

H4: Market Forces Bias significantly influences the investment decisions of individual investors

According to Table 4.10, the standardised path coefficient for market forces bias in relation to investment decision-making is 0.175, with a t-value of 4.738 (greater than 1.96). This confirms a significant impact of herding bias on investment decisions, supporting H4.

4.5.2 Coefficient of Determination (R^2)

The coefficient of determination (R^2) is a measure of the explanatory power of the model. It reflects the combined effect of exogenous variables on the endogenous variable(s), ranging from 0 to 1, where 1 indicates perfect explanatory accuracy.

Since R^2 is widely used across various fields, researchers typically rely on general benchmarks to assess its adequacy. According to Hair et al. (2014), an R^2 value of 0.75, 0.50, and 0.25 represents substantial, moderate, and weak predictive accuracy, respectively.

However, excessive reliance on R^2 can be misleading. When comparing different model specifications involving the same endogenous constructs, focusing solely on R^2 may lead to selecting a less efficient model. This is because R^2 tends to increase when additional exogenous constructs, even those with insignificant correlations, are included in the model.

In the current study, the R^2 value for Investment decisions is 0.377, as shown in Table 4.10. This indicates that the model explains 37.7% of the variation in investment decisions, demonstrating moderate explanatory power based on the selected predictors.

4.5.3 Effect size (f^2)

The effect size for each path in the model is determined using Cohen's f^2, which measures the impact of an exogenous construct on the endogenous construct by assessing the change in R^2 when a specific construct is removed. To compute f^2, two PLS path models are estimated: the full model, which includes all hypothesised relationships and provides the R^2 of the complete model, and the reduced model, which excludes a specific exogenous construct, yielding the R^2

of the reduced model. The difference between these R^2 values is used to calculate f^2, which indicates the strength of the effect of each predictor variable.

Effect size (f^2) is another important criterion that indicates the impact of a specific independent latent variable on whether a dependent latent variable is high, moderate, or low due to the contribution of this specific independent variable on the R^2 of dependent variable. It is calculated as the increase in the R^2 value of the latent variable to which the path is connected relative to the latent variable's proportion of unexplained variance (Chin, 1998). In other words, F-Square is the change in R-Square when an exogenous variable is removed from the model. Guidelines for assessing the values of f^2 suggested by Cohen (1988) are that values of 0.02, 0.15, and 0.35 represent the exogenous latent variables' small, medium, and large effects. Table 4.11 presents the values of f^2 for the structural model. The results indicate that all relationships demonstrate a small effect size, except for one relationship, which shows a medium effect. The f^2 values range between 0.048 to 0.100, falling within the threshold for small to medium effects as per Cohen’s (1988) guidelines.

4.5.4 Predictive Relevance and Predictive Power

To assess the model’s predictive capability, two key measures were considered: Stone-Geisser’s Q^2 and the Cross-Validated Predictive Ability Test (CVPAT)**.**

4.5.4.1 Stone-Geisser’s Q^2 (In-Sample Predictive Relevance)

Stone-Geisser’s Q^2 value was calculated using the blindfolding procedure in SmartPLS. This measure evaluates the in-sample predictive relevance of the model by assessing how well the exogenous constructs predict the endogenous construct. A Q^2 value greater than zero suggests that the model has predictive relevance (Sarstedt et al., 2016). The results in Table 4.11 show that the Q^2 value for Investment Decision (ID) is 0.365**,** which is significantly above zero, confirming that the model has in-sample predictive relevance.

Table 4.11: Summary of Predictive Relevance (Q^2) , Effect size (f^2) and R2

Exogeneous Construct	F Square	R Square	Q Square
Heuristic Bias	0.063	37.7%	0.365
Prospect Bias	0.100		
Herding Bias	0.07		
Market Forces Bias	0.048		

Source: Primary Data

4.5.4.2 Cross-Validated Predictive Ability Test (CVPAT) (Out-of-Sample Predictive Power)

CVPAT evaluates whether the model can make accurate predictions on new data, rather than just fitting the current dataset well. The results in Table 4.12 indicate that the model exhibits significant predictive ability, as the CVPAT values confirm that the model's predictions are statistically better than a benchmark model.

Table 4.12: Cross-Validated Predictive Ability Test (CVPAT)

Construct	***Q²predict***	***RMSE*** (Root Mean Square Error)	***MAE*** (Mean Absolute Error)	***Average loss difference***	***t value***	***p value***
Overconfidence bias	0.951	0.785	0.618	-0.617	14.898	0.000
Representativeness bias	0.968	0.632	0.476	-0.478	15.680	0.000
Anchoring bias	0.952	0.782	0.613	-0.435	12.114	0.000
Availability bias	0.958	0.727	0.566	-0.561	14.350	0.000
Gambler’s Fallacy bias	0.948	0.832	0.657	-0.428	10.562	0.000
Regret aversion bias	0.967	0.652	0.513	-0.638	15.607	0.000
Loss aversion bias	0.955	0.753	0.582	-0.455	12.448	0.000
Mental accounting	0.967	0.649	0.502	-0.628	14.918	0.000
Investment Decision	0.943	0.869	0.706	-0.433	10.916	0.000

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

The predictive accuracy of the model was assessed using Q^2predict and PLS-Predict. The Q^2predict values for all constructs were positive, indicating that the model possesses predictive relevance. Additionally, the t-values ranging from 10.562 to 15.680 and the p-values ($p < 0.05$) for all the constructs confirm that the predictive results are statistically significant.

4.6 Importance-Performance Map Analysis (IPMA)

Importance-Performance Map Analysis (IPMA) is an advanced analytical tool within PLS-SEM that provides deeper insights into the relative significance (importance) and effectiveness (performance) of independent variables in predicting the dependent variable. Unlike traditional PLS-SEM, which focuses solely on path coefficients, IPMA extends the analysis by incorporating the performance scores of latent constructs. This dual perspective helps identify variables that significantly impact investment decisions but may underperform in terms of investor perception or effectiveness.

IPMA was applied to the structural model after accepting the hypothesis, providing a summary of the impact and agreement levels of the different variables included in the structural model. The IPMA analysis represents both the "importance" and "performance" aspects of the relationship between the biases and the investment decisions of individual investors.

Table 4.13: Importance Performance Map Analysis- Results

Nature of variable	**Construct Name**	**Importance Analysis**	**Performance Analysis**
Independent Variable	Heuristic Bias	0.217	58.102
Independent Variable	Prospect Bias	0.293	58.861
Independent Variable	Herding Bias	0.215	59.459
Independent Variable	Market Forces Bias	0.177	61.760

Source: Primary Data

Prospect Bias emerges as the most influential factor (Importance: 0.293, Performance: 58.861), indicating its strong role in shaping decisions, although its moderate performance suggests that targeted interventions could enhance investor outcomes. Heuristic Bias (Importance: 0.217, Performance: 58.102) also demonstrates a moderate-to-high impact, but its relatively low performance highlights the need to improve investors' awareness and control over mental shortcuts that may lead to irrational decisions. Herding Bias (Importance: 0.215, Performance: 59.459) shows a moderate influence with slightly above-average performance, suggesting that while some investors recognise their tendency to follow the crowd, there remains considerable room for encouraging independent thinking. Lastly, Market Forces Bias (Importance: 0.177, Performance: 61.760) is the least impactful but has the highest performance level, indicating that investors are relatively responsive to market signals.

The IPMA graph indicating the importance and performance level of the biases included in the model is shown below:

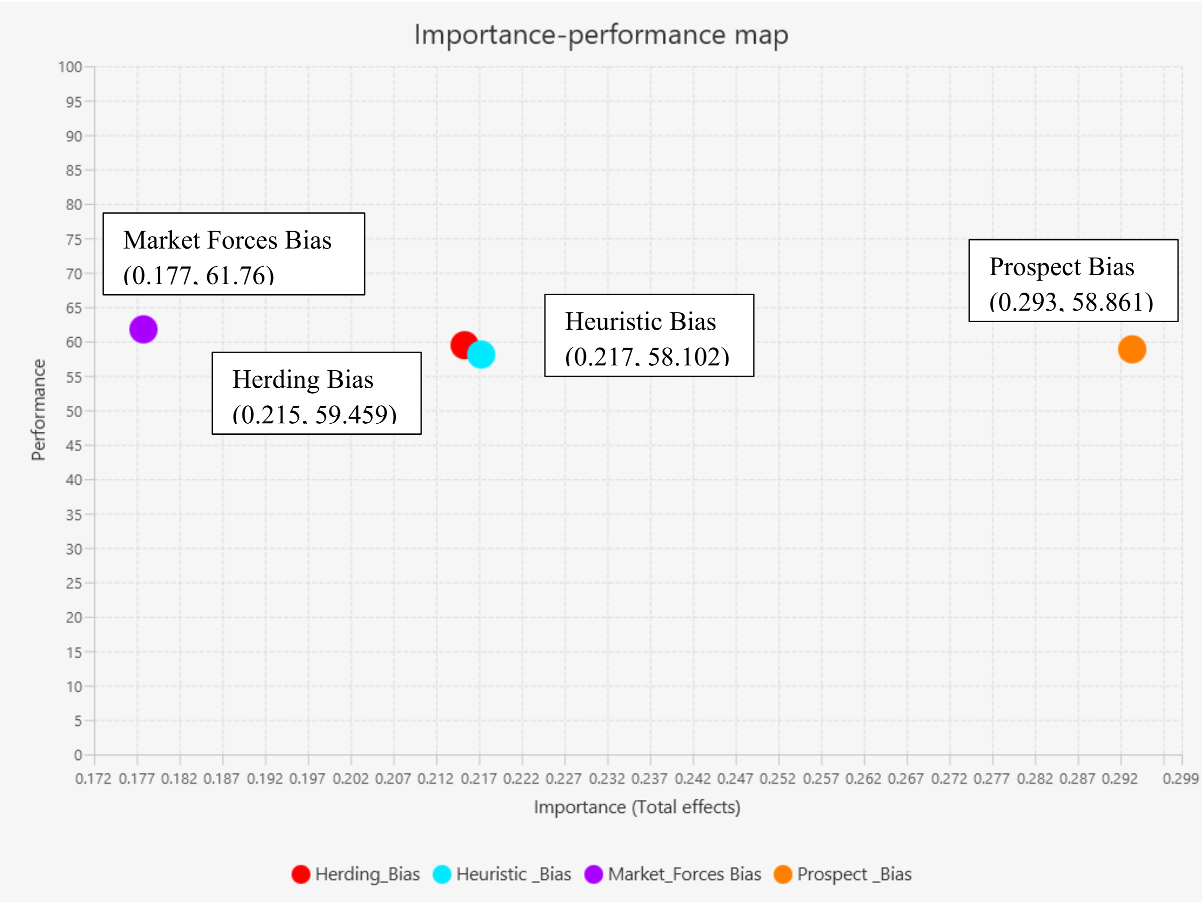

Figure 4.2: Importance Performance Map

The graphical representation of Importance and Performance Analysis (IPMA) is used to assess the performance and importance of the constructs. The x-axis represents the total effect or the importance of the constructs, while the y-axis shows the performance scores, which are the average values of the construct scores within the range of 0–100. According to Sarstedt et al. (2016), IPMA helps highlight the strengths and weaknesses of the constructs by comparing their importance and performance. High importance and low performance indicate areas for improvement or further focus.

4.7 Necessary Condition Analysis (NCA)

Necessity Condition Analysis (NCA) is an analytical approach that identifies whether specific behavioural biases are necessary for investment decisions. Unlike traditional regression-based analyses that assess the impact and strength of relationships, NCA determines whether a particular variable is essential for an outcome to occur.

By introducing NCA as the final analytical tool in this chapter, the study moves beyond simply identifying the presence, impact, and importance of biases to determining which biases are indispensable for making investment decisions. This distinction is critical because while certain biases may significantly influence investment decisions, only a few may be necessary for investors to act rationally or consistently in the stock market.

Necessary Condition Analysis (NCA) has been increasingly recognised as valuable across various business and management disciplines. A comprehensive review by Dul et al. (2023) highlights its application in entrepreneurship, human resource management, international business, marketing, operations, public and non-profit management, strategic management, and tourism. In finance, while specific applications of NCA are still emerging, the methodology holds significant potential. Dul (2016) emphasises that NCA is particularly suited for identifying critical constraints and conditions that must be present for a desired outcome.

Moreover, the theoretical foundations of NCA are rooted in understanding constraints that limit outcomes. Dul (2016) discusses how the absence of critical factors, such as trust in financial markets, can lead to systemic failures. This perspective is invaluable in economic research, where identifying and mitigating such bottlenecks can reform policy and strategic decisions.

To complement PLS-SEM, Necessary Condition Analysis (NCA) was conducted within SMART PLS 4 to determine whether specific behavioural biases serve as necessary conditions for investment decisions. For this, the conceptual model proposed includes four postulates relating to direct linkages between “heuristic bias” (H1), “prospect bias” (H2), “herding bias” (H3), “market forces bias” (H4), and individual investment decision. These hypotheses need to be supported to use NCA. This combined PLS-SEM and NCA approach provides a holistic understanding of how behavioural biases influence investment decisions.

4.7.1 Bottleneck and Percentile Analysis in Necessary Condition Analysis

Bottleneck Analysis is a key step in Necessary Condition Analysis (NCA) that helps determine the minimum level of a necessary condition required for different levels of an outcome. It provides practical insights into what threshold of a predictor, the behavioural bias, must be met to achieve a particular level of investment decisions. Table 4.14 shows the absolute bottlenecks at different decision-making percentiles, indicating the critical constraints that prevent further improvement in investment decisions. This table helps identify the tipping points at which biases play a role. It highlights the constraint effect of a variable by determining how much of it is required for higher levels of the outcome. If a necessary condition is not met, the outcome cannot occur, regardless of other contributing factors.

Table 4.14: Bottleneck Table - NCA

Percentile Levels	**Investment Decision Making**	**Heuristic Bias**	**Prospect Bias**	**Herding Bias**	**Market Forces Bias**
0%	1.154	NN	NN	NN	NN
10%	1.539	1.596	NN	NN	NN
20%	1.923	1.631	1.681	NN	NN
30%	2.308	1.901	1.681	NN	NN
40%	2.692	1.901	1.681	NN	1.512
50%	3.077	1.901	1.681	NN	1.512
60%	3.462	1.901	1.681	NN	1.512
70%	3.846	1.901	1.681	NN	1.512
80%	4.231	1.901	1.681	NN	1.512
90%	4.615	1.914	2.506	1.987	1.512
100%	5.000	3.659	3.070	2.013	3.938

Source: Primary Data

The percentiles (0% to 100%) represent different levels of investment decisions across respondents. Higher percentiles (e.g., 90%, 100%) correspond to higher levels of investment decisions. Investment decision scores range from 1.154 (0th percentile) to 5.000 (100th percentile). This means the highest Investment decision level in the dataset is 5.000, while the lowest is 1.154.

Heuristic Bias as a Necessary Condition at the 10th percentile, heuristic bias (1.596) starts appearing as a necessary condition. From the 20th percentile onwards, a heuristic bias of at least 1.901 is required for higher investment decisions. At the 100th percentile, the heuristic bias jumps to 3.659, indicating that very high levels of Investment decisions require a significantly stronger heuristic bias. This suggests that heuristic bias plays a consistent role in enabling investment decisions at all levels.

Prospect Bias becomes relevant from the 20th Percentile. At 0% and 10%, prospect bias is not a necessary condition (NN). From 20% onward, a minimum level of 1.681 is required. The threshold increases at the 90th percentile (2.506) and 100th percentile (3.070), showing that higher Investment decisions require more substantial prospect bias.

Herding Bias is a bottleneck only at higher levels of Investment decisions. Herding bias is not necessary for most percentiles (0%–80%) (NN). It becomes relevant only at the 90th percentile (1.987) and increases to 2.013 at the 100th percentile. This means herding bias is 'not' a critical factor at lower levels, but is necessary for extremely high investment decision scores.

Market Forces Bias is Necessary from the 40th percentile onward. It first appears at 40% (1.512) and remains at the same level up to the 90th percentile. At the 100th percentile, market forces bias increases sharply to 3.938. This suggests that while it is a stable necessity across moderate investment decision levels, extremely high investment decisions require a much stronger impact of market forces bias.

Each percentile represents the level of investment decisions, while the corresponding values for biases indicate the minimum level required at each stage. Investment decisions range from 1.154 (0th percentile) to 5.000 (100th percentile). High investment decisions are associated with an increase in the necessary level of biases.

Table 4.15: Bottleneck Percentile Table -NCA

Percentile	**Investment Decision Making**	**Heuristic Bias**	**Prospect Bias**	**Herding Bias**	**Market Forces Bias**
0%	1.154	0.000	0.000	0.000	0.000
10%	1.539	0.000	0.000	0.000	0.000
20%	1.923	0.000	0.000	0.000	0.000
30%	2.308	0.000	0.000	0.000	0.000
40%	2.692	0.000	0.000	0.000	0.000
50%	3.077	1.314	0.000	0.000	0.000
60%	3.462	5.401	1.606	0.000	0.000
70%	3.846	10.511	5.255	0.000	9.927
80%	4.231	16.642	10.511	0.000	22.628
90%	4.615	28.613	14.599	10.219	35.766
100%	5.000	44.672	23.212	30.073	48.905

Source: Primary Data

Heuristic Bias is required from the 50th percentile onward at 50% investment decisions, and a minimum heuristic bias of 1.314 is necessary. The requirement increases significantly at higher levels (5.401 at 60%, 28.613 at 90%, and 44.672 at 100%). This implies that as the complexity of investment decisions increases, reliance on heuristic biases grows.

Prospect Bias becomes Necessary at the 60th Percentile. From 0% to 50%, prospect bias is not a necessary condition. At 60%, a minimum of 1.606 is required, and it grows to 23.212 at 100%. This suggests that risk perception and loss aversion play a bigger role in high-level investment decisions.

Herding Bias is absent until the 90th Percentile. From 0% to 80%, herding bias is not a necessary condition (0.000). At 90%, at least 10.219 is required, sharply increasing to

30.073 at 100%. This suggests that herding behaviour is crucial only for the most advanced investors.

Market Forces Bias Appears at the 70th Percentile Up to 60%; market forces bias is not required (0.000). At 70%, at least 9.927 is necessary, increasing to 48.905 at 100%. This means that market forces become a crucial factor in high-level investment decisions.

4.7.2 Model of NCA in PLS-SEM

The Necessary Condition Analysis (NCA) within the PLS-SEM framework highlights the extent to which specific behavioural biases act as necessary conditions for effective investment decisions. Unlike conventional regression-based approaches that assess the strength of relationships, NCA identifies whether a particular bias is an essential prerequisite for achieving a certain level of investment decision-making performance.

Figure 4.16 illustrates the necessity effect of herding bias, heuristic bias, market forces bias, and prospect bias on investment decisions, with corresponding necessity effect sizes indicated by the path coefficients. These coefficients represent the degree to which each bias is required to achieve optimal investment decisions. The dashed intercept line accounts for variance not explained by the identified biases.

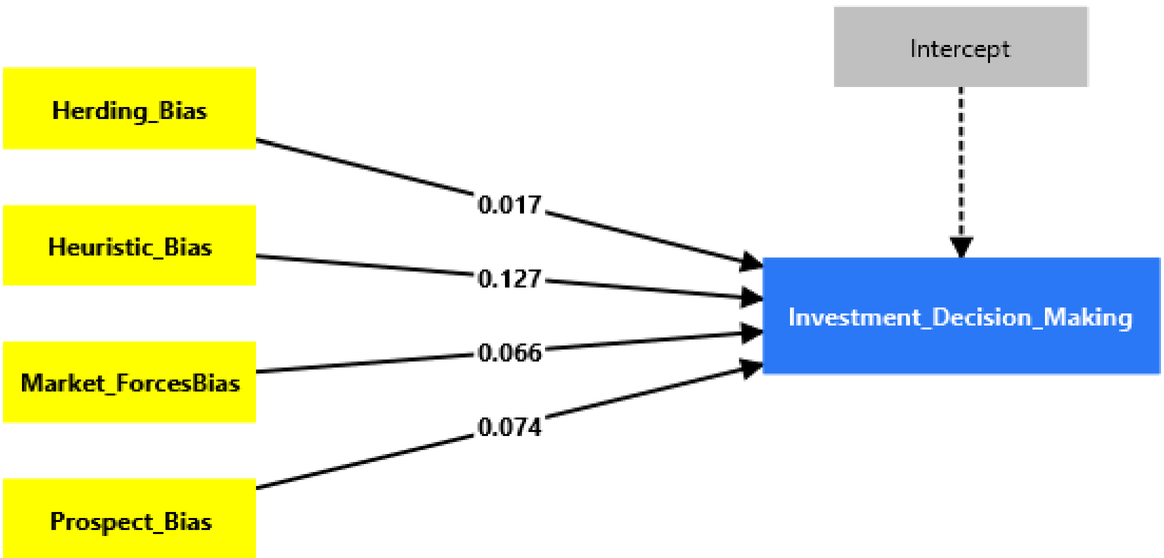

Figure 4.3: Behavioural Bias in NCA on Investment Decisions

Table 4.16: Effect size of Behavioural Biases in NCA

Exogenous Variables	**Effect size 'd'**	**P- value**
Heuristic Bias	0.166	0.127
Prospect Bias	0.094	0.074
Herding Bias	0.017	0.017
Market Forces Bias	0.128	0.066

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

The effect size in NCA quantifies the strength of the necessity constraint that an exogenous variable imposes on the endogenous variable. It tells how much of the variance in Investment Decisions is constrained by each behavioural bias. A higher effect size 'd' means a stronger necessity constraint. The variable is essential for achieving higher levels of investment decisions.

