ASSESSING THE IMPACT OF TECHNOLOGY BUSINESS INCUBATOR SUPPORT SERVICES ON STARTUPS PERFORMANCE

A THESIS SUBMITTED IN PARTIAL FULLFILLMENT FOR THE DEGREE OF

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By

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DECLARATION

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

Place: Taleigao Plateau

Date: **Concy Liberata Noronha**

CERTIFICATE

This hereby certify that the above Declaration of the candidate , Concy Liberata Noronha is true and the work was carried out under my supervision.

Prof. K.B. Subhash
Professor, Goa Business School
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(Guide)

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"I can do all things through Christ who strengthens me." – Philippians 4:13

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This work is not mine alone—it belongs to all of you who stood beside me, believed in me, and walked this path with me.

Concy Liberata Noronha

Dedicated to

My Lord and Saviour Jesus Christ

&

My Precious Family

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ABBREVIATIONS

TBI	Technology Business Incubators
TIs	Technology Incubators
TBEs	Technology-based Enterprises
GDP	Gross Domestic Product
KYC	Know Your Customer
CI	Creative Industry
PLS-SEM	Partial Least Squares Structural Equation Modelling
MGA	Multi-Group Analysis
IPMA	Importance Performance Map Analysis
NCA	Necessary Condition Analysis
cIPMA	Combined Importance-Performance Map Analysis
PoI	Perception of Importance
PoE	Perception of Effectiveness
SC	Startup Characteristics
DIIA	Degree of Incubator's Intervention and Assistance
FU	Frequency of Usage
SP	Startup Performance
VC	Venture Capitalists
RBV	Resource-Based View
IMO	Input-Mediator-Outcome
NCA	Necessary Condition Analysis
B2G	Business-to-Government
B2C	Business-to-Customer
SLR	Systematic Literature Review
UTBI	University Technology Business Incubators
NTBF	Non-Technology-Based Firm
DST	Department of Science and Technology
NSTEDB	National Science and Technology Entrepreneurship Development Board
DPIIT	Department for Promotion of Industry and Internal Trade
KPIs	Key Performance Indicators
CMV	Common Method Variance
PCA	Principal Component Analysis
CR	Composite Reliability
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait (HTMT) Ratio
VIF	Variance Inflation Factor
SRMSR	Standardised Root Mean Square Residual
NFI	Normed Fit Index
MAE	Mean Absolute Error
MICOM	Measurement Invariance of Composite Models

CHAPTER I

INTRODUCTION

This chapter provides an overview of the study and its relevance to entrepreneurship and innovation. It highlights the importance of Technology Business Incubators (TBIs) in supporting startups and improving their performance. The chapter outlines the research problem, objectives, and hypotheses, and briefly explains the study's framework and scope. It serves as the starting point for understanding the background and direction of the research.

1.1 BACKGROUND OF THE STUDY

The key factor promoting both economic growth and societal well-being of a nation is entrepreneurship. It serves as an effective driving force for economic expansion, fostering the kind of creativity necessary to seize new opportunities, increase productivity, and create employment (Katjiteo, 2024). Entrepreneurship culture facilitates functional and structural transformations in society, and hence, entrepreneurial activity serves as a significant barometer of economic development. It serves as a standard against which all economies can be measured, facilitating comparisons with other economies.

The ecosystem perspective acknowledges that firms, particularly new ventures, are not isolated entities but are situated within a broader social, cultural, and institutional environment that influences their development and impacts their likelihood of success (Jha, 2018). Therefore, it is essential to understand the various constituents that comprise the entrepreneurial ecosystem, the relationships and interactions between them, and the processes that can foster a strong ecosystem. According to the World Economic Forum, in 2014, India stood as the third-largest and fastest-growing ecosystem in the world, with a steady increase in the number of new companies being formed. In recent years, as more actors have joined the ecosystem, the available support for start-ups has increased in all dimensions: office space and infrastructure, business support in terms of mentoring and networking, as well as the availability of financial capital (Korreck, 2019).

A symbiotic relationship exists among various groups of individuals who contribute diverse forms of expertise and knowledge. Entrepreneurs are naturally drawn to these concentrated ecosystems to efficiently access critical resources that enhance their chances of launching and sustaining their ventures. Business support organisations, such as incubators and accelerators, play a crucial role in reinforcing the ecosystem. Governments also contribute significantly by fostering entrepreneurial talent through initiatives such as partnering with public incubators, offering incentives like patent cost reimbursements, and establishing seed funds for business-to-government (B2G) start-ups (Korreck, 2019). Additionally, key players in the ecosystem include angel investors and venture capitalists, typically high-net-worth individuals who invest in promising start-ups and serve as interconnected and complementary partners.