Heuristic bias is highly necessary, and a substantial level of heuristic bias is required for strong investment decisions. Prospect bias shows some necessity, Herding shows minimal constraint in decisions, while Market forces bias shows the moderate necessity to constrain investment decisions significantly.

4.7.3 The Combined use of NCA and PLS-SEM

Table 4.17 outlines how to interpret findings when using both PLS-SEM and NCA. While PLS-SEM shows whether a construct significantly influences an outcome on average, NCA reveals if a minimum level of that construct is essential for the outcome to occur as proposed by Richter et al. (2020). The scenarios help clarify both influence and necessity.

Table 4.17: The Relevant Scenarios to Interpret the Findings

SCENARIO	PLS SEM	NCA	CONCLUSION
Exogenous construct is a....	significant determinant	and a necessary condition	On average, an increase in the exogenous construct will increase the outcome. However, a certain level of the exogenous construct is necessary for the outcome to manifest.
Exogenous construct is a....	significant determinant	but no necessary condition	On average, an increase in the exogenous construct will increase the outcome; no minimum level of the construct is needed to ensure that the outcome will manifest
Exogenous construct is a...	non-significant determinant	but a necessary condition	A certain level of the exogenous construct is necessary for the outcome to manifest. However, a further increase is not recommended, as it will not increase the outcome any further

Source: Richter, N. F., Schubring, S., Hauff, S., Ringle, C. M., & Sarstedt, M. (2020).

Table 4.18: PLS-SEM and NCA- Results

Exogenous Variable	PLS SEM		NCA	
	Path Co-efficient	P value	Original Effect Size	P value
Heuristics	0.228	0.000	0.166	0.127
Prospects Bias	0.282	0.000	0.094	0.074
Herding Bias	0.216	0.000	0.017	0.017
Market Forces Bias	0.175	0.000	0.128	0.066

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

PLS-SEM indicates that herding bias has a significant influence on investment decisions. NCA reveals that a certain level of herding bias is necessary; some investment decisions may not occur without it. This implies that while herding bias impacts investment behaviour, it also serves as a prerequisite for certain investment decisions to occur.

4.8 Findings

Examining data from individual investors in Maharashtra, Goa, and Karnataka offers valuable insights into the various aspects of their investment decisions. This objective analysed the key biases influencing investment decisions.

1. (H1): Heuristic Bias, which includes Overconfidence Bias, Representativeness Bias, Availability Bias, Anchoring Bias, and Gambler's Fallacy Bias, has a significant influence on equity investors' investment decisions. PLS -SEM analysis shows a positive path coefficient of 0.228 (t-statistic = 5.654), which is statistically significant at the 5% level, indicating that heuristic bias substantially impacts investors' investment decisions.
2. (H2): Prospect Bias, encompassing Mental Accounting Bias, Loss Aversion Bias, and Regret Aversion Bias, significantly affects equity investors' investment decisions. This is supported by PLS-SEM analysis, with a positive path coefficient of 0.282 (t-statistic = 7.324), statistically significant at the 5% level, suggesting that prospect bias strongly influences investment decisions in the stock market.
3. (H3): PLS -SEM analysis confirms that Herding Bias significantly impacts individual investors' investment decisions, with a positive path coefficient of 0.216 (t-statistic = 6.087), statistically significant at the 5% level. This finding indicates that herding bias is crucial in shaping investors' investment decisions.
4. (H4): Market Force Bias also significantly influences investment decisions, as demonstrated by PLS-SEM analysis. The positive path coefficient of 0.175 (t-statistic = 4.738), statistically significant at the 5% level, suggests that market force bias is an important factor in the decision-making process of individual investors.
5. Using IPMA analysis: With an importance value of 0.177 and a performance score of 61.760, Market Forces bias demonstrates relatively lower importance in influencing

investment decisions but still ranks closely in performance level to the dependent variable. This indicates that while investors recognise market conditions as a factor, they do not see it as the most critical driver of their investment decisions.

6. Using IPMA analysis, Herding bias has a higher importance score of 0.215 but a slightly lower performance level of 59.459. This finding suggests that investors find Herding Bias meaningful in their decisions, albeit not as high-performing or influential as Market Forces Bias in this model.

7. Using IPMA analysis, Heuristic bias ranks close to Herding bias with an importance score of 0.217 and a performance score of 58.102. This reflects that while heuristics influence decision-making, investors may view this bias as less impactful or relevant than other biases.

8. Using IPMA analysis, with the highest importance score among the biases at 0.293 and a performance score of 58.861, Prospect Bias emerges as the most critical behavioural bias influencing investment decisions. This importance level indicates that investors consider prospect-related factors more prominently in their decisions, even though their performance level does not match the dependent variables.

9. NCA reveals that a certain level of herding bias is necessary; some investment decisions may not occur without it. This implies that while herding bias impacts investment behaviour, it also serves as a prerequisite for certain investment decisions to occur.

4.9 Summary

This chapter explores the impact of behavioural biases on investment decisions among individual investors in Maharashtra, Goa, and Karnataka. The analysis identifies four key biases, heuristic biases, prospect biases, herding biases, and market forces biases, as influential factors in shaping investment decisions. Heuristic Bias, which includes overconfidence, representativeness, availability, anchoring, and the gambler's fallacy, significantly affects investor decisions. Prospect Bias, encompassing mental accounting, loss aversion, and regret aversion, emerges as the most critical factor, strongly influencing investment behaviour. Herding Bias also plays a substantial role, as investors tend to follow market trends and collective behaviour. Market Forces Bias, while less influential, still contributes to decision-making by shaping investor perceptions of external conditions. The Importance-Performance

Map Analysis (IPMA) highlights that Prospect Bias holds the highest importance, while Market Forces Bias ranks lower in significance but maintains a strong performance. Necessary Condition Analysis (NCA) further reveals that Heuristic and Prospect Biases are essential for effective investment decisions, whereas Herding and Market Forces Biases become more relevant under specific conditions. These findings highlight the central role of prospect bias in investor behaviour, while other biases contribute to varying degrees based on different investment decision-making contexts.

CHAPTER 5
DATA ANALYSIS AND INTERPRETATION - THE MODERATING ROLE OF FINANCIAL LITERACY

This chapter examines the moderating effect of financial literacy on the relationship between heuristic bias, prospect bias, herding bias, and market forces bias and the investment decisions of individual investors. The moderation analysis is conducted using the SMART PLS-SEM software to determine the extent to which financial literacy moderates the relationship.

5.1 Financial Literacy Measurements

5.1.1 Measure 1: Lusardi and Mitchell Approach

Lusardi and Mitchell (2007, 2009) developed one of the most widely adopted measures of financial literacy, comprising two key components. The first component, basic financial literacy, is assessed using five numeracy-based questions, including three on the time value of money and two on purchasing power calculations. The second component, advanced financial literacy, evaluates individuals' knowledge through eight investment-related questions covering stocks, bonds, mutual funds, risk, and diversification. This comprehensive approach provides a structured framework for assessing financial literacy through different levels of complexity.

5.1.2 Measure 2: Item Response Theory (IRT) Approach

Knoll and Houts (2012) introduced an alternative approach to measuring financial literacy using Item Response Theory (IRT) to develop a comprehensive financial literacy scale. This measure was constructed based on data from three national surveys: the American Life Panel (ALP), the Health and Retirement Study (HRS), and the National Financial Capability Study (NFCS). It consists of two main components: thirteen questions assessing knowledge of investments, stocks, bonds, diversification, and risk, and an additional seven questions focusing on fundamental financial concepts such as the time value of money, purchasing power, borrowing (including mortgages and credit cards), and insurance. This IRT-based framework provides a more comprehensive evaluation of financial literacy by considering the varying difficulty levels of questions and their ability to differentiate between individuals with different levels of financial knowledge.

5.1.3 Measure 3: Approach based on OECD/INFE and Other International Surveys

This measure incorporates financial literacy assessments conducted by major international organisations, including the Organisation for Economic Co-operation and Development (OECD) International Network on Financial Education (INFE), the Health and Retirement Study (HRS), and the National Financial Capability Study (NFCS). India uses the framework developed by the OECD International Network on Financial Education (INFE). The OECD framework evaluates financial literacy across three dimensions: knowledge, behaviour, and attitude, using a twenty-one-point scoring system, with studies conducted in thirty-six countries, including India, the UK, and the USA (Atkinson & Messy, 2012; Morgan & Trinh, 2019). Additionally, assessments from Research and New Development (RAND)'s American Life Panel (ALP), HRS, and the National Strategy for Financial Education (NSFE) focus on basic literacy elements such as numeracy, compound interest, inflation, and stock market knowledge, primarily within the USA and OECD countries (Lusardi, 2008).

These frameworks provide a structured approach to understanding financial literacy across different populations and economic contexts.

5.1.4 Financial Literacy Measurements in India

The OECD-INFE Framework, as adapted for India, evaluates financial literacy through three key dimensions: financial knowledge, financial behaviour, and financial attitude. The financial knowledge component includes understanding basic financial concepts such as interest rates, inflation, time value of money, risk diversification, and familiarity with investment products. Financial behaviour assesses individuals' actions related to budgeting, saving, borrowing responsibly, planning for the future, and avoiding over-indebtedness. Financial attitude also examines personal outlooks toward long-term financial planning, saving habits, and risk preferences. The framework assigns a total score of 21 points, 7 for knowledge, 9 for behaviour, and 5 for attitude, which can be normalised to 100 for cross-country comparisons. In the Indian context, this framework is implemented with contextual adaptations, including localised currency references, examples of domestic investment products, and culturally relevant financial scenarios, making it more appropriate and effective in capturing the financial literacy levels of Indian respondents.

Several studies in India have assessed financial literacy using different measures. Measure 1 was included in studies by Cole and Shastry (2009), Agarwal et al. (2015) and Bhushan & Medury (2014). Measure 2 in research by Goyal (2013), Sharma and Harsha (2013), Gupta (2017) and Baker et al. (2019). Measure 3 in research works by Agarwalla et al. (2013), Choudhary and Kamboj (2017), Ambarkhane et al. (2015), and Rai et al. (2019). These studies, which are used in research papers and PhD dissertations, highlight the diverse approaches used to evaluate financial literacy in India, reflecting variations in methodology, focus, and target populations.

5.1.5 Financial Literacy Measurement for this Study

Measures 2 and 3 (OECD Framework) are adopted for this study to ensure a comprehensive financial literacy assessment. Measure 2 categorises financial literacy into basic and advanced literacy, with the advanced component specifically tailored to stock market investors, focusing on their knowledge of investment instruments and financial decision-making. Measure 3, particularly the OECD framework, is also incorporated to evaluate financial knowledge, behaviour, and attitude using an internationally recognised scoring system. This combined approach provides a robust framework for analysing how the level of financial literacy moderates the impact of behavioural biases on investment decisions, ensuring both depth and relevance to the study's objectives.

5.2 Financial Literacy Scoring

Financial literacy is commonly assessed using two primary methods: Subjective (self-assessed) financial literacy and objective (performance-based) financial literacy. Studies across various countries highlight two key approaches to measuring financial literacy. The first approach involves an objective assessment, where respondents take a performance-based test to evaluate their financial knowledge and ability to apply financial concepts in real-world scenarios, typically through multiple-choice or true/false questions (Alessie et al., 2011). The second approach relies on self-assessment, where individuals report their perceived financial knowledge, attitudes toward financial instruments, and confidence in making financial decisions. However, research suggests that self-assessed financial literacy often does not align with actual financial knowledge, as individuals tend to be overconfident in their abilities (Wang, 2009). Performance-based assessments are widely used because they provide an objective measure of knowledge, whereas self-reported assessments may reflect confidence rather than actual competence (Goyal, 2013). Overconfidence in financial knowledge can lead to cognitive biases that affect financial decision-making (Barber et al., 2020; Barber et al., 2013).; Finke et al. (2017). In this study, financial literacy is measured using both approaches, wherein the performance-based approach had seven questions on basic financial literacy, seven on advanced financial literacy, and sixteen on the self-assessment approach. The financial literacy level is determined by calculating the percentage of correct responses, with respondents classified as highly financially literate, medium and low financial literacy.

5.2.1 Financial Literacy Score

The respondents' financial knowledge is assessed based on 30 questions incorporated into the survey instrument, each with equal weight in determining their financial knowledge level. Following the recommendations of the OECD ([OECD] International Network on Financial Education, 2022) and previous Indian studies, Atkinson and Messy (2012); Choudhary and Kamboj (2017), each correct response earns one point, with a maximum possible score of 30. The financial knowledge score for each respondent is determined by counting the total number of correct answers.

The overall financial literacy score is calculated as the sum of three components: financial knowledge (14 points), financial behaviour (10 points), and financial attitude (6 points), resulting in a maximum possible score of 30. A financial literacy score of 24 or higher indicates a high level of financial literacy, a score between 18 and 23 signifies moderate financial literacy, while a score of 17 or below reflects a low level of financial literacy (Choudhary & Kamboj, 2017; Sharma & Harsha, 2013).

"*The overall financial literacy score is obtained as the sum of the three previous scores* *(financial knowledge (7), financial behaviour (9) and financial attitudes (5). It can take any value between 1 and 21 and can be normalised to 100 for reporting by multiplying by 100/21.*"[4]

5.2.2 Overall Financial Literacy

The results indicate that, on average, respondents answered 53.55 per cent of the questions correctly. The mean percentage of correct scores is inferred using the benchmark set in previous research studies (Chen & Volpe, 1998; Volpe et al., 2002). (Yahaya et al., 2019). The benchmark divided percentage correct scores into three categories: > 80% (High Literacy), 60 - 79% (Medium Literacy) and < 60% (Low Literacy). Thus, based on this benchmark, it is evident that individual investors (respondents) have a **low level** of financial literacy.

OVERALL FINANCIAL LITERACY = 53.55 percent

5.3 The Moderating Role of Financial Literacy on Individual Investors

Moderation refers to a scenario where the relationship between two variables is not constant but instead varies depending on the influence of a third variable, known as the moderator (Hair et al., 2014). The primary goal of moderation analysis is to assess and test how the independent variable's effect on the dependent variable changes as a function of the moderator (Baron & Kenny, 1986). The moderator can either strengthen or weaken this relationship and, in some cases, may even reverse its direction. In this study, financial literacy is the moderator, influencing the relationship between behavioural biases and investment decisions.

To validate moderation, the interaction effect between the predictor (X) and the moderator (M) must be computed to determine its statistical significance in predicting the dependent variable (Y). To analyse this interaction effect, the study employs SMART PLS-SEM 4.

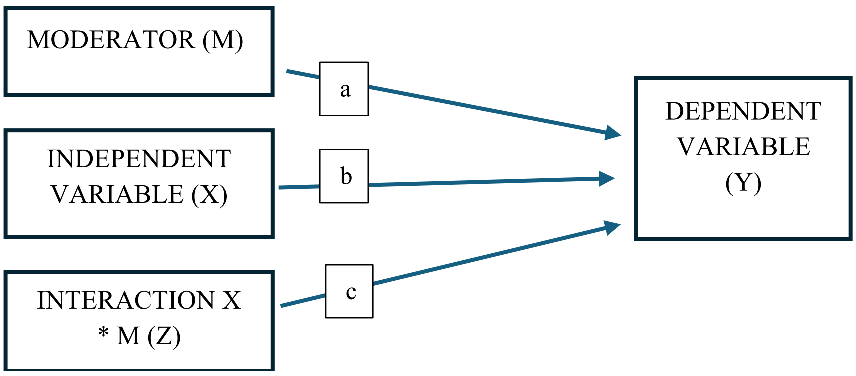

Figure 5.1: Moderation Analysis Model
Compiled by the Researcher

The moderation model, illustrated in Figure 5.1, includes three causal paths. Path "a" represents the impact of financial literacy (M) as a moderator, Path "b" denotes the influence of behavioural biases (X) as the independent variable, and Path "c" (X*M) captures the interaction effect between the moderator and the independent variable on the dependent variable (Y). If the interaction effect in Path "c" is statistically significant, it supports the moderation hypothesis. However, the moderation hypothesis is not supported if the interaction effect is not statistically significant.

The financial literacy level of individual investors is assumed to moderate the relationship between heuristic bias, prospect bias, herding bias, market forces bias, and investment decisions of individual investors. The financial literacy of investors is measured with the help of financial knowledge, financial attitude, and financial behaviour. The Heuristic bias, Prospect bias, Herding bias, and Market forces bias are assumed as exogenous/independent constructs in the structural model, and investment decisions of equity investors is treated as endogenous/dependent constructs.

The following hypotheses are examined with the help of the interaction moderation method applied in the SMART PLS-SEM software:

H5: Financial literacy significantly moderates the relationship between heuristic bias and investment decisions of individual investors

H6: Financial literacy significantly moderates the relationship between prospect bias and investment decisions of individual investors

H7: Financial literacy significantly moderates the relationship between herding bias and investment decisions of individual investors

H8: Financial literacy significantly moderates the relationship between market forces bias and investment decisions of individual investors

The structural model used to examine the moderating effect of financial literacy is shown below:

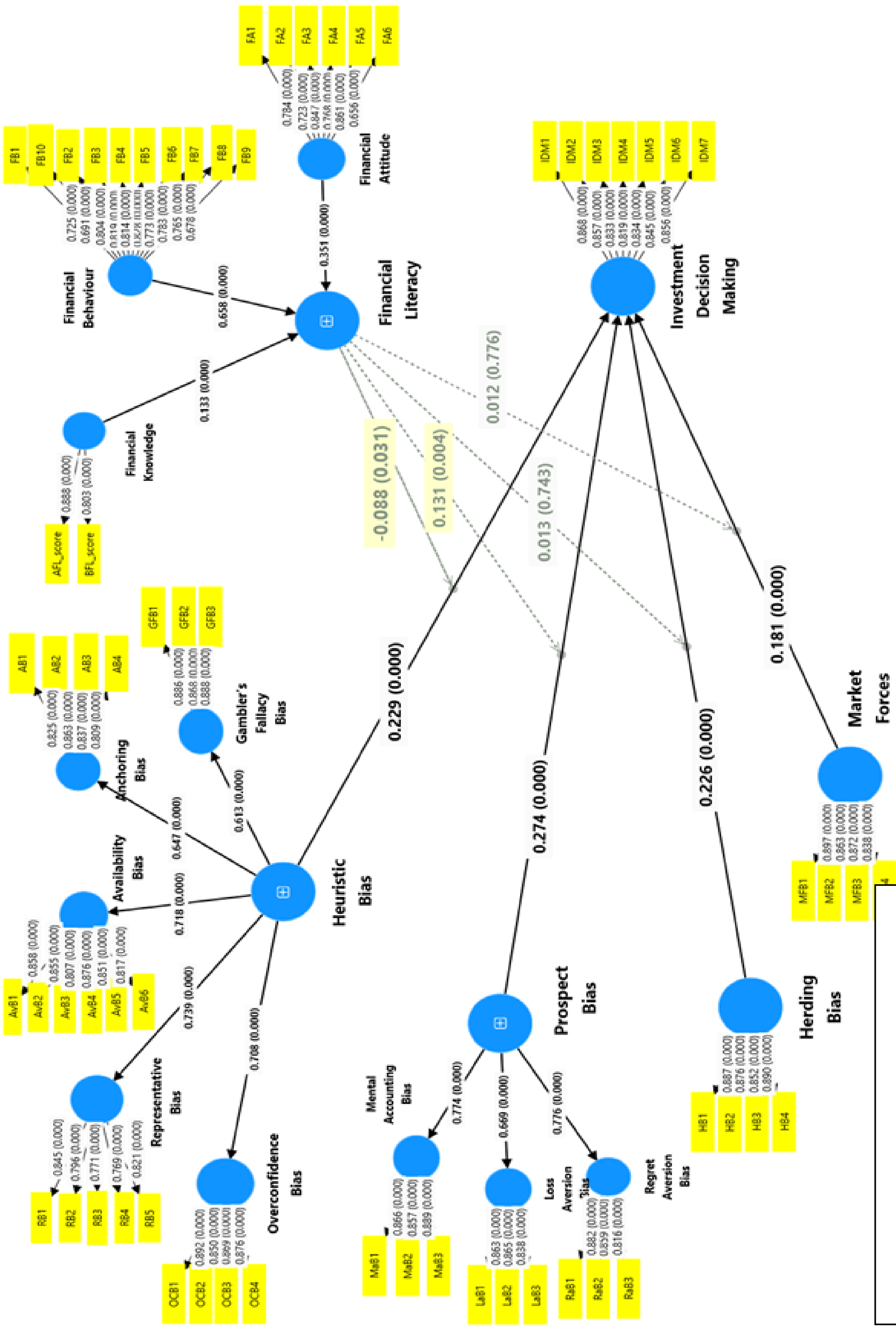

Figure 5.2: Interaction model

Table 5.1: The Moderating Effect of Financial Literacy

Path Analysis		Path Coefficient	Standard Error	T-stats	P values
Heuristic Bias -> Investment Decisions		0.231	0.043	5.373	0.000
Prospect Bias -> Investment Decisions		0.273	0.038	7.253	0.000
Herding Bias -> Investment Decisions		0.229	0.036	6.248	0.000
Market forces Bias-> Investment Decisions		0.179	0.035	5.101	0.000
Hypothesis for Moderation Analysis					
H5	Financial Literacy x Heuristic Bias -> Investment Decisions	-0.075	0.041	2.167	0.033
H6	Financial Literacy x Prospect Bias -> Investment Decisions	0.124	0.047	2.791	0.006
H7	Financial Literacy x Herding Bias -> Investment Decisions	0.01	0.047	0.281	0.779
H8	Financial Literacy x Market forces Bias -> Investment Decisions	0.008	0.041	0.281	0.780
Financial Literacy -> Investment Decisions		-0.002	0.032	0.005	0.996

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

The results of the moderation analysis indicate that financial literacy among individual investors plays a significant role in moderating the biases affecting their investment decisions. Among all biases, prospect bias has the strongest effect on investment decisions ($\beta = 0.273$, $p < 0.000$), followed by heuristic bias, herding bias and market forces bias.

H5: Financial literacy significantly moderates the relationship between heuristic bias and investment decisions of individual investors

Financial literacy negatively moderates the relationship between heuristic bias and investment decisions (Path coefficient = -0.075, t-statistic = 2.167). This negative path coefficient indicates that when financial literacy is low, the influence of heuristic bias on investment decisions is stronger. Investors with a low financial literacy level are more susceptible to relying on heuristics, such as mental shortcuts or rules of thumb, which can lead to suboptimal or biased investment decisions.

The slope coefficient indicating the moderating effect of financial literacy on heuristic bias is shown below:

Figure 5.3: Moderation Effect on Heuristic Bias

The gap between the red and green lines suggests that when financial literacy is low, heuristic bias has a stronger positive impact on investment decisions, indicating greater reliance on mental shortcuts. The negative moderation effect means that as financial literacy increases, this influence weakens, reducing the role of heuristic bias in investment decisions.

H6: Financial literacy significantly moderates the relationship between prospect bias and investment decisions of individual investors

When financial literacy is low, the positive moderating effect weakens. This means the relationship between prospect bias and investment decisions (Path coefficient = 0.124, t-statistic = 2.791) is less pronounced.

The positive moderating effect of financial literacy on the relationship between prospect bias and investment decisions indicates that investors with higher financial literacy are more sensitive to framing effects in their investment decisions. This suggests that greater financial knowledge enhances the impact of prospect bias, possibly by increasing risk awareness and sensitivity to gains and losses, leading to stronger behavioural influences. Conversely, investors with lower financial literacy are less influenced by prospect bias, likely due to a limited understanding of outcome framing. In other words, prospect bias has a weaker impact on the investment decisions of individuals with low financial literacy than on those with higher financial literacy.

The slope coefficient indicating the moderating effect of financial literacy on Prospect bias is shown below:

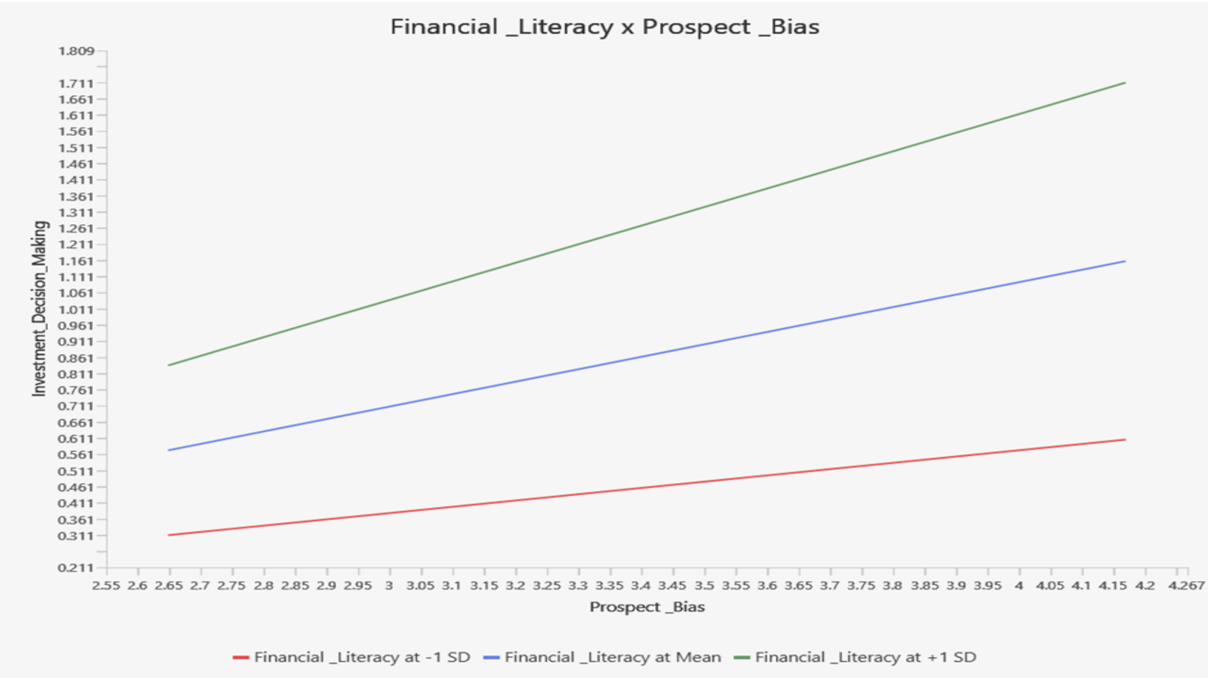

Figure 5.4: Moderation Effect on Prospect Bias

The wider gap between the red and green lines indicates that lower financial literacy weakens the effect of prospect bias on investment decision-making. This means investors with low financial literacy are less responsive to prospect bias.

H7: Financial literacy significantly moderates the relationship between herding bias and investment decisions of individual investors

Financial literacy does not significantly moderate the relationship between herding bias and investment decisions (Path coefficient = 0.01, t-statistic = 0.281). This suggests that financial literacy does not alter the impact of herding bias on investment decisions. This indicates that investors, both with low and high financial literacy, are equally influenced by other investors' investment decisions.

H8: Financial literacy significantly moderates the relationship between market forces bias and investment decisions of individual investors

Financial literacy does not significantly moderate the relationship between market forces bias and investment decisions (Path coefficient = 0.008, t-statistic = 0.281). This indicates that financial literacy, whether high or low, does not influence how external market forces affect investment decisions. Investors' level of financial knowledge does not change their responsiveness to market conditions.

The direct effect of financial literacy on investment decisions is not significant. This means financial literacy alone does not directly influence investment decisions. Instead, it impacts investment decisions by interacting with specific behavioural biases.

5.4 Findings

1. Among all biases, prospect bias has the strongest effect on investment decisions ($\beta = 0.273$, $p < 0.001$), followed by heuristic bias, herding bias and market forces bias.

2. With low financial literacy, heuristic biases strongly affect investment decisions. The negative moderation means that as financial literacy increases, the effect of these biases decreases ($\beta = -0.075$, $p = 0.033$).

3. Financial literacy amplifies the effect of prospect bias ($\beta = 0.124$, $p = 0.006$), suggesting that financially literate investors are more sensitive to potential gains and losses.

4. Financial literacy does not significantly moderate the relationship between herding bias and investment decision-making ($\beta = 0.01$, $p = 0.779$), suggesting that investors, regardless of their financial literacy, are equally prone to following the investment decisions of others.

5. Financial literacy does not significantly affect the relationship between market forces bias and investment decision-making ($\beta = 0.008$, $p = 0.780$), indicating that external market conditions impact investors uniformly, regardless of their financial literacy level.

6. Financial literacy does not directly impact investment decision-making ($\beta = -0.002$, $p = 0.996$). This suggests that financial knowledge, behaviour, and attitudes influence investment decisions primarily by interacting with behavioural biases rather than as an independent variable.

5.5 Summary

The moderating role of financial literacy presents mixed findings. The negative moderation and low financial literacy indicate that the effect of these biases is more substantial, suggesting that low financially literate investors rely more on mental shortcuts. Investors with lower financial literacy are less influenced by how potential outcomes are framed or presented. In other words, prospect bias has a weaker impact on the investment decisions of individuals with low financial literacy than on those with higher financial literacy.

Financial literacy does not significantly moderate the impact of herding and market forces biases, implying that these biases influence investors regardless of their financial literacy.

Finally, the study finds that financial literacy alone does not directly impact investment decisions. It highlights that its role is more indirect, shaping investors' reactions to behavioural biases rather than driving investment decisions independently. These findings emphasise the complex interplay between financial literacy and behavioural biases in investment decisions.

CHAPTER 6

DATA ANALYSIS AND INTERPRETATION - THE MODERATING ROLE OF INVESTOR DEMOGRAPHICS

Investment decision-making is a complex process influenced by cognitive, emotional and social factors. While the findings of objective one have demonstrated the significant role of behavioural biases in shaping investment decisions, the explanatory power of the model (R^2 = 37.7%) indicates that additional variables may contribute to a more comprehensive understanding of investor decision behaviour. Demographic factors such as gender, age, marital status, occupation, education, income and investment experience may likely moderate the relationship between behavioural biases and investment decisions.

Understanding these moderating effects is crucial, as different demographic groups may exhibit varying susceptibility to behavioural biases due to differences in financial knowledge, experience, risk tolerance, and socio-economic conditions. Younger investors may respond differently to market fluctuations than older investors, while income levels could influence how individuals perceive and react to the financial framing of investment opportunities. Therefore, incorporating demographic variables into the analysis provides a more focused view of investor behaviour, helping to identify group-specific patterns that may not be evident in an aggregate-level analysis.

This chapter employs Partial Least Squares Structural Equation Modelling (PLS-SEM) based Multi-Group Analysis (MGA) to examine these effects. This method enables comparing different investor groups by testing whether the relationships between behavioural biases and investment decisions differ significantly across demographic categories. By segmenting the sample based on key demographic characteristics, the analysis seeks to determine if certain biases exert a stronger or weaker influence on investment decisions within specific groups.

6.1 Need for Multi-Group Analysis (MGA)

The R^2 value of 37.7% indicates that while behavioural biases significantly influence investment decisions, they do not fully explain the investor behaviour of the data sample. Demographic factors may introduce variations in how biases operate, necessitating an examination of whether the impact of biases differs across investor groups. MGA helps determine whether these demographic variables moderate the strength of relationships between behavioural biases and investment decisions.

6.1.1 Multi-Group Analysis (MGA) in PLS-SEM

To assess whether demographic factors moderate the relationship between behavioural biases and investment decisions, Multi-Group Analysis (MGA) in PLS-SEM is employed. This technique allows for comparing structural relationships across different demographic segments, such as gender, age, marital status, occupation, education, income and investment experience. A key consideration in applying MGA is the number of groups included in the analysis. While many studies limit comparisons to only two groups, such as male vs. female or young vs. old investors, this approach may oversimplify the variations within the dataset. Instead, dividing the sample into three or more meaningful subgroups allows for a more comprehensive understanding of how demographic differences influence investment behaviour. Prior research (Assaker et al., 2015; Raj, 2025) highlights the importance of expanding group divisions to capture nuanced variations rather than relying on binary comparisons.

Conducting MGA requires more than simply testing the model within different demographic subgroups. A crucial methodological step is to test for significant differences in path coefficients across groups statistically. This ensures that any observed variations in relationships between behavioural biases and investment decisions are not due to random fluctuations but represent meaningful distinctions among investor segments. Studies that fail to conduct these statistical comparisons may inaccurately interpret differences as meaningful when they could be due to sampling variability. Therefore, employing permutation-based and bootstrapping techniques to assess the significance of inter-group differences ensures that the moderating effects of demographic variables are rigorously validated (Hernández-Perlines, 2016).

6.1.2 Steps to Conduct PLS-MGA

PLS-MGA is a non-parametric technique that examines whether path coefficients in a PLS-SEM model significantly differ across different groups (e.g., gender, age, education). This helps in understanding whether demographic factors moderate the relationships in the model.

6.1.2.1 Data Preparation and Grouping

The first step in conducting a Multi-Group Analysis (PLS-MGA) involves preparing the dataset and defining the groups for comparison. This begins with identifying the moderator variable, such as gender, income, or education, which will be used to segment the data. Once the moderator is selected, the dataset is divided into two or more groups based on relevant categories; for this objective, investor demographics, namely gender, marital status, income, age, education, occupation and investment experience, are used as moderators for the relationship between behavioural biases and investment decisions.

6.1.2.2 Measurement Model Assessment

The Measurement Model Assessment ensures that the constructs are valid and reliable before proceeding with the Multi-Group Analysis (PLS-MGA). This step involves evaluating internal consistency reliability, convergent validity, and discriminant validity across groups. Internal consistency is assessed using Cronbach's alpha and Composite Reliability (CR) to confirm that items within a construct consistently measure the same concept. Convergent validity is checked through Average Variance Extracted (AVE), ensuring that each construct explains sufficient variance in its indicators. Additionally, discriminant validity is verified using the Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio (HTMT) to confirm that constructs are distinct. A robust measurement model is crucial for conducting PLS-MGA to compare structural relationships across different demographic groups.

6.2 Multi-Group Moderation Analysis

6.2.1 The Moderating Effect of Gender

The following hypothesis is examined using the group moderation effect:

H9: Gender significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors

Table 6.1: Gender vs Behavioural Biases and Investment Decisions

Hypothesis	Path Analysis	Path Coefficient Male	Path Coefficient Female	Diff in the impact (Male-Female)	P-value
H9a	Heuristic Bias -> Investment Decisions	0.173	0.480	-0.318	0.017
H9b	Prospect Bias -> Investment Decisions	0.596	0.246	0.339	0.000
H9c	Herding Bias -> Investment Decisions	0.156	0.240	-0.089	0.186
H9d	Market Forces Bias -> Investment Decisions	0.264	0.141	0.138	0.075

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

H9a: Gender significantly moderates the relationship between the Heuristic bias and investment decisions of the individual investors

The effect of heuristic bias is significantly stronger for female investors (0.480) compared to male investors (0.173), with a negative difference (-0.318) and a significant p-value (0.017). Female investors appear more influenced by heuristics in their investment decisions. This suggests they may rely more on mental shortcuts or intuitive judgments.

H9b: Gender significantly moderates the relationship between the Prospect bias and investment decisions of the individual investors

Prospect bias has a much stronger impact on male investors (0.596) compared to female investors (0.246)**,** with a positive and highly significant difference (0.339, p = 0.000)**.** Male investors are more sensitive to potential gains/losses, indicating they may exhibit stronger emotional responses to loss aversion or risk seeking in investment decisions.

H9c: Gender significantly moderates the relationship between the Herding bias and investment decisions of the individual investors

The influence of herding bias is slightly stronger among female investors (0.240) than male investors (0.156), but this difference is not statistically significant (p = 0.186). Both genders may be equally susceptible to following crowd behaviour, with no strong evidence of gender-based moderation.

H9d: Gender significantly moderates the relationship between the market forces bias and investment decisions of the individual investors

Market forces bias impacts male investors (0.264) more than female investors (0.141). The difference approaches significance ($p = 0.075$) but is not statistically conclusive. There may be a tendency for males to respond more to market signals and trends, but further investigation is needed.

Thus, the investment decision-making of female investors is more strongly influenced by heuristic bias, whereas male investors are more significantly influenced by prospect bias. In the case of herding bias and market forces bias, the impact on investment decisions appears similar across both genders, with no statistically significant difference observed.

6.2.2 The Moderating Effect of Marital status

The following hypothesis is examined using the group moderation effect:

H10: Marital status significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors

Table 6.2: Marital Status vs Behavioural Biases and Investment Decisions

Hypothesis	Path Analysis	Path Coefficient Unmarried	Path Coefficient Married	Diff in the impact (UM-M)	P-value
H10a	Heuristic Bias -> Investment Decisions	0.454	0.261	0.190	0.104
H10b	Prospect Bias -> Investment Decisions	0.500	0.351	0.158	0.132
H10c	Herding Bias -> Investment Decisions	0.094	0.290	-0.197	0.002
H10d	Market Forces Bias -> Investment Decisions	0.179	0.162	0.027	0.748

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

H10a: Marital status significantly moderates the relationship between the Heuristic bias and investment decisions of the individual investors

The influence of heuristic bias is stronger among female investors (0.480) than male investors (0.173), and this difference is statistically significant (p = 0.017). Gender moderates the effect of heuristic bias on investment decisions, with female investors being more prone to rely on mental shortcuts or judgments than their male counterparts.

H10b: Marital status significantly moderates the relationship between the Prospect bias and investment decisions of the individual investors

Prospect bias impacts unmarried investors (0.500) more than married investors (0.351), but the difference is also not statistically significant (p = 0.132). Therefore, marital status does not significantly moderate this relationship.

H10c: Marital status significantly moderates the relationship between the Herding bias and investment decisions of the individual investors

The effect of herding bias is significantly stronger among married investors (0.290) compared to unmarried investors (0.094), and the difference is statistically significant (p = 0.002). This indicates that marital status moderates the relationship, with married investors being more influenced by the social information of others.

H10d: Marital status significantly moderates the relationship between the market forces bias and investment decisions of the individual investors

The impact is slightly higher for unmarried investors (0.179) than for married investors (0.162). Still, this difference is negligible and not statistically significant (p = 0.748), suggesting no moderating role of marital status.

For heuristic bias, prospect bias, and market forces bias, the differences in impact between married and unmarried investors are not statistically significant, indicating that marital status does not moderate these relationships meaningfully. Herding bias has a significantly greater influence on married investors' investment decisions than on unmarried investors.

6.2.3 The Moderating Effect of Age

The interaction moderation effect is used to examine the moderation effect of the interaction between age and the different behavioural biases, and moderation is said to exist if the slope coefficients of the interaction variable (age* behavioural bias) are found statistically significant. The following hypothesis is examined using the interaction moderation effect:

H11: Age of the investors significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors

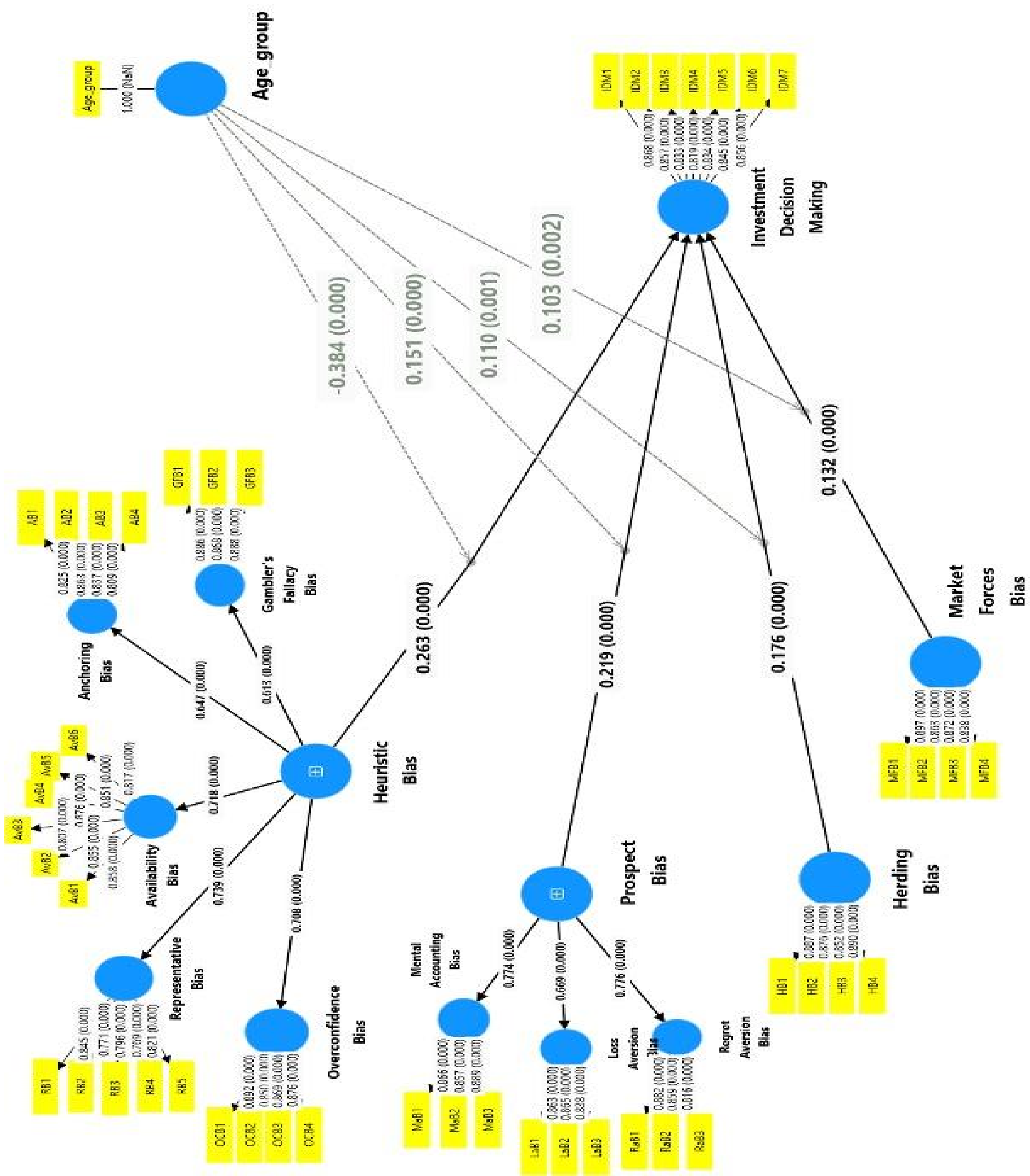

Figure 6.1: Moderation effect of Age (Interaction Model)

Table 6.3: Age vs Behavioural Biases and Investment Decisions

Path Analysis		**Path Coefficient**	**Standard deviation**	**T statistics**	**p values**
Heuristic Bias -> Investment Decisions		0.266	0.035	7.411	0.000
Prospect _Bias -> Investment Decisions		0.215	0.033	6.625	0.000
Herding Bias -> Investment Decisions		0.178	0.031	5.583	0.000
Market Forces Bias -> Investment Decisions		0.137	0.030	4.415	0.000
Hypothesis	Moderation Analysis				
H11a	Age x Heuristic Bias -> Investment Decisions	-0.384	0.032	12.060	0.000
H11b	Age x Prospect Bias -> Investment Decisions	0.149	0.030	5.046	0.000
H11c	Age x Herding Bias -> Investment Decisions	0.115	0.032	3.483	0.001
H11d	Age x Market Forces Bias -> Investment Decisions	0.101	0.032	3.240	0.002
Age -> Investment Decision		-0.063	0.034	1.834	0.070

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

All four behavioural biases significantly impact investment decision-making. Among them, heuristic bias exerts the strongest influence with ($\beta = 0.266$, $p < 0.001$), followed by prospect bias, herding bias, and market forces bias.