Since the launch of the Start-up policy in 2016, the Indian Government has geared up to boost innovation, promote entrepreneurship, and generate employment opportunities. This has led to the rapid growth of India’s start-up ecosystem. The various stakeholders in the ecosystem comprise academic institutions, governments, industrial bodies, and corporate and business incubators. The Handbook for Non-Profit Incubator Managers (Susmita & Ashwin, 2019) states that, among the different ecosystem stakeholders, business incubators have played a critical and instrumental role in the growth of start-ups. The primary objective of business incubation programmes is to increase the chances of entrepreneurial success and survival of incubates within the programme, as well as successful exit from the programme. This objective is attainable if, in addition to providing administrative services, facilities, funding, and comprehensive transfer of entrepreneurial know-how needed for start-up success, these resources are provided to entrepreneurs efficiently and effectively.

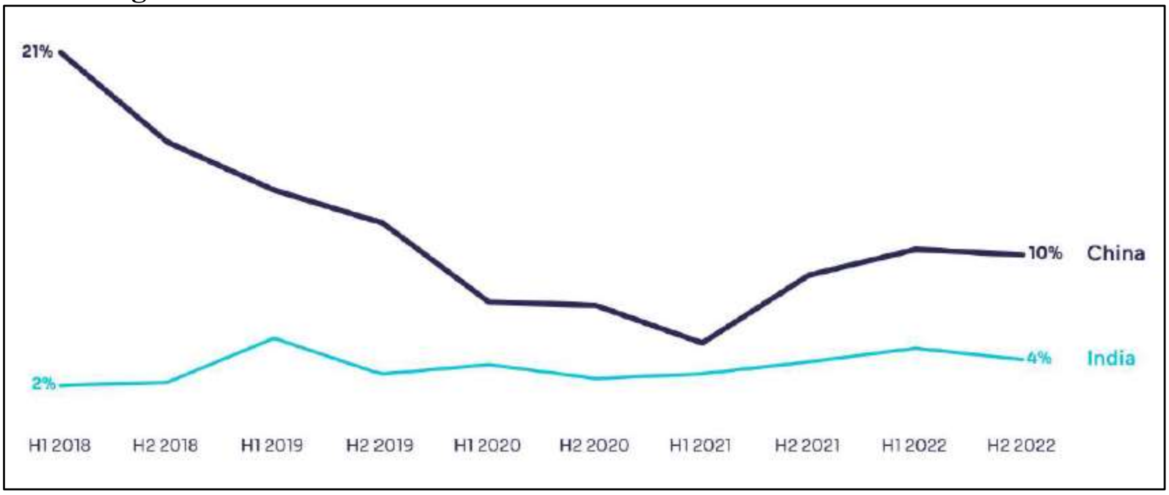
In India's rapidly evolving economic landscape, startups and their ecosystem have emerged as pivotal drivers of growth and innovation. Recognising their potential to contribute significantly to GDP and employment, the Indian government and various private entities have heavily invested in creating a nurturing ecosystem for these nascent companies. Among the myriad support structures, Technology Business Incubators (TBIs) stand out as critical facilitators, providing essential resources, mentorship, and networks to foster the development of technology-oriented startups.

According to StartupIndia (2024), India has the third-largest startup ecosystem in the World. The startup ecosystem in India has undergone significant changes, quickly catching up to that of China and the United States (Startup Genome, 2022). The overall Ecosystem Value of the nation has increased significantly. The expansion highlights India's growing significance as a pivotal player in the global startup landscape. It is a prominent player in South Asia's startup sector, with 38 of its cities included among the top 1000 worldwide startup hotspots. As of 2023, India is ranked 21st globally in the Global Startup Ecosystem Index, indicating its notable position and influence in the global startup ecosystem (StartupBlink, 2024).

According to Forbes (2024), India's Gross Domestic Product (GDP) is estimated to be $4,112 billion, with a GDP per person of $ 2,850 and a 6.3% annual growth rate. As of 2024, India's GDP ranks fifth globally. The information technology, services, manufacturing, and agriculture sectors are the main drivers of the Indian economy's rapid expansion and diversification. The nation benefits from a sizable domestic market, a youthful and technologically savvy workforce, and a burgeoning middle class.