H11a: Age significantly moderates the relationship between the Heuristic bias and investment decisions of the individual investors

This relationship is statistically significant (Path Coefficient = 0.266, p = 0.000)**,** with the highest path coefficient among all biases, indicating that heuristic bias strongly influences investment decisions. Investors are likely using mental shortcuts or intuitive judgments when making financial investments.

H11b: Age significantly moderates the relationship between the Prospect bias and investment decisions of the individual investors

This is also a statistically significant relationship **(**Path Coefficient = 0.215, p = 0.000)**.** A relatively high path coefficient suggests that loss aversion and framing of investment opportunities have a considerable impact on investors' decisions. However, the influence is slightly lower than that of heuristic bias.

H11c: Age significantly moderates the relationship between the Heding bias and investment decisions of the individual investors

With a significant p-value and moderate path coefficient (Path Coefficient = 0.178, p = 0.000)**,** herding bias shows that following others' behaviour plays a notable role in shaping investment decisions.

H11d: Age significantly moderates the relationship between the Market forces bias and investment decisions of the individual investors

Although the path coefficient (Path Coefficient = 0.137, p = 0.000) is the lowest among the four, the relationship is still statistically significant. This implies that external market trends and macroeconomic factors affect decisions, but to a lesser extent than internal cognitive biases.

All four behavioural biases significantly impact investment decisions. Among them, heuristic bias exerts the strongest influence, followed by prospect bias**,** herding bias, and market forces bias. The relationship between age and investment decisions is negative but not statistically significant at the 5% level (β = -0.063, SE = 0.034, t = 1.834, p = 0.070). This suggests that older investors tend to have a slightly lower tendency in investment decisions, although the effect is marginal.

6.2.4 The Moderating Effect of Education

The following hypothesis is examined using the group moderation effect:

H12: Education significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors

Table 6.4: Education vs Behavioural Biases and Investment Decisions

Hypothesis	Path Analysis	Comparison	Path Coefficient	p-value
H12a	Heuristic Bias -> Investment Decisions	Graduate vs Postgraduate	-0.159	0.091
		Graduate vs Professional	0.365	0.004
		Post Graduate vs Professional	0.524	0.000
H12b	Prospect Bias -> Investment Decisions	Graduate vs Postgraduate	-0.067	0.451
		Graduate vs Professional	-0.243	0.017
		Post Graduate vs Professional	-0.176	0.122
H12c	Herding bias -> Investment Decisions	Graduate vs Postgraduate	0.198	0.013
		Graduate vs Professional	-0.034	0.708
		Post Graduate vs Professional	-0.232	0.010
H12d	Market Forces Bias -> Investment Decisions	Graduate vs Postgraduate	0.148	0.045
		Graduate vs Professional	0.012	0.909
		Post Graduate vs Professional	-0.136	0.212

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

H12a: Education significantly moderates the relationship between the Heuristics bias and investment decisions of the individual investors

Negative moderation effect (β = -0.159, p = 0.091) is significant at 5 %, for Graduate vs Post Graduate, suggesting that the influence of heuristic bias on investment decisions is slightly weaker for postgraduates compared to graduates.

A positive and significant moderation effect (β = 0.365, p = 0.004) for Graduate vs Professional is found, indicating that heuristic bias has a stronger impact on professionals' investment decisions than graduates.

A positive and highly significant moderation effect (β = 0.524, p = 0.000) for Post Graduate vs Professional shows that professionals are more influenced by heuristic bias in their investment decisions than postgraduates.

H12b: Education significantly moderates the relationship between the Prospect bias and investment decisions of the individual investors

Negative but non-significant moderation effect (β = -0.067, p = 0.451) is found for Graduate vs Post Graduate, indicating no meaningful difference between graduates and postgraduates.

Negative and significant moderation effect (β = -0.243, p = 0.017) is found for Graduate vs Professional, suggesting professionals experience a weaker influence of prospect bias on their investment decisions than graduates.

Negative but not statistically significant (β = -0.176, p = 0.122) is found for Post Graduate vs Professional, implying no significant difference between postgraduates and professionals.

H12c: Education significantly moderates the relationship between the Herding bias and investment decisions of the individual investors

A positive and significant moderation effect (β = 0.198, p = 0.013) is found for Graduate vs Post Graduate, meaning herding bias has a stronger impact on postgraduates' investment decisions than graduates.

A non-significant moderation effect (β = -0.034, p = 0.708) is found for Graduate vs Professional, indicating no difference between graduates and professionals.

Negative and significant moderation effect (β = -0.232, p = 0.010), indicating that professionals are less influenced by herding bias than postgraduates for the Post Graduate vs Professional comparison.

H12d: Education significantly moderates the relationship between the Market forces bias and investment decisions of the individual investors

A positive and significant moderation effect (β = 0.148, p = 0.045) is found for Graduate vs Post Graduate, suggesting market forces bias affects postgraduates' investment decisions more than graduates.

A non-significant moderation effect for Graduate vs Professional (β = 0.012, p = 0.909) indicates no difference between graduates and professionals.

A negative but non-significant moderation effect (β = -0.136, p = 0.212), that is, no significant difference between postgraduates and professionals, is found for the Post Graduate vs Professional category.

Thus, Professionals tend to be more influenced by heuristic bias than graduates and postgraduates. Postgraduates show stronger effects of herding bias and market forces bias than graduates. The impact of prospect bias is weaker for professionals compared to graduates. Many differences between groups are non-significant, indicating some biases affect education segments similarly.

6.2.5 The Moderating Effect of Occupation

The following hypothesis is examined using the group moderation effect:

H13: Occupation significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors

Table 6.5: Occupation vs Behavioural Biases and Investment Decisions

Hypothesis	Path Analysis	Comparison	Path Coefficient	p-value
H13a	Heuristic Bias -> Investment Decisions	Pvt employee vs Govt employee	0.136	0.043
		Pvt Employee vs Business/Self employed	0.035	0.677
		Govt employee vs Business/Self employed	-0.102	0.162
H13b	Prospect Bias -> Investment Decisions	Pvt employee vs Govt employee	0.204	0.000
		Pvt Employee vs Business/Self employed	0.007	0.919
		Govt employee vs Business/Self employed	-0.198	0.005
H13c	Herding bias -> Investment Decisions	Pvt employee vs Govt employee	-0.505	0.000
		Pvt Employee vs Business/Self employed	0.660	0.000
		Govt employee vs Business/ Self employed	1.165	0.000
H13d	Market Forces Bias -> Investment Decisions	Pvt employee vs Govt employee	0.136	0.004
		Pvt Employee vs Business/ Self employed	-0.047	0.584
		Govt employee vs Business/ Self employed	-0.183	0.000

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

H14a: Occupation significantly moderates the relationship between the Heuristic bias and investment decisions of the individual investors

The path coefficient ($\beta = 0.136$, $p = 0.043$) indicates a statistically significant difference between Private and Government Employees. Private employees are more influenced by heuristic bias in investment decisions than government employees. This may reflect the private sector's fast-paced, goal-driven nature, where heuristic shortcuts are more commonly used for quick decisions.

The difference in the Private vs Business /self-employed segment is not statistically significant (β = 0.035, p = 0.677), indicating a similar influence of heuristic bias on both groups.

The government vs Business/self-employed relationship is also insignificant (β = -0.102, p = 0.162), suggesting that while government employees show slightly lower heuristic influence than business professionals, the gap is not statistically strong.

H14b: Occupation significantly moderates the relationship between the Prospect bias and investment decisions of the individual investors

A strong and significant positive effect is observed (β = 0.204, p = 0.000) in the Private vs Government Employees comparison, meaning private employees are considerably more influenced by prospect bias, that is, by risk framing, loss aversion, than government employees.

No significant difference (β = 0.007, p = 0.919) was found between Private vs Business/self-employed, suggesting both private and business/ self-employed are equally affected by prospect bias.

A statistically significant negative difference (β = -0.198, p = 0.005) was found between Government vs Business/ self-employed, indicating that the business/ self-employed segment is more influenced by prospect bias than government employees.

H14c: Occupation significantly moderates the relationship between the Herding bias and investment decisions of the individual investors

A strong and significant negative effect (β = -0.505, p = 0.000) was found among Private vs Government Employees, suggesting that government employees are far more influenced by herding behaviour than private employees. This may be due to institutional thinking or conservative investment patterns common among government workers.

The difference is strongly positive and significant among Private vs Business/ self-employed (β = 0.660, p = 0.000), indicating business/ self-employed are more influenced by herding bias than private employees.

The highest and most significant difference was found among Government vs Business/ self-employed (β = 1.165, p = 0.000), which shows business/ self-employed are the most prone to herding behaviour**,** possibly due to competitive pressure and market-driven decision environments.

H14d: Occupation significantly moderates the relationship between the market forces bias and investment decisions of the individual investors

A significant positive difference was found in the Private vs Government Employees segment ($\beta = 0.136$, $p = 0.004$), which shows that private employees are more sensitive to market-related cues and external factors than government employees when making investment decisions.

The difference is insignificant for Private vs Business/ self-employed ($\beta = -0.047$, $p = 0.584$), indicating similar levels of influence by market forces bias between these groups.

A statistically significant negative difference was found among Government vs Business/ self-employed ($\beta = -0.183$, $p = 0.000$), suggesting that business/ self-employed are more influenced by market forces bias than government employees.

Therefore, the influence of heuristic bias is significantly higher among private employees than government employees, but it is similar to that of business/ self-employed. Government employees are least influenced by prospect bias, while private and business/ self-employed individuals are significantly more affected. Business/ self-employed individuals are highly susceptible to herding bias, followed by government employees, with private employees the least influenced. Government employees are least impacted by market forces bias, while private employees and business/ self-employed are more attuned to market signals.

6.2.6 The Moderating Effect of Income

The following hypothesis is examined using the group moderation effect:

H14: Income significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors

Table 6.6: Income vs Behavioural Biases and Investment Decisions

Hypothesis	**Path Analysis**	**Path Coefficient less than 50k**	**Path Coefficient Above 50k**	**Diff in the impact (less than 50 k – above 50k)**	**p-value**
H14a	Heuristic Bias -> Investment Decision Making	0.117	0.053	0.064	0.005
H14b	Prospect Bias -> Investment Decision Making	0.450	0.048	0.402	0.001
H14c	Herding Bias -> Investment Decision Making	0.200	0.042	0.158	0.751
H14d	Market Forces Bias -> Investment Decision Making	0.139	0.050	0.089	0.557

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

H14a: Income significantly moderates the relationship between the Heuristic bias and investment decisions of the individual investors

The effect of heuristic bias is significantly stronger among investors earning less than ₹50,000 (path coefficient = 0.117) compared to those earning above ₹50,000 (path coefficient = 0.053), with a difference of 0.064 that is statistically significant (p = 0.005). This indicates that income level moderates the relationship, with lower-income investors being more prone to relying on cognitive shortcuts like anchoring and availability when making investment decisions.

H14b: Income significantly moderates the relationship between the Prospect bias and investment decisions of the individual investors

The influence of prospect bias is markedly higher for investors earning less than ₹50,000 (path coefficient = 0.450) than for those earning above ₹50,000 (path coefficient = 0.048). The difference of 0.402 is highly significant (p = 0.001).

This suggests that lower-income investors are more affected by loss aversion and risk perception, highlighting a strong moderation effect of income in the relationship between prospect bias and investment decisions.

H14c: Income significantly moderates the relationship between the Herding bias and investment decisions of the individual investors

The effect of herding bias is higher among lower-income investors (path coefficient = 0.200) compared to higher-income investors (path coefficient = 0.042); the difference of 0.158 is not statistically significant (p = 0.751). This implies that income does not significantly moderate the impact of herding bias on investment decisions, and both income groups appear similarly influenced by social cues and peer behaviour.

H14d: Income significantly moderates the relationship between the Market forces bias and investment decisions of the individual investors

The influence of market forces bias is stronger for investors earning less than ₹50,000 (path coefficient = 0.139) than for those earning above ₹50,000 (path coefficient = 0.050), but the difference of 0.089 is not statistically significant (p = 0.557).

This indicates that income does not significantly moderate this relationship, and both income groups are comparably responsive to external market signals like economic trends and news.

Income significantly moderates the impact of heuristic and prospect biases, with lower-income investors more strongly influenced by these cognitive and emotional biases. However, income does not significantly affect the effect of herding or market forces biases on investment decisions.

6.2.7 The Moderating Effect of Investment Experience

The following hypothesis is examined using the group moderation effect:

H15: Investment experience significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors

Table 6.7: Investment Experience vs Behavioural Biases and Investment Decision

Hypothesis	**Path Analysis**	**Path Coefficient less than 3 years**	**Path Coefficien3 to 5 years**	Diff **in the impact (less than 3 years – 3 to 5 years)**	**p-value**
H15a	Heuristic Bias -> Investment Decisions	0.298	0.183	0.127	0.060
H15b	Prospect Bias -> Investment Decisions	0.350	0.250	0.100	0.186
H15c	Herding Bias -> Investment Decisions	0.088	0.295	-0.214	0.001
H15d	Market Forces Bias -> Investment Decisions	0.183	0.168	0.016	0.797

Source: Primary Data
Significance is evaluated at a 5% level ($p < 0.05$)

H15a: Investment experience significantly moderates the relationship between the Heuristic bias and investment decisions of the individual investors

The influence of heuristic bias is stronger among investors with less than 3 years of experience (path coefficient = 0.298) compared to those with 3 to 5 years of experience (path coefficient = 0.183). Still, the difference of 0.127 is only marginally significant (p = 0.060). This indicates that investment experience may moderately influence the reliance on mental shortcuts, with less experienced investors showing greater susceptibility to heuristic-driven decision making.

H15b: Investment experience significantly moderates the relationship between the Prospect bias and investment decisions of the individual investors

The impact of prospect bias is higher for investors with less than 3 years of experience (path coefficient = 0.350) than those with 3 to 5 years (path coefficient = 0.250), but the difference of 0.100 is not statistically significant (p = 0.186). This suggests that investment experience does not significantly moderate the effect of prospect bias, and both groups are influenced similarly by loss aversion and risk framing.

H15c: Investment experience significantly moderates the relationship between the Herding bias and investment decisions of the individual investors

The influence of herding bias is significantly stronger among investors with 3 to 5 years of experience (path coefficient = 0.295) than those with less than 3 years (path coefficient = 0.088), and the difference of -0.214 is statistically significant (p = 0.001). This indicates that investment experience moderates the relationship, with more experienced investors being more influenced by the decisions and behaviour of others in the market.

H15d: Investment experience significantly moderates the relationship between the Market forces bias and investment decisions of the individual investors

The impact of market forces bias is slightly higher among investors with less than 3 years of experience (path coefficient = 0.183) than those with 3 to 5 years (path coefficient = 0.168). Still, the difference of 0.016 is not statistically significant (p = 0.797). This confirms that investment experience does not significantly moderate this relationship, and both groups respond similarly to external cues such as economic trends and market movements while making investment decisions.

Herding bias is significantly more influential among moderately experienced investors (3–5 years). Heuristic bias shows marginal moderation, with less experienced investors more affected. Prospect and market forces biases are not significantly moderated by investment experience; both groups respond similarly to these influences.

6.3 Findings

This objective explored the moderating effects of demographic factors on the relationship between behavioural biases and investment decisions among individual investors. The significant demographic moderators identified include gender, marital status, age, educational background, investors' occupation, and income level.

H9: The investment decisions of female investors are more strongly influenced by heuristic bias, whereas male investors are more significantly influenced by prospect bias. In the case of herding bias and market forces bias, the impact on investment decisions appears similar across both genders, with no statistically significant difference observed.

H10: For heuristic bias, prospect bias, and market forces bias, the differences in impact between married and unmarried investors are not statistically significant, indicating that marital status does not moderate these relationships meaningfully. Herding bias has a significantly greater influence on the investment decision-making of married investors than unmarried investors.

H11: All four behavioural biases significantly impact investment decisions through a direct relationship. Among them, heuristic bias exerts the strongest influence, followed by prospect bias, herding bias, and market forces bias. The relationship between age and investment decisions was negative but not statistically significant.

H12: Professionals tend to be more influenced by heuristic bias than graduates and postgraduates. Postgraduates show stronger effects of herding bias and market forces bias than graduates. The impact of prospect bias is weaker for professionals compared to graduates.

H13: The influence of heuristic bias is significantly higher among private employees than government employees. Government employees are least influenced by prospect bias, while private and business/self-employed individuals are significantly more affected. Business/ self-employed individuals are highly susceptible to herding bias, followed by government employees, with private employees the least influenced. Government employees are least impacted by market forces bias, while private employees and business/ self-employed are more attuned to market signals.

H14: Income significantly moderates the impact of heuristic and prospect biases, with lower-income investors more strongly influenced by these cognitive and emotional biases. However, income does not significantly affect the effect of herding or market forces biases on investment decisions.

H15: Herding bias exerts a significantly stronger influence on investors with three to five years of experience. Heuristic bias demonstrates marginal moderation, being more impactful among less experienced investors. In contrast, investment experience does not significantly moderate the effects of prospect bias and market forces bias, as both investment experience groups exhibit similar responses to these factors.

6.4 Summary

The chapter examines how demographic factors moderate the relationship between behavioural biases and investment decisions. Gender influences heuristic and prospect biases, with women affected more by heuristics and men by prospect biases. Married investors exhibit stronger herding bias, while all age groups moderate biases. Education impacts susceptibility, with graduates more prone to herding and heuristic biases and professionals to prospect bias. Private sector employees and business/self-employed individuals are most influenced by herding and market forces, while lower-income investors respond more to prospect bias. Investors with 3 to 5 years of experience show stronger herding tendencies. These findings highlight the need for tailored investment strategies.

CHAPTER 7

FINDINGS AND CONCLUSION

This study explores the influence of behavioural biases on individual investors' investment decisions. It also examines the moderating role of financial literacy and investor demographics in the relationship between behavioural biases and investment decisions. The first five chapters of this thesis establish the research foundation, provide an in-depth literature review, outline the research methodology, and employ PLS-SEM for data analysis to evaluate the investment decision model.

7.1 Summary of the Hypotheses

Table 7.1: Results of Hypothesis Testing

Hypotheses	Hypotheses	Supported / Not supported
Objective 1: Hypothesis examining the influence of Behavioural Biases on Investment Decisions of individual investors.		
H1	Heuristic Bias significantly influences the investment decisions of individual investors	Supported
H2	Prospect Bias significantly influences the investment decisions of individual investors	Supported
H3	Herding bias significantly influences the investment decisions of individual investors	Supported
H4	Market forces bias Heuristic Bias significantly influences the investment decisions of individual investors	Supported
Objective 2: Hypothesis examining the moderating effect of financial literacy on the relationship between behavioural biases and investment decisions.		
H5	Financial literacy significantly moderates the relationship between heuristic bias and investment decisions of individual investors	Supported

H6	Financial literacy significantly moderates the relationship between prospect bias and investment decisions of individual investors	Supported
H7	Financial literacy significantly moderates the relationship between herding bias and investment decisions of individual investors	Not Supported
H8	Financial literacy significantly moderates the relationship between market forces bias and investment decisions of individual investors	Not Supported
Objective 3: Hypotheses examining the moderating role of investor demographics in the relationship between Behavioural biases and investment decisions.		
H9	*Gender significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors*	
H9a	Gender significantly moderates the relationship between heuristic bias and investment decisions of individual investors.	Supported
H9b	Gender significantly moderates the relationship between heuristic bias and investment decisions of individual investors.	Supported
H9c	Gender significantly moderates the relationship between heuristic bias and investment decisions of individual investors.	Not supported
H9d	Gender significantly moderates the relationship between heuristic bias and investment decisions of individual investors.	Not supported
H10	*Marital status significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors*	
H10a	Marital status significantly moderates the relationship between heuristic bias and investment decisions of individual investors.	Not supported

H10b	Marital status significantly moderates the relationship between heuristic bias and investment decisions of individual investors.	Not supported
H10c	Marital status significantly moderates the relationship between heuristic bias and investment decisions of individual investors.	Supported
H10d	Marital status significantly moderates the relationship between heuristic bias and investment decisions of individual investors.	Not supported
H11	*Age significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors*	
H11a	Age significantly moderates the relationship between heuristic bias and investment decisions of individual investors.	Supported
H11b	Age significantly moderates the relationship between prospect bias and investment decisions of individual investors.	Supported
H11c	Age significantly moderates the relationship between herding bias and investment decisions of individual investors.	Supported
H11d	Age significantly moderates the relationship between market forces bias and investment decisions of individual investors.	Supported
H12	*Education significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors*	
H12a	Education significantly moderates the relationship between the heuristic bias and investment decisions of the individual investors.	Partially Supported
H12b	Education significantly moderates the relationship between the prospect bias and investment decisions of the individual investors.	Partially Supported
H12c	Education significantly moderates the relationship between the herding bias and investment decisions of the individual investors.	Partially Supported

H12d	Education significantly moderates the relationship between the market forces bias and investment decisions of the individual investors.	Partially Supported
H13	*Occupation significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors*	
H13a	Occupation significantly moderates the relationship between the heuristic bias and investment decisions of the individual investors.	Partially Supported
H13b	Occupation significantly moderates the relationship between the prospect bias and investment decisions of the individual investors.	Partially Supported
H13c	Occupation significantly moderates the relationship between the herding bias and investment decisions of the individual investors.	Fully Supported
H13d	Occupation significantly moderates the relationship between the market forces bias and investment decisions of the individual investors.	Partially Supported
H14	*Income significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors*	
H14a	Income significantly moderates the relationship between the heuristic bias and investment decisions of the individual investors.	Supported
H14b	Income significantly moderates the relationship between the prospect bias and investment decisions of the individual investors.	Supported
H14c	Income significantly moderates the relationship between the herding bias and investment decisions of the individual investors.	Not supported
H14d	Income significantly moderates the relationship between the market forces bias and investment decisions of the individual investors.	Not supported

H15	*Investment experience significantly moderates the relationship between the behavioural biases and investment decisions of the individual investors*	
H15a	Investment experience significantly moderates the relationship between the heuristic bias and investment decisions of the individual investors.	Not supported
H15b	Investment experience significantly moderates the relationship between the prospect bias and investment decisions of the individual investors.	Not supported
H15c	Investment experience significantly moderates the relationship between the herding bias and investment decisions of the individual investors.	Supported
H15d	Investment experience significantly moderates the relationship between the market forces bias and investment decisions of the individual investors.	Not supported

Compiled by the Researcher

7.2 Key Findings

Objective 1: To analyse the influence of behavioural biases on the investment decisions of individual investors.

This first objective examined the influence of behavioural biases, namely heuristic bias, prospect bias, herding bias and market forces bias on investment decisions of individual investors in the states of Maharashtra, Goa and Karnataka. To analyse the data, PLS -SEM, Importance-Performance Map Analysis (IPMA), and Necessary Condition Analysis (NCA) were employed. The findings from these analyses are presented below:

7.2.1 Behavioural Biases and Investment Decisions

7.2.1.1 Heuristic Bias and Investment Decisions

Individual investors rely on heuristic methods to simplify investment decisions, often focusing on individual stock price movements while overlooking broader market trends and context. This heuristic processing can limit the scope of alternatives considered and reduce the accuracy of investment decisions. The study identifies five prominent heuristic biases, overconfidence, representativeness, availability, anchoring, and the gambler's fallacy, that significantly influence investment behaviour. These biases lead to flawed assessments, over-reliance on mental shortcuts, and the establishment of unrealistic anchors in decisions. Although biases influence investors, they are often not acknowledged or controlled when making investment decisions. However, there's a positive side; these biases motivate investors to take action, like investing in the stock market, rather than avoiding it entirely. The findings of this study align with previous research by Jain et al. (2021) which similarly emphasise the impact of heuristic biases on investment decisions.

7.2.1.2 Prospect Bias and Investment Decisions

Prospect theory is central to understanding investment decisions, particularly in framing potential outcomes. Investors tend to emphasise avoiding losses more than acquiring gains, a bias known as loss aversion. The study highlights the influence of prospect bias as a relevant bias in shaping decisions in the study, with investors often overweighing the disutility of losses relative to the utility of equivalent gains. Prospect bias is also the foremost influencer in the investment decision process, according to a recent study by Abhijith and Bijulal (2025). This tendency is consistent with the findings of Cao et al. (2021). This bias can lead investors to make overly cautious decisions, such as holding on to losing investments to avoid losses or prematurely selling winning investments due to the fear of potential losses.

7.2.1.3 Herding Bias and Investment Decisions

While investment decisions ideally should be based on thorough fundamental analysis, the tendency for investors to engage in herding behaviour often skews their judgment. Herding occurs when individuals follow the actions of others, driven by the desire to avoid being left behind or due to a lack of confidence in their analysis. This bias can be extreme in environments of uncertainty, where investors feel reassured by the actions of others, even when these decisions are not rooted in sound analysis. The findings of this study are in line with the work of Rahayu et al. (2021) and Hayat and Anwar (2016), who observed that herding behaviour is often motivated by reputational concerns or a lack of independent knowledge. Investors may feel compelled to follow the crowd, leading to market inefficiencies, asset bubbles, or sudden market corrections.

7.2.1.4 Market Forces Bias and Investment Decisions

Market forces bias refers to the tendency for investors to focus on broader macroeconomic trends or market movements, often at the expense of company-specific factors. This bias can lead to irrational decisions as investors may place too much weight on general market conditions rather than analysing the fundamentals of individual investments. Market volatility or periods of economic uncertainty lead investors to make decisions based on overall market sentiment rather than assessing specific companies' strengths or weaknesses. The study's findings are consistent with the research of Jain and Kesari (2022), highlighting how market-wide forces, rather than company-specific factors, can lead to suboptimal investment decisions. Focusing too heavily on market trends can prevent investors from overlooking the long-term growth potential of individual stocks, ultimately leading to poor investment decisions.

7.2.1.5 Importance-Performance Map Analysis and Behavioural Biases

This study provides significant insights into the impact of various behavioural biases on Individual investors' decisions, utilising Importance-Performance Map Analysis (IPMA) to assess the importance and performance of these biases.

Prospect Bias emerges as the most critical factor, aligning with Prospect Theory (Kahneman, 1979). While it has the highest degree of importance, a moderate performance score indicates that it often leads to suboptimal investments, such as holding onto losses or prematurely selling gains, limiting potential returns. Herding Bias, though slightly less influential, significantly affects investment decisions. IPMA findings highlight its lower performance score, suggesting that crowd-following behaviours often result in reactive and sentiment-driven decisions, consistent with studies by Bikhchandani et al. (1992), Bikhchandani & Sharma, (2000) and Shiller (2000). Heuristic Bias, including overconfidence and representativeness, shows high importance but lower performance. IPMA confirms that reliance on mental shortcuts frequently leads to poor risk assessments and excessive trading, as noted by Tversky and Kahneman (1974) and Barber and Odean (2013). Market Forces Bias, while less theoretically significant, demonstrates strong practical relevance. IPMA highlights its influence during periods of market-wide optimism or fear, where macroeconomic trends overshadow company-specific fundamentals, supporting findings by Jain and Kesari (2022).

7.2.1.6 Necessary Condition Analysis and Behavioural Biases

The impact of behavioural biases on investment decisions through a combined PLS-SEM and Necessary Condition Analysis (NCA) approach is analysed. PLS-SEM confirms that behavioural biases such as herding bias, heuristic bias, market forces bias, and prospect bias significantly influence investment decisions. (Jain et al., 2023), and Nguyen et al. (2021) Rahayu et al. (2021) and Hayat and Anwar (2016), Jain and Kesari (2022) highlight that beyond their statistical significance, some investment decisions would not happen at all unless the investor experienced a certain level of bias, without a minimum level of overconfidence or herding, the investor might not take the courage to invest.

The findings of the first objective highlight the dual role of behavioural biases; they influence investor behaviour and act as essential precursors to certain investment decisions, suggesting that some financial actions may rely on a minimum level of bias to be initiated.

Objective 2: To examine the moderating effect of financial literacy on the relationship between behavioural biases and investment decisions.

This objective analysed the moderating role of financial literacy to determine whether individual investors with higher levels of financial literacy are less influenced by behavioural biases when making investment decisions. An interaction moderating model was adopted to assess the strength and direction of the relationship between the behavioural biases and investment decisions.

7.2.2 Financial Literacy, Behavioural Biases and Investment Decisions

The financial literacy of the individual investors in this study was low. This finding aligns with previous research by Arianti (2018), Subedi (2023), Thapa and Kc (2020), and Arif (2015), all of whom reported low levels of financial literacy among investors. Financial literacy negatively moderates the relationship between heuristic bias and investment decisions. This negative path coefficient indicates that when financial literacy is low, the influence of heuristic bias on investment decisions is stronger. Investors with a low financial literacy level are more prone to relying on heuristics, such as mental shortcuts or rules of thumb, which can lead to suboptimal or biased investment decisions.

This study's findings align with the inverse of those reported by Lusardi and Mitchell (2014), Suresh (2024), Wijaya et al. (2023) and Alessie et al. (2011), who found that high financial literacy is associated with reduced behavioural biases and better financial decisions. In contrast, the current study finds that low levels of financial literacy increase investors' reliance on heuristic biases, such as overconfidence, anchoring, and representativeness, during investment decision-making.

Investors with lower financial literacy are less influenced by how potential outcomes are framed or presented. In other words, prospect bias has a weaker impact on the investment decisions of individuals with low financial literacy than on those with higher financial literacy.

This finding contradicts the argument that financially knowledgeable individuals have greater risk awareness, making them more cautious when evaluating financial opportunities. Additionally, studies by Bhandari et al. (2008), Khan and Islam (2023) indicate that while financial literacy enhances decision-making, it does not entirely eliminate loss aversion, as even well-informed investors exhibit biases when investing.

Financial literacy does not significantly moderate the relationship between herding bias and investment decision-making, implying that even financially literate investors may follow others' actions. Prior research supports this observation, as herding behaviour is often driven by social influences, media coverage, and investor sentiment rather than purely rational financial analysis and is not moderated by financial literacy (Ranaweera & Kawshala, 2022). Even sophisticated financial investors may herd due to psychological pressure, market rumours, and uncertainty during volatile periods (Sias, 2004), Wijaya et al. (2023)

Financial literacy does not significantly affect the relationship between market forces bias and investment decision-making, indicating that external market conditions impact investors uniformly, regardless of their financial literacy level. This finding aligns with studies suggesting that macroeconomic factors affect experienced and novice investors, as even highly knowledgeable investors adjust their portfolios based on external financial signals (Nathrah, 2016). This is the opposite of findings by Suresh (2024), Ashfaq et al. (2024)

Lastly, financial literacy alone does not directly impact investment decisions. This suggests that financial knowledge, behaviour, and attitudes influence investment decisions primarily by interacting with behavioural biases rather than as an independent factor. Previous studies by Ashfaq et al. (2024), Wijaya et al. (2023), Adil et al. (2022), and Baihaqqy et al. (2020) indicate that financial literacy directly impacts investment decisions of individual investors.

Objective 3: To study the moderating role of investor demographics in the relationship between behavioural biases and investment decisions for an individual investor.

This objective studied the moderating role of investor demographics in the relationship between behavioural biases and investment decisions by employing the Multi-Group Analysis (MGA) to identify differences across demographic groups.

7.2.3 Investor Demographics, Behavioural Biases and Investment Decisions

Females are more influenced by heuristic bias, while males exhibit stronger prospect bias in investment decisions. This aligns with previous research that highlights gender differences in behavioural biases. Studies by Mishra and Metilda (2015), Glaser and Weber (2010), Mushinada and Veluri (2018), and Bushra et al. (2024) indicate that men tend to be more overconfident, which correlates with prospect bias, as they are more prone to risk-taking and evaluating gains and losses asymmetrically. Similarly, Barber and Odean (2013), Bhandari and Deaves (2006) found that women tend to rely more on mental shortcuts while making financial decisions.

Married investors exhibit a stronger herding bias compared to unmarried investors. This is consistent with previous research that suggests marital status influences financial behaviour due to increased risk-sharing and decision-making within a household. Married investors might be more inclined to follow collective financial trends to ensure family stability, aligning with findings by Lin (2011).

All age groups moderate all biases in investment decision-making, indicating that age interacts with behavioural tendencies. Prior research supports this, with Finke and Huston (2021), who found that cognitive biases evolve with experience and maturity. Younger investors rely more on heuristics due to limited experience, while older investors may exhibit more prospect bias.

Graduates exhibit stronger herding behaviour than postgraduates, while professionally qualified investors show an even more decisive influence than postgraduates. This aligns with research indicating that formal education does not necessarily eliminate herd behaviour, as found in studies by Beyer and Bowden (1997). Similarly, heuristic bias appears stronger among graduates compared to professionally qualified investors, with postgraduates also showing a higher reliance on heuristics than professionally qualified investors. This is supported by research suggesting that advanced education enhances critical thinking, thereby reducing reliance on mental shortcuts (Mushinada and Veluri, 2018). Prospect bias is more pronounced in professionally qualified investors than graduates, implying that more profound financial knowledge makes investors more sensitive to potential gains and losses. This is consistent with studies showing that education heightens risk perception and loss aversion, reinforcing that well-informed investors tend to evaluate financial opportunities more cautiously (Lin 2011).

Private sector employees exhibit stronger herding behaviour than business owners, followed by government employees. This aligns with findings that structured work environments and institutional work culture influence employees' financial behaviour, making them more likely to follow market trends and peer actions (Sahi et al., 2013) Similarly, the study indicates, that investors with a business background are most influenced by market forces, followed by private sector employees, with government employees being the least affected. This is consistent with research showing that entrepreneurs are more responsive to market fluctuations, as they actively monitor economic trends and adapt their investment strategies accordingly (Mishra and Metilda, 2015; Mittal, 2010). These findings suggest that occupational background significantly shapes investment decision-making, with private-sector employees and business owners being more susceptible to external market signals and collective investor behaviour.

Low-income investors are more influenced by prospect bias than higher-income investors. This supports existing research, such as Mushinada and Veluri (2018), which suggests that individuals with lower incomes exhibit greater loss aversion and sensitivity to potential financial gains or losses.

Investors with 3 to 5 years of experience are more influenced by herding bias than those with less than 3 years of experience. This is consistent with research by Sahi et al. (2013) and Mishra and Metilda (2015), suggesting that intermediate investors with some experience but are not yet highly skilled tend to follow other investors more than novices or highly experienced investors.

7.3 Contribution of the Study

The study has contributed in multiple dimensions, enhancing the understanding of behavioural biases in investment decisions and providing novel insights into how demographic and financial literacy factors moderate these biases. The key contributions of the study are:

7.3.1.1 Advancing Behavioural Finance Research

The study adds to the existing literature by empirically validating the collective impact of heuristic, prospect, herding, and market forces biases on investment decisions using PLS-SEM. While previous studies have identified these biases, this study integrates them into a unified model, providing a holistic perspective on their combined influence. Additionally, the research enhances the measurement framework by refining and expanding item scales to more accurately capture the constructs, thereby improving the robustness and applicability.

7.3.1.2 Financial Literacy as a Moderator

A critical contribution of the study is demonstrating that financial literacy does not directly impact investment decisions but moderates the influence of behavioural biases. Specifically, financial literacy is low among individual investors under study. The moderating effect of financial literacy on heuristic biases was negative and significant, and positive and significant on prospect biases, which is a unique and rare finding. This understanding helps bridge the gap in the literature.

7.3.1.3 Influence of Investor Demographics

The study provides empirical evidence on how demographic factors such as gender, marital status, age, education, occupation, income, and investment experience moderate behavioural biases in investment decisions through a segmental analysis using Multi-Group Analysis through PLS-SEM.

The study contributes to behavioural finance literature by highlighting how demographic factors influence behavioural biases in investment decisions. It challenges the assumption that higher education reduces biases. By offering a segmental demographic analysis of these relationships using Multi-Group Analysis, this research fills a notable gap, where such differentiated insights across education, occupation, and income groups are limited.

7.3.1.4 Contribution to Investment Strategy

The study contributes by identifying biases that significantly impact investment decisions and which ones are underperforming based on their perceived importance, as revealed through

IPMA and NCA. This can help design investor-centric financial strategies that mitigate harmful biases while leveraging useful ones.

7.3.1.5 Theoretical Contribution to Decision-Making Models

By incorporating behavioural biases, financial literacy, and demographic moderators, the study contributes to investment decision models in behavioural finance. It enhances the existing theoretical frameworks by demonstrating how biases interact with investor characteristics, providing a refined and predictive model of investment behaviour.

7.4 Managerial Implications

This research holds notable importance for India's financial ecosystem, particularly in understanding how behavioural biases and financial literacy shape investment decisions among individual investors. It carries managerial implications for investors, financial institutions, policy-makers, and educators, providing strategic insights to strengthen rational investment practices.

- The study offers practical value for individual investors and financial advisory firms by highlighting the strong influence of biases such as heuristic bias, prospect bias, herding bias, and market forces bias. Recognising these biases can promote more informed, rational, and confident investment decisions. Financial advisors can guide their clients towards objective investment decisions.

- The study highlights the vital moderating role of financial literacy, especially with investors with low financial literacy, in shaping investment behaviour. Financial institutions, educators, and policymakers are urged to develop targeted financial literacy programs that go beyond basic concepts to address behavioural tendencies. Such initiatives can empower low-literacy investor groups towards rational financial decisions.

- A comprehensive evaluation of the moderation effect of investor demographics on behavioural biases and investment decisions enables financial service providers and investment advisors to develop investment strategies based on investor age, income, education, and investment experience, to offer more personalised and effective guidance to improve investment outcomes.

- It is recommended that financial regulators and policymakers integrate behavioural insights into investor protection mechanisms. Embedding this into regulatory frameworks and investor education campaigns can reduce market anomalies and improve overall capital market efficiency.

- Since the findings reveal that behavioural biases persist even among experienced investors, financial advisory firms are encouraged to adopt structured decision-making tools and mental shortcuts debiasing techniques in their investor relations and advisory functions to mitigate these effects.

- Managers and financial advisors can leverage structured questionnaires along with the use of empirical tools such as Structural Equation Modelling (SEM), Importance-Performance Map Analysis (IPMA), for decision-support modelling to enhance investment strategies that align closely with investor psychology.

- Finally, stakeholders, including financial planners, market analysts, and educational institutions, are urged to incorporate behavioural training modules and decision-making simulations into investor programs to cultivate greater awareness and resistance to psychological traps in real-world investment scenarios.

7.5 Limitations of the Study

Despite adopting a comprehensive and methodologically rigorous approach, the study encounters the following limitations:

- The study's sample was limited to individual investors residing in select Indian states, namely Maharashtra, Goa, and Karnataka, using convenience and snowball sampling techniques. While the sample size of 685 respondents, which is statistically adequate for Structural Equation Modelling (SEM), a broader geographical distribution could have improved the representativeness and generalizability of the findings.

- The self-reported nature of data collected through structured questionnaires may be subject to response biases, such as social desirability and recall bias. Although measures were taken to ensure reliability and validity, the accuracy of responses may be affected by the participants' subjective perceptions.

- The study's cross-sectional design restricts the ability to establish causal relationships between behavioural biases, financial literacy, and investment decisions. Longitudinal data could provide more robust insights into changes in investor behaviour over time.

- The findings are context-specific to the Indian retail/individual investor environment. They may not be directly generalisable to other countries with differing regulatory frameworks, cultural norms, financial market maturity, or investor education levels.

7.6 Scope for Future Research

The present study opens several avenues for future exploration to enhance the understanding of individual investor behaviour in the Indian capital market. These directions may address the existing limitations of the study:

- Future studies can extend the geographical scope by incorporating data from a wider set of Indian states or international contexts. This would enhance the generalizability of the findings and allow cross-cultural comparisons of behavioural biases and financial literacy levels.
- The present study employs a cross-sectional design. Longitudinal studies could track investor behaviour and financial literacy changes over time, providing a dynamic understanding of how these factors evolve and interact with market conditions.
- While the current research investigates ten key behavioural biases, further studies can delve into individual biases or explore alternative biases, such as framing effect, endowment effect, or sentiment bias, to assess their impact on investment decisions under different market environments.
- The moderating roles of financial literacy and investor demographics were examined in this study. Future research may explore additional moderating or mediating variables, such as personality traits, digital literacy, or risk tolerance, to uncover further psychological or situational influences on investment decisions.
- Methodologically, the study applies advanced techniques like Structural Equation Modelling (SEM), Importance-Performance Map Analysis (IPMA), and Necessary Condition Analysis (NCA). Subsequent research can employ experimental or qualitative methods to capture in-depth behavioural insights or adopt alternative

modelling frameworks such as fuzzy-set Qualitative Comparative Analysis (fsQCA) for layered findings.

- The relationship between financial education interventions and changes in behavioural biases could be investigated to evaluate the effectiveness of investor awareness programs and policy efforts in enhancing rational investment behaviour.
- Comparative studies between different investor segments, such as institutional vs. individual investors or urban vs. rural investors, may reveal distinct patterns of bias susceptibility and decision-making frameworks that can guide targeted financial education strategies.
- Further studies may also examine how digital platforms, Robo-advisors, and algorithm-based tools influence or mitigate behavioural biases, especially in the context of growing fintech adoption in emerging economies.
- Future studies should consider employing high-frequency trading data to more accurately capture the real-time presence of herding behaviour among investors. This would enable researchers to identify intraday behavioural patterns and responses to market stimuli.
- Future research can incorporate data from multiple countries to enhance the generalizability of findings. This would allow for a comparative analysis of behavioural biases across cultural, regulatory, and economic environments.
- Future research can benefit from employing machine learning-based neural network models such as Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) to predict investor behaviour and model complex patterns in behavioural finance data.
- Upcoming studies should integrate behavioural biases into portfolio selection and optimisation frameworks. This approach would provide more realistic and behaviourally informed investment strategies that reflect investor tendencies.
- Further research should compare M-Type (Market-oriented) and E-Type (Emotion-oriented) investors using separate samples. Such comparative studies would help determine whether these investor categories differ significantly in their susceptibility to behavioural biases.