The Startup Genome (2023) report highlights the significant advancements within India's startup ecosystem and compares its growth trajectory to that of China (Figures 1.1 and 1.2). On April 14th, 2023, India overtook China as the world's most populous country. This historic milestone marked a significant shift in global demographics, returning India to a position it last occupied during the 1700s under the Mughal Empire (Caballero & Fengler, 2023).

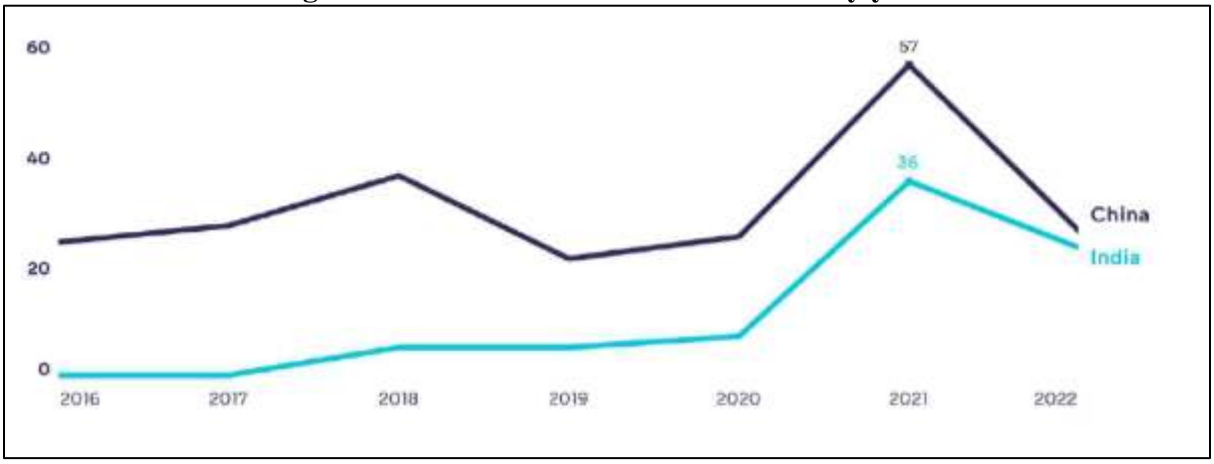
Figure 1.1: Series A Deal Count Global Market Share of China and India



Source: Startup Genome,2023

Furthermore, the Indian government has made significant investments in infrastructure, accelerated economic development, and implemented investment-oriented policies and reforms. This has resulted in the country becoming a prominent centre for manufacturing and technology. The national budget for 2023 included provisions designed to promote entrepreneurial success, including initiatives to streamline the Know Your Customer (KYC) procedure and implement a unified filing system, in an effort to build on this growth. In addition to tax benefits for eligible startups, the budget outlined initiatives to establish thirty Skill India International Centres throughout the nation.

Figure 1.2: Number of Unicorns created by year



Source: Startup Genome, 2023

In addition to other measures that encourage the expansion of startups, the Indian government has previously supported initiatives aimed at building a strong startup ecosystem. India Stack, a nationwide technology infrastructure designed to facilitate digital payments and authentication, and open the door to a paperless economy, is its most ambitious project to date. With over a billion users, this infrastructure has the potential to propel growth in Fintech, digital commerce, and other new industries. Prime Minister Mr Narendra Modi said these businesses constitute the "backbone" of a new India when he proclaimed January 16 to be National Startup Day (Startup Genome, 2022).

The establishment and support of Technology Business Incubators (TBIs) play a crucial role in fostering the growth and success of startups, particularly in emerging economies like India. According to research, TBIs provide vital resources, including physical infrastructure, financial support, business assistance, and networking opportunities, which significantly impact entrepreneurship development (Sultana & Gupta, 2023). In addition, TBIs offer specialised knowledge capital tailored to technology-based (TB) entrepreneurs, aiding in the proof of concept and industry-specific expertise, while also supporting creative-industry (CI) entrepreneurs with product development and business fundamentals (Siddiqui & Ahmad, 2022). The Indian government's emphasis on promoting innovative startups and entrepreneurship, coupled with the rise of the Indian startup ecosystem as a major contributor to the country's GDP, underscores the importance of studying the impact of TBI support services on startups in India. This thesis aims to empirically analyse how the support services provided by TBIs influence the success and growth of startups in the Indian entrepreneurial landscape.