Each of these research directions has the potential to enrich the literature on behavioural finance, contribute to more effective investor education initiatives, and support better decision-making practices in the ever-evolving financial markets.

7.7 Conclusion

The study undertook an examination of behavioural biases and their influence on the investment decisions of individual investors, with a focus on the moderating role of financial literacy and investor demographics.

Based on the foundational theories in behavioural finance, the study began by identifying key behavioural biases, namely heuristic bias, prospect bias, herding bias and market forces bias and explored their impact on investment decisions. A conceptual model was developed and empirically tested using data collected from 685 individual investors from the states of Maharashtra, Goa and Karnataka. Data collection was conducted through an online method, using a structured questionnaire with a five-point Likert scale. Sampling techniques included judgmental, convenience, and snowball methods.

The analysis employed Confirmatory Factor Analysis (CFA) and SMART Partial Least Squares Structural Equation Modelling (PLS-SEM). Additionally, Importance Performance Map Analysis (IPMA) and the Necessary Condition Analysis (NCA) were used to examine the influence of the selected biases on investment decisions. The moderating effect of financial literacy was tested using the interaction model, while the moderating role of investor demographics was assessed using Multi-Group Analysis (MGA).

Out of the eight main hypotheses proposed, six were supported. Among the 28 sub-hypotheses, 11 were fully supported, 7 were partially supported, and 10 were not supported. All ten behavioural biases recorded mean scores above the midpoint, indicating a notable presence of irrational behaviour among individual investors. A significant influence of these biases on investment decisions was observed, with prospect bias having the strongest overall impact. Market forces bias ranked highest in performance, while prospect bias emerged as the most important in shaping decision-making. Herding bias was identified as an essential prerequisite for investment decisions among individual investors.

Financial literacy levels were found to be low in the sample. It negatively moderated the relationship between heuristic bias and investment decisions, while positively moderating the impact of prospect bias on investment decisions. However, no significant moderating effect of financial literacy was found for herding or market forces bias.

The study further confirmed the significant moderating role of gender, age, and income in the relationship between behavioural biases and investment decisions. Marital status and Investment experience did not show any moderating effect. Education and occupation were found to moderate the relationship between behavioural biases and investment decisions partially.

Financial literacy emerged as a critical factor in moderating the influence of behavioural biases on investment decisions. However, the results were mixed, and overall levels of financial literacy among investors were found to be low. Notably, financial literacy did not have a direct impact on investment decisions.

These findings have practical implications for individual investors, financial advisors, and policymakers. Enhancing financial literacy, particularly among individual stock market investors, can effectively mitigate the impact of behavioural biases and promote more rational investment decisions.

Finally, this research contributes to the expanding body of literature on behavioural finance and offers valuable insights for strengthening investor education and shaping regulatory policies within the Indian capital market.

REFERENCES

Abdeldayem, M. M. (2016). Is there a relationship between financial literacy and investment decisions in the Kingdom of Bahrain. Journal of Management and Accounting Studies, 4(02), 68-78.

Abdulridha, F., & Hussin, N. (2024). Examining The Moderating Role of Financial Literacy Between Determinants of Individual Behaviour and Investment Decision-Making for Iraqi Investors.

Abhijith, R., & Bijulal, D. (2025). Decoding Investor's Irrationality: A Fuzzy AHP Exploration of Behavioural Biases. *Vision*, 09722629251329995.

Abideen, Z. U., Ahmed, Z., Qiu, H., & Zhao, Y. (2023). Do behavioral biases affect investors' investment decision making? Evidence from the Pakistani equity market. *Risks*, *11*(6), 109.

Abul, S. J. (2019). Factors influencing individual investor behaviour: Evidence from the Kuwait stock exchange. *Asian Social Science*, *15*(3), 27-39.

Adams, L. L. M., & Gale, D. (1982). Solving the quandary between questionnaire length and response rate in educational research. *Research in Higher Education*, *17*, 231-240.

Adil, M., Singh, Y., & Ansari, M. S. (2022). How financial literacy moderate the association between behaviour biases and investment decision?. *Asian Journal of Accounting Research*, *7*(1), 17-30.

Agarwal, A., & Rao, N. V. M. (2023, July). Exploring the Impact of Behavioral Biases and Demographic Factors on Investment Decision-Making: Evidence from Indian Retail Investors. In *International Conference on Financial Markets & Corporate Finance* (pp. 87-102). Singapore: Springer Nature Singapore.

Agarwal, K. (2020). A study on investor buying behaviour and Financial Literacy in Urban India.

Agarwal, S., Amromin, G., Ben-David, I., Chomsisengphet, S., & Evanoff, D. D. (2015). Financial literacy and financial planning: Evidence from India. *Journal of Housing Economics*, *27*, 4-21.

Agarwalla, S. K., Barua, S. K., Jacob, J., & Varma, J. R. (2013). Financial literacy among working young in urban India. *Indian Institute of Management Ahmedabad, WP*, (2013-10), 02.

Ahmed, z. (2019). Determinants of individual investors investment decision in pakistan stock exchange (doctoral dissertation, universiti teknologi malaysia).

Ahn, K., Cong, L., Jang, H., & Kim, D. S. (2024). Business cycle and herding behavior in stock returns: Theory and evidence. Financial Innovation, 10(1), 6.

Ainia, N. S. N., & Lutfi, L. (2019). The influence of risk perception, risk tolerance, overconfidence, and loss aversion towards investment decision making. Journal of Economics, Business, & Accountancy Ventura, 21(3), 401-413.

Ainul, M. P. A. (2024). The Influence of Representativeness Bias, Loss Aversion, and Herding Behavior on Young Investor Investment Decision in West Sumatera (Doctoral dissertation, Universitas Andalas).

Alessie, R. J., Van Rooij, M., & Lusardi, A. (2011). *Financial literacy, retirement preparation and pension expectations in the Netherlands* (No. w17109). National Bureau of Economic Research.

Allgood, S., & Walstad, W. B. (2016). The effects of perceived and actual financial literacy on financial behaviors. *Economic inquiry*, *54*(1), 675-697.

Ambarkhane, D., Venkataramani, B., & Singh, A. S. (2015). Financial literacy index for college students. *Annual research Journal of symbiosis centre for A management studies*, *3*(1), 1-25.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin*, *103*(3), 411.

Areiqat, A. Y., Abu-Rumman, A., Al-Alani, Y. S., & Alhorani, A. (2019). Impact of behavioral finance on stock investment decisions applied study on a sample of investors at Amman stock exchange. *Academy of Accounting and Financial Studies Journal*, *23*(2), 1-17

Aren, S., & Aydemir, S. D. (2015). The moderation of financial literacy on the relationship between individual factors and risky investment intention. *International Business Research*, *8*(6), 17.

Aren, S., & Hamamci, H. N. (2021). Biases in managerial decision making: overconfidence, status quo, anchoring, hindsight, availability. *Journal of Business Strategy Finance and Management*, *3*(1-2), 8.

Arianti, B. F. (2018). The influence of financial literacy, financial behavior and income on investment decision. *Economics and Accounting Journal*, *1*(1), 1-10.

Arif, K. (2015). Financial literacy and other factors influencing individuals' investment decision: Evidence from a developing economy (Pakistan). *Journal of Poverty, Investment and Development*, *12*(1), 74-84.

Arrondel, L., Debbich, M., & Savignac, F. (2015). Stockholding in France: the role of financial literacy and information. *Applied Economics Letters*, *22*(16), 1315-1319.

Asad, H., Khan, A. & Faiz, R. (2018). Behavioral biases across the stock market investors. *Pakistan Economic and Social Review*, *56*(1), 185-209.

Ashfaq, M., Shafique, A., & Selezneva, V. (2024). Exploring the missing link: Financial literacy and Cognitive biases in Investment Decisions. *Journal of Modelling in Management*, *19*(3), 871-898.

Assaker, G., Hallak, R., Assaf, A. G., & Assad, T. (2015). Validating a structural model of destination image, satisfaction, and loyalty across gender and age: Multigroup analysis with PLS-SEM. *Tourism Analysis*, *20*(6), 577-591

Ates, S., Coskun, A., Sahin, M. A., & Demircan, M. L. (2016). Impact of financial literacy on the behavioral biases of individual stock investors: evidence from Borsa Istanbul. *Business and Economics Research Journal*, *7*(3), 1.

Banerjee, A. V. (1992). A simple model of herd behavior. *The quarterly journal of economics*, *107*(3), 797-817.

Athota, V. S., Pereira, V., Hasan, Z., Vaz, D., Laker, B., & Reppas, D. (2023). Overcoming financial planners' cognitive biases through digitalization: A qualitative study. *Journal of business research*, *154*, 113291.

Atkinson, A., & Messy, F. A. (2012). Measuring financial literacy: Results of the OECD/International Network on Financial Education (INFE) pilot study.

Aziz, S., Mehmood, S., Khan, M. A., & Tangl, A. (2024). Role of behavioral biases in the investment decisions of Pakistan Stock Exchange investors: Moderating role of investment experience. *Investment Management & Financial Innovations*, *21*(1), 146.

Baihaqqy, M. R. I., Disman, N., Sari, M., & Ikhsan, S. (2020). The effect of financial literacy on the investment decision. *Budapest International Research and Critics Institute-Journal (BIRCI-Journal)*, *3*(4), 3073-3083.

Bakar, S., & Yi, A. N. C. (2016). The impact of psychological factors on investors' decision making in Malaysian stock market: a case of Klang Valley and Pahang. *Procedia Economics and Finance*, *35*, 319-328.

Baker, H. K., & Nofsinger, J. R. (2002). Psychological biases of investors. *Financial services review*, *11*(2), 97-116.

Baker, H. K., & Puttonen, V. (2017). How behavioral biases can hurt your investing. In *Investment traps exposed* (pp. 107-145). Emerald Publishing Limited.

Baker, H. K., Filbeck, G., & Ricciardi, V. (2019). The Psychology of Financial Professionals and Their Clients. *Investments & Wealth Monitor*, 15-20.

Baker, H. K., Kumar, S., Goyal, N., & Gaur, V. (2019). How financial literacy and demographic variables relate to behavioral biases. *Managerial Finance*, *45*(1), 124-146.

Barber, B. M., & Odean, T. (2001). The internet and the investor. *Journal of Economic Perspectives*, *15*(1), 41-54.

Barber, B. M., & Odean, T. (2013). The behavior of individual investors. In *Handbook of the Economics of Finance* (Vol. 2, pp. 1533-1570). Elsevier.

Barber, B. M., Huang, X., Ko, K. J., & Odean, T. (2020). Leveraging overconfidence. *Available at SSRN 3445660*.

Barberis, N., & Huang, M. (2001). Mental accounting, loss aversion, and individual stock returns. *the Journal of Finance*, *56*(4), 1247-1292.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, *1*, 1053-1128.

Barberis, N., Huang, M., & Santos, T. (2001). Prospect theory and asset prices. *The quarterly journal of economics*, *116*(1), 1-53.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of financial economics*, *49*(3), 307-343.

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.

Beatrice, V., Murhadi, W. R., & Herlambang, A. (2021). The effect of demographic factors on behavioral biases. *Jurnal Siasat Bisnis*, *25*(1), 17-29.

Beaver, W. H. (1981). Market efficiency. *Accounting Review*, 23-37.

Bekaert, G., & Harvey, C. R. (2002). Research in emerging markets finance: looking to the future. *Emerging markets review*, *3*(4), 429-448.

Bell, D. E. (1982). Regret in decision-making under uncertainty. *Operations research*, *30*(5), 961-981.

Bell, E., & Bryman, A. (2007). The ethics of management research: an exploratory content analysis. *British journal of management*, *18*(1), 63-77.

Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural modeling. *Sociological methods & research*, *16*(1), 78-117.

Berg, S. A., & Moss, J. H. (2022). Anchoring and judgment bias: disregarding under uncertainty. *Psychological Reports*, *125*(5), 2688-2708.

Beyer, S., & Bowden, E. M. (1997). Gender differences in seff-perceptions: Convergent evidence from three measures of accuracy and bias. *Personality and Social Psychology Bulletin*, *23*(2), 157-172.

Bhandari, G., & Deaves, R. (2006). The demographics of overconfidence. *The Journal of Behavioral Finance*, *7*(1), 5-11.

Bhandari, G., Hassanein, K., & Deaves, R. (2008). Debiasing investors with decision support systems: An experimental investigation. *Decision Support Systems*, *46*(1), 399-410.

Bhanu, B. K. (2023). Behavioral finance and stock market anomalies: Exploring psychological factors influencing investment decisions. *Commer. Econ. Manag*, *23*.

Bikas, E., Jurevičienė, D., Dubinskas, P., & Novickytė, L. (2013). Behavioural finance: The emergence and development trends. *Procedia-social and behavioral sciences*, *82*, 870-876.

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff papers*, *47*(3), 279-310.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy*, *100*(5), 992-1026.

Bodie, Z., & Brière, M. (2013). Optimal asset allocation for sovereign wealth funds: Theory and practice. *Boston U. School of Management Research Paper*, (2013-11).

Buelens, B., Burger, J., & van den Brakel, J. A. (2018). Comparing inference methods for non-probability samples. *International Statistical Review*, *86*(2), 322-343.

Bushra, B., Srivastav, S., & Kapoor, S. (2024). Impact of gender, age, and education on investors' behavior: an empirical study of Delhi-NCR. *International Journal of System Assurance Engineering and Management*, 1-15.

Business Standard. (2022, December 26). *Financial literacy poor across urban, rural population: RBI survey*. https://www.business-standard.com/article/current-affairs/financial-literacy-poor-across-urban-rural-population-rbi-survey-122122600711_1.html

Business Standard. (2024, July 1). Nearly 72% women now take investment decisions independently, says study. https://www.business-standard.com/finance/personal-finance/nearly-72-women-now-take-investment-decisions-independently-says-study-124070100816_1.html

Business Standard. (2024, July 26). *Only 38% Indians debt-free, 40% lack emergency fund: What a survey reveals*. https://www.business-standard.com/finance/personal-finance/only-38-indians-debt-free-40-lack-emergency-fund-what-a-survey-reveals-124072601107_1.html

Calvet, L., Célérier, C., Sodini, P., & Vallée, B. (2016). Financial innovation and stock market participation. *Finanzinnovation und Aktienmarktbeteiligung*, *1*, 35.

Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological bulletin*, *56*(2), 81.

Cao, M. M., Nguyen, N. T., & Tran, T. T. (2021). Behavioral factors on individual investors' decision making and investment performance: A survey from the Vietnam Stock Market. *The Journal of Asian Finance, Economics and Business*, *8*(3), 845-853.

Caporale, G. M., & Plastun, A. (2019). On stock price overreactions: frequency, seasonality and information content. *Journal of Applied Economics*, *22*(1), 602-621.

Chai, S., Kim, M., & Rao, H. R. (2011). Firms' information security investment decisions: Stock market evidence of investors' behavior. *Decision Support Systems*, *50*(4), 651-661.

Chandra, A. (2009). Individual investors' trading behavior and the competence effect. *IUP Journal of Behavioral Finance*, *6*(1), 56.

Chandra, P. K., Pangkey, L. B., & Soetanto, T. V. (2023). Young Adults' Investment Decisions in Surabaya: The Influence of Financial Literacy and Risk Perception. *International Journal of Organizational Behavior and Policy*, *2*(2), 87-96.

Chang, C. H., & Lin, S. J. (2015). The effects of national culture and behavioral pitfalls on investors' decision-making: Herding behavior in international stock markets. *International Review of Economics & Finance*, *37*, 380-392.

Chen, G. M., Kim, K. A., Nofsinger, J. R., & Rui, O. M. (2004). *Behavior and performance of emerging market investors: Evidence from China*. Working paper.

Chen, G., Kim, K. A., Nofsinger, J. R., & Rui, O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of behavioral decision making*, *20*(4), 425-451.

Chen, H., & Volpe, R. P. (1998). An analysis of personal financial literacy among college students. *Financial services review*, *7*(2), 107-128.

Chiang, T. C., Li, J., Tan, L., & Nelling, E. (2013). Dynamic herding behavior in Pacific-Basin markets: Evidence and implications. *Multinational Finance Journal*, *17*(3/4), 165-200.

Choudhary, K., & Kamboj, S. (2017). A study of financial literacy and its determinants: Evidence from India. *Asian Journal of Accounting Perspectives*, *10*(1), 52-72.

Chowa, G. A., Despard, M. R., & Osei-Akoto, I. (2012). Financial knowledge and attitudes of youth in Ghana.

Cohen, J. (1988). The effect size. Statistical power analysis for the behavioral sciences. *Abingdon: Routledge*, 77-83.

Cole, S. A., & Shastry, G. K. (2009). *Smart money: The effect of education, cognitive ability, and financial literacy on financial market participation* (pp. 09-071). Boston, MA: Harvard Business School.

Collis, J., & Hussey, R. (2014). Collecting qualitative data. In *Business research* (pp. 129-152). Palgrave, London.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *psychometrika*, *16*(3), 297-334.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *the Journal of Finance*, *53*(6), 1839-1885

Das, A. R., & Panja, S. (2022). An empirical investigation on the influence of behavioural factors on investment decision making. *Vision*, 09722629221131101.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact?. *The Journal of finance*, *40*(3), 793-805.

De Bondt, W. F., & Thaler, R. H. (1995). Financial decision-making in markets and firms: A behavioral perspective. *Handbooks in operations research and management science*, *9*, 385-410.

Deaves, R., Lüders, E., & Schröder, M. (2010). The dynamics of overconfidence: Evidence from stock market forecasters. *Journal of Economic Behavior & Organization*, *75*(3), 402-412

Deutskens, E., De Ruyter, K., Wetzels, M., & Oosterveld, P. (2004). Response rate and response quality of internet-based surveys: An experimental study. *Marketing letters*, *15*, 21-36.

Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European economic review*, *40*(3-5), 603-615.

Dhar, R., & Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management science*, *52*(5), 726-740.

Dhungana, B. R., Bhandari, S., Ojha, D., & Sharma, L. K. (2022). Effect of cognitive biases on investment decision making: A case of Pokhara Valley, Nepal. *Quest Journal of Management and Social Sciences*, *4*(1), 71-84.

Dillman, D. A. (2011). *Mail and Internet surveys: The tailored design method--2007 Update with new Internet, visual, and mixed-mode guide*. John Wiley & Sons.

Dul, J. (2016). Necessary condition analysis (NCA) logic and methodology of "necessary but not sufficient" causality. *Organizational Research Methods*, *19*(1), 10-52.

Dul, J. (2024). A different causal perspective with Necessary Condition Analysis. *Journal of Business Research*, *177*, 114618.

Dul, J., Hauff, S., & Bouncken, R. B. (2023). Necessary condition analysis (NCA): review of research topics and guidelines for good practice. *Review of Managerial Science*, *17*(2), 683-714.

Dureha, S., & Jain, V. (2022). An empirical study on the relationship between financial literacy and emotional biases. *Cardiometry*, (23), 413-422.

Economou, F., Hassapis, C., & Philippas, N. (2018). Investors' fear and herding in the stock market. *Applied Economics*, *50*(34-35), 3654-3663.

Edwards, P., Roberts, I., Clarke, M., DiGuiseppi, C., Pratap, S., Wentz, R., & Kwan, I. (2002). Increasing response rates to postal questionnaires: systematic review. *Bmj*, *324*(7347), 1183.

Elhussein, N. H. A., & Abdelgadir, J. N. A. (2020). Behavioural bias in individual investment decisions: Is it a common phenomenon in stock markets? *International Journal of Financial Research*, *11*(6), 25.

Fagerström, S. (2008). Behavioural Finance: The psychological impact and Overconfidence in financial markets

Falah, F. F., & Haryono, N. A. (2023). The influence of herding, anchoring, disposition, personal income, and financial literacy on Generation Z's investment decision making in Surabaya City. *Technium Soc. Sci. J.*, *45*, 210.

Falsetti, G. (2025). *The impact of AI-driven robo-advisors on decision-making process and personalization of investors*(Bachelor's thesis, University of Twente).

Fama, E. F. (1970). Efficient capital markets. *Journal of finance*, *25*(2), 383-417.

Finke, M. S., Howe, J. S., & Huston, S. J. (2017). Old age and the decline in financial literacy. *Management Science*, *63*(1), 213-230.

Fong, J. H., Koh, B. S., Mitchell, O. S., & Rohwedder, S. (2021). Financial literacy and financial decision-making at older ages. *Pacific-Basin Finance Journal*, *65*, 101481.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Frank, O., & Snijders, T. (1994). Estimating the size of hidden populations using snowball sampling. *Journal of Official Statistics-Stockholm-*, *10*, 53-53.

Fransiska, M., Sumani, W., & Pangestu, S. (2018). Herding behavior in Indonesian investors. *International Research Journal of Business Studies*, *11*(2), 129-143.

Gabhane, D., Sharma, A., & Mukherjee, R. (2023). Behavioral finance: exploring the influence of cognitive biases on investment decisions. *Boletin de Literatura Oral-The Literary Journal*, *10*(1), 3133-3141.

Gazel, S. (2015). The regret aversion as an investor bias. *International Journal of Business and Management Studies*, *4*(02), 419-424.

Geetha, N., & Ramesh, M. (2011). A study on people's preferences in Investment Behaviour. *International Journal of Engineering and Management Research*, *1*(6), 285-306.

Gilson, R. J., & Kraakman, R. H. (1984). The mechanisms of market efficiency. *Va. L. Rev.*, *70*, 549.

Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. *The Geneva Risk and Insurance Review*, *32*, 1-36.

Glaser, M., & Weber, M. (2010). Overconfidence. *Behavioral finance: Investors, corporations, and markets*, 241-258.

Gloede, O., & Menkhoff, L. (2014). Financial professionals' overconfidence: is it experience, function, or attitude?. *European Financial Management*, *20*(2), 236-269.

Gonzalez-Igual, M., Santamaria, T. C., & Vieites, A. R. (2021). Impact of education, age and gender on investor's sentiment: A survey of practitioners. *Heliyon*, *7*(3).

Goodfellow, C., Bohl, M. T., & Gebka, B. (2009). Together we invest? Individual and institutional investors' trading behaviour in Poland. *International Review of Financial Analysis*, *18*(4), 212-221.

Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of financial economics*, *78*(2), 311-339.

Grinblatt, M., & Keloharju, M. (2009). Sensation seeking, overconfidence, and trading activity. *The Journal of finance*, *64*(2), 549-578.

Gupta, S. (2017). To study the relationship of financial literacy and investment behaviour of salaried class individuals of delhi. *International Education and Research Journal*, *3*(5).

Gurung, R., Dahal, R. K., Ghimire, B., & Koirala, N. (2024). Unraveling behavioral biases in decision making: A study of Nepalese investors. *Investment Management & Financial Innovations*, *21*(1), 25.

Haidari, M. N. (2023). Impact of Decision-Making on Investment Performance: A Comprehensive Analysis. *Journal of Asian Development Studies*, *12*(4), 980-990.

Hair Jnr, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis.

Hair Jr, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of business research*, *109*, 101-110

Hair, J. F., Henseler, J., Dijkstra, T. K., & Sarstedt, M. (2014). Common beliefs and reality about partial least squares: comments on Rönkkö and Evermann.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the academy of marketing science*, *40*, 414-433.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), 100027.

Hair, Jr., Hult, GTM, Ringle, CM, Sarstedt, M.(2014). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Sage Publications. *European Journal of Tourism Research*, *6*(2), 211-213.

Haritha, P. H., & Uchil, R. (2024). An empirical analysis of social and market dynamics influencing investment decision-making of equity investors in India. *International Journal of Business and Globalisation*, *38*(3), 405-424.

Hasan, I., Tunaru, R., & Vioto, D. (2023). Herding behavior and systemic risk in global stock markets. *Journal of Empirical Finance*, *73*, 107-133

Hassan Al-Tamimi, H. A., & Anood Bin Kalli, A. (2009). Financial literacy and investment decisions of UAE investors. *The journal of risk finance*, *10*(5), 500-516.

Hayat, A., & Anwar, M. (2016). Impact of behavioral biases on investment decision; moderating role of financial literacy. *Moderating Role of Financial Literacy (September 23, 2016)*.

Henry, G. T. (1990). *Practical sampling* (Vol. 21). Sage.

Hesam Jahanmiri, M., Roodposhti, R., & Nikoomaram, H. (2018). Anchoring bias a criterion for explain profitability of 52-weeks high and momentum strategies. *Pacific Business Review International*, *10*(7).

Hirshleifer, D. (2001). Investor psychology and asset pricing. *The journal of Finance*, *56*(4), 1533-1597.

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics*, *7*(1), 133-159.

Hon-Snir, S., Kudryavtsev, A., & Cohen, G. (2012). Stock market investors: Who is more rational, and who relies on intuition. *International Journal of Economics and Finance*, *4*(5), 56-72.

Hong, H., Kubik, J. D., & Stein, J. C. (2004). Social interaction and stock-market participation. *The journal of finance*, *59*(1), 137-163.

Huang, L. (2018). The role of investor gut feel in managing complexity and extreme risk. *Academy of Management Journal*, *61*(5), 1821-1847.

Huber, J., Kirchler, M., & Stöckl, T. (2010). The hot hand belief and the gambler's fallacy in investment decisions under risk. *Theory and decision*, *68*, 445-462.

Huberman, G. (2001). Familiarity breeds investment. *The Review of Financial Studies*, *14*(3), 659-680.

Hvide, H. K. (2002). Pragmatic beliefs and overconfidence. *Journal of Economic Behavior & Organization*, *48*(1), 15-28.

Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of empirical finance*, *11*(4), 585-616.

Imas, A., Lamé, D., & Wilson, A. J. (2016). Regret in One-Shot and Recurrent Decisions: A Cautionary Tale.

Iram, S., A. Bilal, and S. Latif. (2021). "Is awareness that powerful? Women's Financial Literacy Support to Prospects Behaviour in Prudent Decision-Making," *Global Business Review*, Vol. 25, No. 11, pp. 1356-1381.

Isidore R, R., & P, C. (2019). The relationship between the income and behavioural biases. *Journal of Economics, Finance and Administrative Science*, *24*(47), 127-144

Ising, A. (2007). Pompian, M.(2006): Behavioral Finance and Wealth Management-How to Build Optimal Portfolios That Account for Investor Biases. *Financial Markets and Portfolio Management*, *21*(4), 491.

Jain, D., & Mandot, N. (2012). Impact of demographic factors on investment decision of investors in Rajasthan. *Journal of Arts, Science & Commerce*, *3*(2), 3

Jain, J., Walia, N., Kaur, M., & Singh, S. (2022). Behavioural biases affecting investors' decision-making process: a scale development approach. *Management Research Review*, *45*(8), 1079-1098.

Jain, J., Walia, N., Singla, H., Singh, S., Sood, K., & Grima, S. (2023). Heuristic biases as mental shortcuts to investment decision-making: a mediation analysis of risk perception. *Risks*, *11*(4), 72.

Jain, N., & Kesari, B. (2022). The impact of behavioral biases on financial risk tolerance of investors and their decision making.

Jamil, S. A., & Khan, K. (2016). Does gender difference impact investment decisions? Evidence from Oman. *International Journal of Economics and Financial Issues*, *6*(2), 456-460.

Kaczynski, A., & Juniper, J. (2022). The inadequacies of utility theory from a macroeconomic modelling perspective. *Journal of Resilient Economies*, *2*(1), 60-70.

Kahneman D., Tversky A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47, 263–291.

Kahneman, D. (2011). Fast and slow thinking. *Allen Lane and Penguin Books, New York*.

Kahneman, T. (1979). D. Kahneman, A. Tversky. *Prospect theory: An analysis of decisions under risk*, 263-291.

Kansal, P., & Singh, S. (2018). Determinants of overconfidence bias in Indian stock market. *Qualitative Research in Financial Markets*, *10*(4), 381-394.

Kaplowitz, M. D., Lupi, F., Couper, M. P., & Thorp, L. (2012). The effect of invitation design on web survey response rates. *Social Science Computer Review*, *30*(3), 339-349.

Kartini, K., & Nahda, K. (2021). Behavioral biases on investment decision: A case study in Indonesia. *The Journal of Asian Finance, Economics and Business*, *8*(3), 1231-1240.

Katper, N. K., Azam, M., Karim, N. A., & Zia, S. Z. (2019). Behavioral biases and investors' decision-making: The moderating role of socio-demographic variables. *International Journal of Financial Engineering*, *6*(03), 1950020.

Kaustia, M., Alho, E., & Puttonen, V. (2008). How much does expertise reduce behavioral biases? The case of anchoring effects in stock return estimates. *Financial Management*, *37*(3), 391-412.

Kengatharan, L., & Kengatharan, N. (2014). The influence of behavioral factors in making investment decisions and performance: Study on investors of Colombo Stock Exchange, Sri Lanka. *Asian Journal of Finance & Accounting*, *6*(1), 1.

Khalili, R., Abdi, R., Rezaei, N., & Pakmaram, A. (2025). Using Mental Accounting in Optimal Portfolio Selection. *Management Strategies and Engineering Sciences*, *7*(1), 8-14.

Khan, I., Afeef, M., Jan, S., & Ihsan, A. (2021). The impact of heuristic biases on investors' investment decision in Pakistan stock market: moderating role of long term orientation. *Qualitative Research in Financial Markets*, *13*(2), 252-274.

Khan, S. K., & Islam, J. (2023). Unlocking the investment puzzle: the influence of behavioral biases & moderating role of financial literacy. *Journal of Social Research Development*, *4*(2).

Khare, T., & Kapoor, S. (2024). Behavioral biases and the rational decision-making process of financial professionals: significant factors that determine the future of the financial market. *Journal of Advances in Management Research*, *21*(1), 44-65.

Khilar, R. P., & Singh, S. (2019). Influence of behavioural biases on investment decision making in Bhubaneswar region. *International Journal of Recent Technology and Engineering*, *8*(3), 8297-8301.

Kirera, f. K., & mburugu, b. M. (2019). Impact of heuristic biases on individual investor decision making process at nairobi securities exchange: a survey of individual investors in meru county. *Journal of Environmental Sustainability Advancement Research*, *5*.

Kishan, K., & Alfan, E. (2019). Malaysian individual investors: what are the factors that influence their financial statement usage?. *Asian Journal of Accounting Perspectives*, *12*(1), 22-48.

Knoll, M. A., & Houts, C. R. (2012). The financial knowledge scale: An application of item response theory to the assessment of financial literacy. *Journal of consumer affairs*, *46*(3), 381-410.

Kothari, C. R. (2004). *Research methodology: Methods and techniques*. New Age International.

Kotian, S., & Aithal, P. S. (2024). The Influence of Socio-Economic Factors on Savings and Investment Decisions of School Teachers-A Study with Reference to Women Teachers in Kodagu District of Karnataka. *International Journal of Management, Technology, and Social Sciences (IJMTS)*, *9*(1), 33-46.

Kourtidis, D., Šević, Ž., & Chatzoglou, P. (2011). Investors' trading activity: A behavioural perspective and empirical results. *The Journal of Socio-Economics*, *40*(5), 548-557

Kriauciunas, A., Parmigiani, A., & Rivera-Santos, M. (2011). Leaving our comfort zone: Integrating established practices with unique adaptations to conduct survey-based strategy research in nontraditional contexts. *Strategic Management Journal*, *32*(9), 994-1010.

Kudryavtsev, A., Cohen, G., & Hon-Snir, S. (2013). "Rational" or "Intuitive": Are Behavioral Biases Correlated Across Stock Market Investors?. *Contemporary economics*, *7*(2), 31-53.

Kumar, S., & Goyal, N. (2016). Evidence on rationality and behavioural biases in investment decision making. *Qualitative Research in Financial Markets*, *8*(4), 270-287.

Kundu, S., & Banerjee, A. (2024). Efficiency of financial production process and its dependence on price anchors: Evidence from India. *IIMB Management Review*, *36*(1), 56-70.

Kyriazos, T. A. (2018). Applied psychometrics: sample size and sample power considerations in factor analysis (EFA, CFA) and SEM in general. *Psychology*, *9*(08), 2207.

Lai, M. M., Chong, L. L., & Tan, S. H. (2010). Behavioral finance in Malaysia. In *Handbook of behavioral finance*. Edward Elgar Publishing.

Lancaster, G. A., Dodd, S., & Williamson, P. R. (2004). Design and analysis of pilot studies: recommendations for good practice. *Journal of evaluation in clinical practice*, *10*(2), 307-312.

Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian economics*, *22*(6), 495-506.

Le Luong, P., & Thi Thu Ha, D. (2011). Behavioral factors influencing individual investors decision-making and performance.: A survey at the Ho Chi Minh Stock Exchange.

Lehenkari, M., & Perttunen, J. (2004). Holding on to the losers: Finnish evidence. *The Journal of Behavioral Finance*, *5*(2), 116-126.

Levy, J. S. (1992). An introduction to prospect theory. *Political psychology*, 171-186.

Li, X., & Wu, L. (2018). Herding and social media word-of-mouth. *Mis Quarterly*, *42*(4), 1331-1352.

Lin, H. W. (2011). Elucidating the influence of demographics and psychological traits on investment biases. *World Academy of Science, Engineering and Technology*, *77*(5), 145-150.

Litimi, H. (2017). Herd behavior in the French stock market. *Review of Accounting and Finance*, *16*(4), 497-515.

Loomes, G., & Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. *The economic journal*, *92*(368), 805-824.

Loughran, T., & Ritter, J. R. (1995). The new issues puzzle. *The Journal of finance*, *50*(1), 23-51.

Lowenstein, L. (2006). Searching for rational investors in a perfect storm: A behavioral perspective. *The Journal of Behavioral Finance*, *7*(2), 66-74.

Lusardi, A. (2008). *Financial literacy: an essential tool for informed consumer choice?* (No. w14084). National Bureau of Economic Research.

Lusardi, A. (2008). *Household saving behavior: The role of financial literacy, information, and financial education programs* (No. w13824). National Bureau of Economic Research.

Lusardi, A., & Mitchell, O. S. (2007). Baby boomer retirement security: The roles of planning, financial literacy, and housing wealth. *Journal of monetary Economics*, *54*(1), 205-224.

Lusardi, A., & Mitchell, O. S. (2009). Financial literacy: Evidence and implications for financial education. *Trends and issues*, *155*, 1-10.

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *American Economic Journal: Journal of Economic Literature*, *52*(1), 5-44.

Lusardi, A., & Mitchell, O. S. (2023). The importance of financial literacy: Opening a new field. *Journal of Economic Perspectives*, *37*(4), 137-154.

Lütje, T. (2009). To be good or to be better: asset managers' attitudes towards herding. *Applied Financial Economics*, *19*(10), 825-839.

Madaan, G., & Singh, S. (2019). An analysis of behavioral biases in investment decision-making. *International Journal of Financial Research*, *10*(4), 55-67.

Mahapatra, M. S., & Mishra, R. (2020). Behavioral influence and financial decision of individuals: A study on mental accounting process among Indian households. *Cogent Economics & Finance*, *8*(1), 1827762.

Mahmood, F., Arshad, R., Khan, S., Afzal, A., & Bashir, M. (2024). Impact of behavioral biases on investment decisions and the moderation effect of financial literacy; an evidence of Pakistan. *Acta Psychologica*, *247*, 104303.

Malik K. U., Malik M. S., Irfan M., & Mehdi H. (2022). The role of heuristic factors in investment performance: Exploring the market anomalies in a volatile environment. *Apuntes del Cenes*, 41(73), 61–82.

Maria, R. (2019). The use of theory and methods of behavioural economics in the process of making financial decisions. *Review of Business and Economics Studies*, (3), 45-82.

Marsden, A., Veeraraghavan, M., & Ye, M. (2008). Heuristics of representativeness, anchoring and adjustment, and leniency: Impact on earnings' forecasts by australian analysts. *Quarterly Journal of Finance and Accounting*, 83-102

Mehta, S., & Chaudhari, J. (2016). The existence of behavioural factors among individual investors for investment decision in stock market: Evidence from Indian stock market. *Global Journal of Research in Management*, *6*(1), 57.

Menkhoff, L. (2010). The use of technical analysis by fund managers: International evidence. *Journal of Banking & Finance*, *34*(11), 2573-2586.

Menkhoff, L., Schmeling, M., & Schmidt, U. (2013). Overconfidence, experience, and professionalism: An experimental study. *Journal of Economic Behavior & Organization*, *86*, 92-101.

Merli, M., & Roger, T. (2013). What drives the herding behavior of individual investors?. *Finance*, *34*(3), 67-104.

Metawa, N., Hassan, M. K., Metawa, S., & Safa, M. F. (2019). Impact of behavioral factors on investors’ financial decisions: case of the Egyptian stock market. *International Journal of Islamic and Middle Eastern Finance and Management*, *12*(1), 30-55.

Mishra, K. C., & Metilda, M. J. (2015). A study on the impact of investment experience, gender, and level of education on overconfidence and self-attribution bias. *IIMB Management Review*, *27*(4), 228-239.

Mittal, M. (2010). Study of differences in behavioral biases in investment decision-making between the salaried and business class investors. *IUP Journal of Behavioral Finance*, *7*(4).

Monteiro, L. (2022, March 6). *Only 16.7% of Indian teenagers are financially literate: Streak Survey*. IBS Intelligence. https://ibsintelligence.com/ibsi-news/only-16-7-of-indian-teenagers-are-financially-literate-streak-survey/

Morgan, P. J., & Trinh, L. Q. (2019). Determinants and impacts of financial literacy in Cambodia and Viet Nam. *Journal of Risk and Financial Management*, *12*(1), 19.

Mouna, A., & Anis, J. (2017). Financial literacy in Tunisia: Its determinants and its implications on investment behavior. *Research in International Business and Finance*, *39*, 568-577.

Mushinada, V. N. C. (2020). Are individual investors irrational or adaptive to market dynamics?. *Journal of Behavioral and Experimental Finance*, *25*, 100243.

Mushinada, V. N. C., & Veluri, V. S. S. (2018). Investors overconfidence behaviour at Bombay stock exchange. *International Journal of Managerial Finance*, *14*(5), 613-632.

Nga, J. K., & Ken Yien, L. (2013). The influence of personality trait and demographics on financial decision making among Generation Y. *Young Consumers*, *14*(3), 230-243

Ngoc, L. T. B. (2014). Behavior pattern of individual investors in stock market. *International*

Nofsinger, J. R. (2017). *The psychology of investing*. Routledge.

Obeng, G. (2020). Behavioural finance; a concept or catalyst explaining distortions in investment decision. *European Journal of Business and Management Research*, *5*(1).

Odean, T. (1998). Are investors reluctant to realize their losses?. *The Journal of finance*, *53*(5), 1775-1798.

Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. *The journal of finance*, *53*(6), 1887-1934.

OECD. (2015). Financial literacy scores guide. https://www.oecd.org/finance/financial-education/Guide-2015-Analysis-Fin-Lit-Scores.pdf

Onabowale, O. (2024). The Rise of AI and Robo-Advisors: Redefining Financial Strategies in the Digital Age. *International Journal of Research Publication and Reviews*, *6*.

Ouarda, M., El Bouri, A., & Bernard, O. (2013). Herding behavior under markets condition: Empirical evidence on the European financial markets. *International Journal of Economics and Financial Issues*, *3*(1), 214-228.

Owusu, S. P., & Laryea, E. (2023). The impact of anchoring bias on investment decision-making: evidence from Ghana. *Review of Behavioral Finance*, *15*(5), 729-749.

Özen, E., & Ersoy, G. (2019). The impact of financial literacy on cognitive biases of individual investors. In *Contemporary issues in behavioral finance* (pp. 77-95). Emerald Publishing Limited.

Parveen, S., Satti, Z. W., Subhan, Q. A., & Jamil, S. (2020). Exploring market overreaction, investors' sentiments and investment decisions in an emerging stock market. *Borsa Istanbul Review*, *20*(3), 224-235.

Polychronakis, N. (2023). *Investment behavioural biases: cognitive vs emotional* (Master's thesis, Πανεπιστήμιο Πειραιώς).

Pompian, M. M. (2009). *Advising Ultra-Affluent Clients and Family Offices*. John Wiley and Sons.

Pompian, M. M. (2012). *Behavioral finance and investor types: managing behavior to make better investment decisions*. John Wiley & Sons.

Prosad, J. M., Kapoor, S., & Sengupta, J. (2015). Behavioral biases of Indian investors: a survey of Delhi-NCR region. *Qualitative research in financial markets*, *7*(3), 230-263.

Pushpa, A., Singh, J. K., Ramirez-Asis, N., Norabuena-Figueroa, R., Fernandez-Celestino, W., & Acosta-Ponce, W. (2023). Does cognitive bias and risk perception impact investment decision? Women investors' perspective. In *Artificial Intelligence, Internet of Things, and Society 5.0* (pp. 377-389). Cham: Springer Nature Switzerland.

Rahayu, S., Rohman, A., & Harto, P. (2021). Herding behavior model in investment decision on emerging markets: Experimental in Indonesia. *The Journal of Asian Finance, Economics and Business*, *8*(1), 53-59.

Rahman, M., & Gan, S. S. (2020). Generation Y investment decision: an analysis using behavioural factors. *Managerial Finance*, *46*(8), 1023-1041.

Rai, K., Dua, S., & Yadav, M. (2019). Association of financial attitude, financial behaviour and financial knowledge towards financial literacy: A structural equation modeling approach. *FIIB Business Review*, *8*(1), 51-60.

Raj, G. (2025). Biases and investment decision: an analysis of demographics using PLS-MGA. *International Journal of Accounting & Information Management*.

Ranaweera, S. S., & Kawshala, B. A. H. (2022). Influence of behavioral biases on investment decision making with moderating role of financial literacy and risk attitude: A study based on colombo stock exchange. *South Asian Journal of Finance*, *2*(1).

Ranyard, R., & Abdel-Nabi, D. (1993). Mental accounting and the process of multiattribute choice. *Acta Psychologica*, *84*(2), 161-177.

Rasheed, M. H., Rafique, A., Kalim, U., & Gul, F. (2021). Elucidating the Impact of behavioral biases in Pakistan Stock Market: Moderating Impact of Financial Literacy. *Journal of Quantitative Methods*, *5*(2), 128-146.

Rashes, M. S. (2001). Massively confused investors making conspicuously ignorant choices (mci–mcic). *The Journal of Finance*, *56*(5), 1911-1927.