1.2 SCOPE OF THE STUDY

This study focuses on examining the influence of Technology Business Incubators (TBIs) on the performance of incubated startups through an empirical investigation of key constructs such as startup characteristics, perception of importance and effectiveness of incubators' support services, frequency of usage of incubators' support services, and the degree of incubators' intervention and assistance.

According to Monsson & Jørgensen (2016), the benefits entrepreneurs derive from incubator programs vary according to their individual characteristics, highlighting the need for tailored support to optimise program outcomes. Following van Rijnsoever & Eveleens(2021), our study identifies five essential resources that the literature consistently recognises as central to the support incubators provide to startups: (1) physical capital, (2) financial capital, (3) business knowledge, (4) networks, and (5) legitimacy (Amezcua et al., 2013; Bruneel et al., 2012; C. P. Eveleens et al., 2017; van Weele et al., 2017). Understanding the perceptions of users of support services is crucial, as it influences decision-making, satisfaction, and future actions. Nair & Blomquist (2019) argue that the incubation process primarily evolves through continuous, personalised interactions between coaches and incubatees, emphasising the importance of relational and experiential learning. The level of intervention and assistance provided by incubators can be understood through the different phases of the incubation process.

The research is confined to startups that have been incubated in selected TBIs across the Indian states of Maharashtra, Karnataka, and Goa, thereby offering insights specific to the Indian startup ecosystem. The study adopts a quantitative approach, using Partial Least Squares Structural Equation Modelling (PLS-SEM) to test hypothesised relationships among constructs and explore moderating and mediating effects, including the moderation by incubators' intervention level, and mediation by perception constructs. Additionally, the study examines the role of gender as a moderating factor using Multigroup Analysis (MGA). It applies the Combined Importance-Performance Map Analysis (cIPMA) to identify priority areas for strategic improvement. Data has been collected using a structured questionnaire administered through both online and offline modes. This research primarily covers incubated startups that are actively operating and have received some level of support services from TBIs, such as mentorship, infrastructure, funding access, or market linkage.

The findings are expected to be particularly relevant for incubation managers, policymakers, startup founders, and researchers, as they identify which support mechanisms are most impactful and which areas require strategic improvement. However, the results may have limited generalizability beyond the geographic and contextual boundaries of the selected Indian states.

1.3 RESEARCH PROBLEM AND QUESTIONS

Despite the rapid expansion of Technology Business Incubators (TBIs) across India as instruments of innovation and entrepreneurship promotion, there remains a limited empirical understanding of how these incubation mechanisms actually influence startup success (Mian et al., 2016; Bruneel et al., 2012). While incubators are designed to provide a range of support services—such as infrastructure, mentoring, networking, access to finance, and business development assistance—their impact varies widely among startups (Hausberg & Korreck, 2020). This variation arises partly from differences in startup characteristics such as prior entrepreneurial experience, technological capability, team composition, and social or psychological capital, which shape how founders perceive and utilize the support offered (Monsson & Jørgensen, 2016; Vanderstraeten & Matthyssens, 2012). Many startups underutilize certain services or misjudge their relevance, resulting in inconsistent performance outcomes (Barbero et al., 2012; M. van Weele et al., 2017). Existing literature largely examines the effectiveness of TBIs from an institutional or policy perspective, with insufficient attention to how startup-specific factors interact with incubator interventions (Albort-Morant & Ribeiro-Soriano, 2016; Mian et al., 2016). Consequently, the mechanisms through which incubator support translates into improved startup performance remain inadequately understood. There is, therefore, a pressing need to investigate how startup characteristics influence their perception of the importance and effectiveness of TBI services, their frequency of usage, and the subsequent impact on overall startup performance (Patton, 2014; Scillitoe & Chakrabarti, 2010). Addressing this research problem will contribute to both academic understanding and policy formulation by identifying how incubators can better tailor their support mechanisms to the heterogeneous needs of startups and thereby enhance their effectiveness in fostering entrepreneurial growth (Grimaldi & Grandi, 2005; Pauwels et al., 2016).

In line with the research problem and the conceptual framework developed for this study, a set of research questions has been formulated to guide the investigation. These questions aim to explore the relationships among startup characteristics, perceptions of incubator services, frequency of usage, and startup performance. The following research questions have been designed to address the study's core objectives and provide a comprehensive understanding of the impact of incubation support services on the outcomes of startups.

1. How do startup characteristics influence the frequency of usage of support services provided by Technology Business Incubators (TBIs)?

2. What is the impact of startup characteristics on the perception of importance and effectiveness of incubators' support services?