Rasool, N., & Ullah, S. (2020). Financial literacy and behavioural biases of individual investors: empirical evidence of Pakistan stock exchange. *Journal of Economics, Finance and Administrative Science*, *25*(50), 261-278.

Rau, R. (2010). Market inefficiency. *Behavioral finance: Investors, corporations, and markets*, 331-349

Raut, R. K. (2020). Past behaviour, financial literacy and investment decision-making process of individual investors. *International Journal of Emerging Markets*, *15*(6), 1243-1263.

Rawat, B. (2023). Effect of behavioral biases on investment decision making in nepalese stock market with the mediating role of investors' sentiment. *Journal of Bhuwanishankar*, *2*(1), 40-61.

RC, G. (2021). Effect of Socio-demographic Factors (Age, Occupation and Education) on Behavioral Biases of Individual Investors' Decision-making-Evidence from The Colombo Stock Exchange. In *Proceedings of the 12th International Conference on Business & Information (ICBI 2021)*.

Reinartz, W., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of research in Marketing*, *26*(4), 332-344.

Remund, D. L. (2010). Financial literacy explicated: The case for a clearer definition in an increasingly complex economy. *Journal of consumer affairs*, *44*(2), 276-295.

Ricciardi, V., & Simon, H. K. (2000). What is behavioural finance?. *Business, Education & Technology Journal*, *2*(2), 1-9.

Richter, N. F., Schubring, S., Hauff, S., Ringle, C. M., & Sarstedt, M. (2020). When predictors of outcomes are necessary: guidelines for the combined use of PLS-SEM and NCA. Industrial Management & Data Systems, ahead-of-print(ahead-of-print). doi:10.1108/imds-11-2019-0638

Ritter, J. R. (2003). Behavioral finance. *Pacific-Basin finance journal*, *11*(4), 429-437.

Rogelberg, S. G., Fisher, G. G., Maynard, D. C., Hakel, M. D., & Horvath, M. (2001). Attitudes toward surveys: Development of a measure and its relationship to respondent behavior. *Organizational Research Methods*, *4*(1), 3-25.

Rubinstein, M. (2001). Rational markets: yes or no? The affirmative case. *Financial Analysts Journal*, *57*(3), 15-29.

Russo, J. E., & Carlson, K. A. (2002). Individual decision making. *Handbook of marketing*, 371-408.

Rwegoshora, H. M. (2016). *A guide to social science research*. Mkuki na Nyota publishers.

Rzeszutek, M., Szyszka, A., & Czerwonka, M. (2015). Investors' expertise, personality traits and susceptibility to behavioral biases in the decision making process. *Contemporary Economics*, *9*(3), 337-352.

Sabir, S. A., Mohammad, H. B., & Shahar, H. B. K. (2019). The role of overconfidence and past investment experience in herding behaviour with a moderating effect of financial literacy: evidence from the Pakistan Stock Exchange. *Asian Economic and Financial Review*, *9*(4), 480.

Sadi, R., Asl, H. G., Rostami, M. R., Gholipour, A., & Gholipour, F. (2011). Behavioral finance: The explanation of investors' personality and perceptual biases effects on financial decisions. *International journal of economics and finance*, *3*(5), 234-241.

Sahi, S. K., Arora, A. P., & Dhameja, N. (2013). An exploratory inquiry into the psychological biases in financial investment behavior. *Journal of behavioral finance*, *14*(2), 94-103.

Saleem, A., Usman, M., & Bashir, Z. (2023). Behavioral biases, financial literacy, and investment decision: A case of individual investors in Pakistan. *Business Review*, *18*(2), 1-19.

Salthouse, T. A. (2019). Trajectories of normal cognitive aging. *Psychology and aging*, *34*(1), 17.

Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies!. *Journal of business research*, *69*(10), 3998-4010.

Sattar, M. A., Toseef, M., & Sattar, M. F. (2020). Behavioral finance biases in investment decision making. *International journal of accounting, finance and risk management*, *5*(2), 69.

Saunders, M. N. (2012). Choosing research participants. *Qualitative organizational research: Core methods and current challenges*, 35-52.

Sekaran, U. (2016). *Research methods for business: A skill building approach*. John Wiley & Sons.

Seraj, A. H. A., Alzain, E., & Alshebami, A. S. (2022). The roles of financial literacy and overconfidence in investment decisions in Saudi Arabia. *Frontiers in psychology*, *13*, 1005075.

Sewell, M. (2011). History of the efficient market hypothesis. *Rn*, *11*(04), 04.

Shabgou, M., & Mousavi, A. (2016). Behavioral finance: behavioral factors influencing investors' decisions making. *Advanced Social Humanities and Management*, *3*(1), 1-6.

Shah, S. Z. A., Ahmad, M., & Mahmood, F. (2018). Heuristic biases in investment decision-making and perceived market efficiency: A survey at the Pakistan stock exchange. *Qualitative Research in Financial Markets*, *10*(1), 85-110.

Sharma, M. S. (2013). To study the level of financial literacy and its impact on investment decision–An In-depth analysis of investors in Gujarat state. *Ganpat University*.

Shefrin, H. (2001). Behavioral corporate finance. *Journal of applied corporate finance*, *14*(3), 113-126.

Shefrin, H. (2001). Do investors expect higher returns from safer stocks than from riskier stocks?. *The Journal of Psychology and Financial Markets*, *2*(4), 176-181.

Shefrin, H. M., & Thaler, R. H. (1988). The behavioral life-cycle hypothesis. *Economic inquiry*, *26*(4), 609-643.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of finance*, *40*(3), 777-790.

Shefrin, H., & Statman, M. (2000). Behavioral portfolio theory. *Journal of financial and quantitative analysis*, *35*(2), 127-151.

Shi, R., Shan, W., Gao, J., & Cheng, C. (2024). Public attention, investor sentiment and stock markets: Evidence from Chinese listed firms. *Investment Analysts Journal*, 1-22.

Shiller, R. J. (2000). Measuring bubble expectations and investor confidence. *The Journal of Psychology and Financial Markets*, *1*(1), 49-60.

Shrestha, S., Karki, P., Shrestha, N., Karki, T., Mahat, D., & Neupane, D. (2025). Role of Loss Aversion, Representativeness, and Overconfidence in Investment Decision-

Making. *International Journal of Humanities, Education, and Social Sciences*, *3*(2), 381-191.

Shusha, A. A., & Touny, M. A. (2016). The attitudinal determinants of adopting the herd behavior: an applied study on the Egyptian exchange. *Journal of Finance and Investment Analysis*, *5*(1), 55-69.

Siraji, M. (2019). Heuristics bias and investment performance: does age matter? evidence from Colombo stock exchange. *Asian Journal of Economics, Business and Accounting*, *12*(4), 1-14.

Sivaramakrishnan, S., Srivastava, M., & Rastogi, A. (2017). Attitudinal factors, financial literacy, and stock market participation. *International journal of bank marketing*, *35*(5), 818-841.

Sreejesh, S., Mohapatra, S., Anusree, M. R., Sreejesh, S., Mohapatra, S., & Anusree, M. R. (2014). Business research design: Exploratory, descriptive and causal designs. *Business research methods: An applied orientation*, 25-103.

Srivastav, S., & Pandey, A. (2023). Demography of Investors and Behavioural Biases: An Empirical Study. *SCMS Journal of Indian Management*, *20*(1).

Statman, M. (1999). Behaviorial finance: Past battles and future engagements. *Financial analysts journal*, *55*(6), 18-27.

Statman, M., Thorley, S., & Vorkink, K. (2006). Investor overconfidence and trading volume. *The Review of Financial Studies*, *19*(4), 1531-1565.

Stern, J. (2022). Well-Being: The Relationship between Utilitarian Philosopphy and Utility Maximisation in Economics. *Available at SSRN 4200419*.

Subedi, D. P. (2023). Financial literacy and investment decisions in nepalese share market. *Management Dynamics*, *26*(1), 11-20.

Sumantri, A., Susanti, N., & Yanida, P. (2024). Effect of representativeness bias, availability bias and anchoring bias on investment decisions. *Economics and Business Quarterly Reviews*, *7*(2).

Suresh, G. (2024). Impact of financial literacy and behavioural biases on investment decision-making. *FIIB Business Review*, *13*(1), 72-86.

Takeda, K., Takemura, T., & Kozu, T. (2013). Investment literacy and individual investor biases: survey evidence in the Japanese stock market. *The Review of Socionetwork Strategies*, *7*, 31-42.

Tan, L., Zhang, X., & Zhang, X. (2023). Retail and institutional investor trading behaviors: evidence from China. *Annual Review of Financial Economics*, *16*.

Tansuchat, P., & Thaicharo, Y. (2025). Cognitive Biases and Investment Choices: Exploring the Psychological Determinants of Financial Decision-Making in Thailand. *Journal of Business and Economic Options*, *8*(1), 43-60.

Taylor, R. N. (1975). Age and experience as determinants of managerial information processing and decision making performance. *Academy of Management journal*, *18*(1), 74-81.

Ten Berge, J. M. (1995). JC Nunnally and IH Bernstein. Psychometric Theory. New York: McGraw-Hill, 1994, xxiv+ 752 pages,£ 51.95. *Psychometrika*, *60*(2), 313-315.

Thaler, R. (1985). Mental accounting and consumer choice. *Marketing science*, *4*(3), 199-214.

Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral decision making*, *12*(3), 183-206.

Thapa, S. K., & Kc, R. (2020). Financial literacy of Nepalese stock market investors. *The Journal of Economic Concerns*, *11*(1), 2705-4802.

Times News Network. (2024, August 31). 22% of Indian stock market investors are women: NSE. The Times of India. https://timesofindia.indiatimes.com/city/ahmedabad/22-of-indian-stock-market-investors-are-women-nse/articleshow/112955114.cms

Trejos, C., van Deemen, A., Rodríguez, Y. E., & Gomez, J. M. (2019). Overconfidence and disposition effect in the stock market: A micro world based setting. *Journal of behavioral and experimental finance*, *21*, 61-69.

Tsoukis, C., Tournemaine, F., Driffill, E.J. (2025). Introduction: The Social and Behavioural Turn in Macroeconomics. In: Social and Behavioural Macroeconomics. Palgrave Macmillan, Cham.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, *185*(4157), 1124-1131.

Tversky, A., & Kahneman, D. (1983). Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment. *Psychological review*, *90*(4), 293.

Umapathy, T. (2024). Behavioral Economics: Understanding Irrationality In Economic Decision-Making. *Migration Letters*, *21*(S2), 923-932.

Umeaduma, C. M. G. (2024). Behavioral biases influencing individual investment decisions within volatile financial markets and economic cycles. *Int J Eng Technol Res Manag*, *8*(03), 191.

Van Hoeserlande, C. (2023). *Overconfidence and trading behaviour* (Doctoral dissertation, Ghent University).

Vehovar, V., Toepoel, V., & Steinmetz, S. (2016). Non-probability sampling. *The Sage handbook of survey methods*, *1*(2016), 329-345.

Vogt, W. P., Gardner, D. C., & Haeffele, L. M. (2012). *When to use what research design*. Guilford Press.

Volpe, R. P., Kotel, J. E., & Chen, H. (2002). A survey of investment literacy among online investors. *Journal of Financial Counseling and Planning*, *13*(1), 1.

Wang, A. (2009). Interplay of investors' financial knowledge and risk taking. *The journal of behavioral finance*, *10*(4), 204-213.

Waweru, N. M., Munyoki, E., & Uliana, E. (2008). The effects of behavioural factors in investment decision-making: a survey of institutional investors operating at the Nairobi Stock Exchange. *International Journal of business and emerging markets*, *1*(1), 24-41.

WE Staff. (2024, December 23). Women make up 1 in every 4 new investors in Indian stock markets: SBI report. Women Entrepreneurs Review. https://www.womenentrepreneursreview.com/news/women-make-up-1-in-every-4-new-investors-in-indian-stock-markets-sbi-report-nwid-6071.html

Wijaya, R., Sembel, R., & Malau, M. (2023). How Heuristics and Herding Behaviour Biases Impacting Stock Investment Decisions with Financial Literacy as Moderating Variable. *South East Asia Journal of Contemporary Business, Economics and Law*, *29*(1), 6-12.

Wong, K. K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing bulletin*, *24*(1), 1-32.

Wong, W. K., Chow, S. C., Hon, T. Y., & Woo, K. Y. (2018). Empirical study on conservative and representative heuristics of Hong Kong small investors adopting momentum and contrarian trading strategies. *International Journal of Revenue Management*, *10*(2), 146-167.

Xia, Y., & Madni, G. R. (2024). Unleashing the behavioral factors affecting the decision making of Chinese investors in stock markets. *Plos one*, *19*(2), e0298797.

Yahaya, R., Zainol, Z., Osman, J. H., Abidin, Z., & Ismail, R. (2019). The effect of financial knowledge and financial attitudes on financial behavior among university students. *International Journal of Academic Research in Business and Social Sciences*, *9*(8), 22-32.

Yalcin, K. C., Tatoglu, E., & Zaim, S. (2016). Developing an instrument for measuring the effects of heuristics on investment decisions. *Kybernetes*, *45*(7), 1052-1071.

Yasmin, F., & Ferdaous, J. (2023). Behavioral biases affecting investment decisions of capital market investors in Bangladesh: A behavioral finance approach. *Investment Management & Financial Innovations*, *20*(2), 149.

Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, *10*(2), 210-251.

Zaiane, S. (2015). Behavioral biases of individual investors: the effect of anchoring. *Eurasian Journal of Social Sciences*, *3*(1), 13-19.

Zeelenberg, M. (1999). Anticipated regret, expected feedback and behavioral decision making. *Journal of behavioral decision making*, *12*(2), 93-106.

Zeif, D., & Yechiam, E. (2022). Loss aversion (simply) does not materialize for smaller losses. *Judgment and Decision making*, *17*(5), 1015-1042

Zhou, R. T., & Lai, R. N. (2009). Herding and information based trading. *Journal of Empirical Finance*, *16*(3), 388-393.

Zikmund, W. G., D'alessandro, S., Winzar, H., Lowe, B., & Babin, B. (2014). *Marketing research*. Sydney: Cengage Learning.

ANNEXURE A: QUESTIONNAIRE

Impact of Financial Literacy on the Behavioural Biases of Individual Investors

QUESTIONNAIRE

Financial Literacy is an essential tool for financial decision making. Financial literacy helps in removing irrationality that may occur when taking investment decisions. Many illogical and biases enter the investment decision process which result in poor returns and sub-optimal portfolio construction. Your response to this questionnaire will be helpful in understand the biases that take place during purchase/ sell of investments. Kindly spare your valuable time and record your response which will be kept confidential.

[A] Demographic Profile

Sr. No.	**Question**	**Options (Tick ✓ one)**
1	Residence	☐ Urban ☐ Semi Urban ☐ Rural
2	Monthly Income	☐ Less than Rs 50,000 ☐ Rs 50,000 and above
3	Gender	☐ Male ☐ Female
4	Marital Status	☐ Married ☐ Unmarried
5	Age	☐ 18–30 years ☐ 31–45 years ☐ 46–60 years ☐ 61 years and above
6	Education Level	☐ Graduate ☐ Post Graduate ☐ Professional
7	Occupation	☐ Private Employee ☐ Government Employee ☐ Business/Self Employed
8.	Investment Experience in the Stock Market	☐ Less than 3 years ☐ 3 years to 5 years

[B] Financial Literacy

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Simple interest is charged on the principal amount by taking into consideration the interest rate and the number of days.					
Compound interest is charged on the principal amount plus all the accumulated interest of previous periods.					
The loan amount and the period of loan determines the amount of interest paid on the loan.					
Risk can be reduced through investing in wide range of assets.					
Money received today is worth more than received in future.					
Investments that have high risk tend to provide high returns.					
Cost of living increases due to high inflation.					
There exists a direct relationship between bond prices and interest rates.					
The main function of the stock market can be described as bringing together people who want to buy shares with those who want to sell shares.					
You own a part of the company when you buy an equity share of the company.					
Investment in stock market is the riskiest of all investments.					
Mutual fund is a risk-free investment.					
Purchasing Power is affected due to inflation					
Holding a mix of shares, bonds, real estate, and mutual funds help in diversification					

Financial Attitude	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I don't feel stressed in an adverse financial situation					
I consider information from all authenticated sources and then invest my money					
I consider savings as an important part of personal finance					
I do not prefer to consuming/spending my money					
My willingness to take risk is a factor I consider before planning my investments					
I have an adequate knowledge about the benefits of insurance					

Financial Behaviour	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I believe in regular savings					
I find it more satisfying to save than to spend the money					
Investment is an important aspect of personal finance					
Investment is commitment of funds to achieve long term goals or objectives					
I invest in different investment instruments i.e. shares, mutual fund, real estate, bonds with minimal knowledge					
I pay my bills and EMIs on time					
I stick to my financial goals and objectives set in my life					
I am aware of money management, investments, insurance, retirement planning, tax planning etc and use it to meet my financial goals					
I utilize the various tax rebates that I'm entitled to when filing my tax returns					
Budgeting and keeping financial records is important					

[C] Behavioural Biases

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I believe that my skills and knowledge of stock market can help me to outperform the market					
I investment frequently than other people					
I feel more confident in my own investment opinion over the opinion of my colleagues or friends					
I know the best time to enter and to exit my investment position from the market					

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I prefer to invest only in familiar stocks.					
I buy 'hot' stocks and avoid stocks that have performed poorly in the recent past.					
I use trend analysis to make investment decisions.					
If stocks of a company are performing well and the same company offers new shares, I will buy the same					
Even if my best researched stock does not perform according to my expectations, still I hold the same.					

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I rely on my experiences in the market for making my next investment					
I usually invest in stocks which has fallen considerably from its previous closing or all times high					
I forecast the changes in stock prices in the future based on recent stock prices					
I use the purchase price of stocks as a reference point in trading or for making an investment decision					

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
You prefer to buy shares of local companies than shares of international companies					
You prefer to invest in stock which has been evaluated by well-known experts.					
Your investment decision depends on new and favourable (positive) information released regarding the shares.					
If someone has tells you about a financial crisis that is to happen in a year's time, you would be convinced					
You prefer to buy stocks on the days when the value of index increases					
You prefer to sell stocks on the days when the value of index decreases					

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
You are normally able to anticipate the end of a good or poor performance of shares					
You tend to ignore the benefits that can accrue by investing in different investment options					
After a fall in the market for few days consecutively, I believe that now the market will move upwards after that					

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
You avoid selling shares that have decreased in value					
You sell shares that have increased in value faster					
You feel more sorrow about holding losing stocks too long than about selling winning stocks too soon					

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
When faced with a sure gain, you are risk averse					
When faced with a sure loss, you are a risk taker					
You avoid selling shares that have decreased in value and readily sell shares that have increased in value					

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
You tend to treat each element/account in your investment portfolio separately					
You sell losing investment from your portfolio					
You ignore the connection between different investment possibilities					

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Other investors' decisions of choosing stock types have impact on your investment decisions					
Other investors' decisions of the stock volume have impact on your investment decisions					
Other investors' decisions of buying and selling stocks have impact on your investment decisions					
You usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market					

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
You have the over-reaction to price changes of stocks					
You analyse only those government policies, regulations, etc to favour certain industries or companies so that you can invest in their shares					
You consider carefully the price changes of stocks that you intend to invest in					
The essential changes within the market dynamics influence my preferences for some companies over others					

D] Investment Decisions

Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
You feel satisfied with the way you make investment decisions					
You make all investment decisions on your own					
You consider all possible factors (viz. interest rate, inflation, global factors, political factors etc.) while making investment decisions					
The return on your portfolio justifies your investment decision					
Your decision making ability helps you to achieve your investment objectives					
You are confident about the accuracy of your investment decisions					

Thank you!

ANNEXURE B: CONFERENCE PRESENTATIONS AND RESEARCH PUBLICATIONS

Conference Presentations

1. Presented a research paper titled "The influence of Behavioural biases on the Investment decision-making of Equity investors" at the International Conference on Sustainable Finance and Accountancy, on the theme: 'Responsible Finance and Financial Resilience' on 29th February and 1st March 2024, organised by Christ College, Bangalore, on a digital platform.
2. Presented a research paper titled "Heuristic bias, Investment decision making: moderating role of Financial Literacy" at the International Conference on "Contemporary issues in Finance, Accounting and Management" on 9th April, 2024 organised by Rosary College of Commerce & Arts, Navelim.
3. Presented a research paper titled "The Impact of Behavioural Biases on Investment Decision-making: A Combined PLS-SEM and Necessary Condition Analysis Approach" at the International Conference on Innovative Research and Development (ICIRD-2025) held at INTI University, Malaysia, on March 1-2, 2025, on a digital platform.
4. Presented a research paper titled "Behavioral Biases and Investment Decisions of Individual Investors: The moderating role of Gender, Income and Education" at the Two-Day Multi-Disciplinary International Conference on "Emerging Trends in Finance, Management, Tourism & Information Technology" held on 11th & 12th April 2025 organised by Rosary College of Commerce & Arts, Navelim.

Research Publications

1. Costa, J., & Gonsalves, A. (2020). An empirical study on investment strategies and behavioural biases of individual investors in Goa. Orissa Journal of Commerce, 41(2), 31–44. https://ojcoca.org/APRIL-JUNE-2020.pdf
2. Gonsalves, A., & Costa, J. (2024). Heuristic bias, investment decision-making: Moderating role of financial literacy. IPE Journal of Management, 14(2), 24–33.

https://www.ipeindia.org/wp-content/uploads/2025/06/IPE-JoM-Vol-14-No-2-Jul-Dec-2024-FINAL.pdf