3. How are these usage patterns affected by startups' perceptions of the importance and effectiveness of these services?

4. Do Perception of Importance (PoI) and Perception of Effectiveness (PoE) mediate the relationship between Startup Characteristics (SC) and Frequency of Usage (FU) of incubator services?

5. Does the Degree of Incubator's Intervention and Assistance strengthen or weaken the impact of Frequency of Usage on Startup Performance and between Startup Characteristics and Frequency of Usage?

6. To what extent does the frequency of usage of incubators' support services influence the performance of startups?

7. Do the characteristics of a startup directly impact its overall performance, without the influence of intermediary factors?

8. How does gender moderate the relationship between startup characteristics, incubator service usage, perceived service value, and startup performance?

1.4 RESEARCH OBJECTIVES

In alignment with the research problem, conceptual framework, and research questions, the following research objectives have been formulated to provide clear direction and focus to the study:

Objective 1: To examine the influence of startup characteristics on the frequency of usage of support services offered by Technology Business Incubators (TBIs).

Objective 2: To assess the impact of startup characteristics on startups' perception of the importance and effectiveness of incubator support services.

Objective 3: To analyse how startups' perceptions of the importance and effectiveness of incubator services influence their frequency of usage.

Objective 4: To examine the mediating role of Perception of Importance (PoI) and Perception of Effectiveness (PoE) in the relationship between Startup Characteristics (SC) and Frequency of Usage (FU) of incubator services.

Objective 5: To investigate whether the Degree of Incubator's Intervention and Assistance moderates (a) the relationship between frequency of usage and startup performance, and (b) the relationship between startup characteristics and frequency of usage.

Objective 6: To evaluate the extent to which the frequency of usage of incubator support services affects startup performance.

Objective 7: To determine whether startup characteristics have a direct effect on startup performance, independent of any mediating constructs.

Objective 8: To explore the moderating role of gender in the relationships among startup characteristics, perceptions of incubator support, frequency of usage, and startup performance.

1.5 RESEARCH HYPOTHESES

The following hypotheses have been developed for the statistical evaluation of the stated objectives, considering the research questions and the objectives formulated for the study:

For **Objective 1**, the research hypotheses are –

Startup Characteristics and First-order components

H1a(i): Experience has a positive contribution towards Startup Characteristics.

H1a(ii): Network has a positive contribution towards Startup Characteristics.

H1a(iii): Skills have a positive contribution towards Startup Characteristics.

H1b: Startup Characteristics have a significant direct impact on Frequency of Usage.

For Objective 2:

H2a: SC have a significant positive impact on PoI.

H2b: SC have a significant positive impact on PoE.

For Objective 3:

H3a: PoI has a significant positive impact on FU.

H3b: PoE has a significant positive impact on FU.

For Objective 4:

H4a: PoI has a significant mediating role between SC and FU.

H4b: PoE has a significant mediating role between SC and FU.

For Objective 5:

H5a: DIIA moderates the relationship between Startup Characteristics and Startup Performance.

H5b: DIIA moderates the relationship between Frequency of Usage and Startup Performance.

For Objective 6:

H6: Frequency of Usage has a significant positive impact on Startup Performance.

For Objective 7:

H7: Startup Characteristics have a significant direct impact on Startup Performance.

For Objective 8:

H8a: Gender moderates the relationship between Startup Characteristics and Frequency of Usage.

H8b: Gender moderates the relationship between Perception of Effectiveness and Frequency of Usage.

H8c: Gender moderates the relationship between Startup Characteristics and Perception of Effectiveness.

H8d: Gender moderates the relationship between Perception of Effectiveness and Frequency of Usage.

H8e: Gender moderates the relationship between Perception of Importance and Frequency of Usage.

H8f: Gender moderates the relationship between Frequency of Usage and Startup Performance.

H8g: Gender moderates the relationship between Startup Characteristics and Startup Performance.

1.6 SIGNIFICANCE OF THE STUDY

The growing significance of entrepreneurship in fostering economic growth has led to the global expansion of Technology Business Incubators (TBIs), which are organised support mechanisms designed to enhance the viability and success of startups. TBIs offer several essential services, including mentorship, financial support, networking opportunities, infrastructure, and business development assistance. While these services are widely regarded as crucial to entrepreneurial success, a significant gap remains in empirical studies examining the extent to which incubator support services influence startup performance. This study aims to bridge this gap by examining the impact of support services provided by TBIs on startup success through a systematic analytical framework, particularly within the context of India.

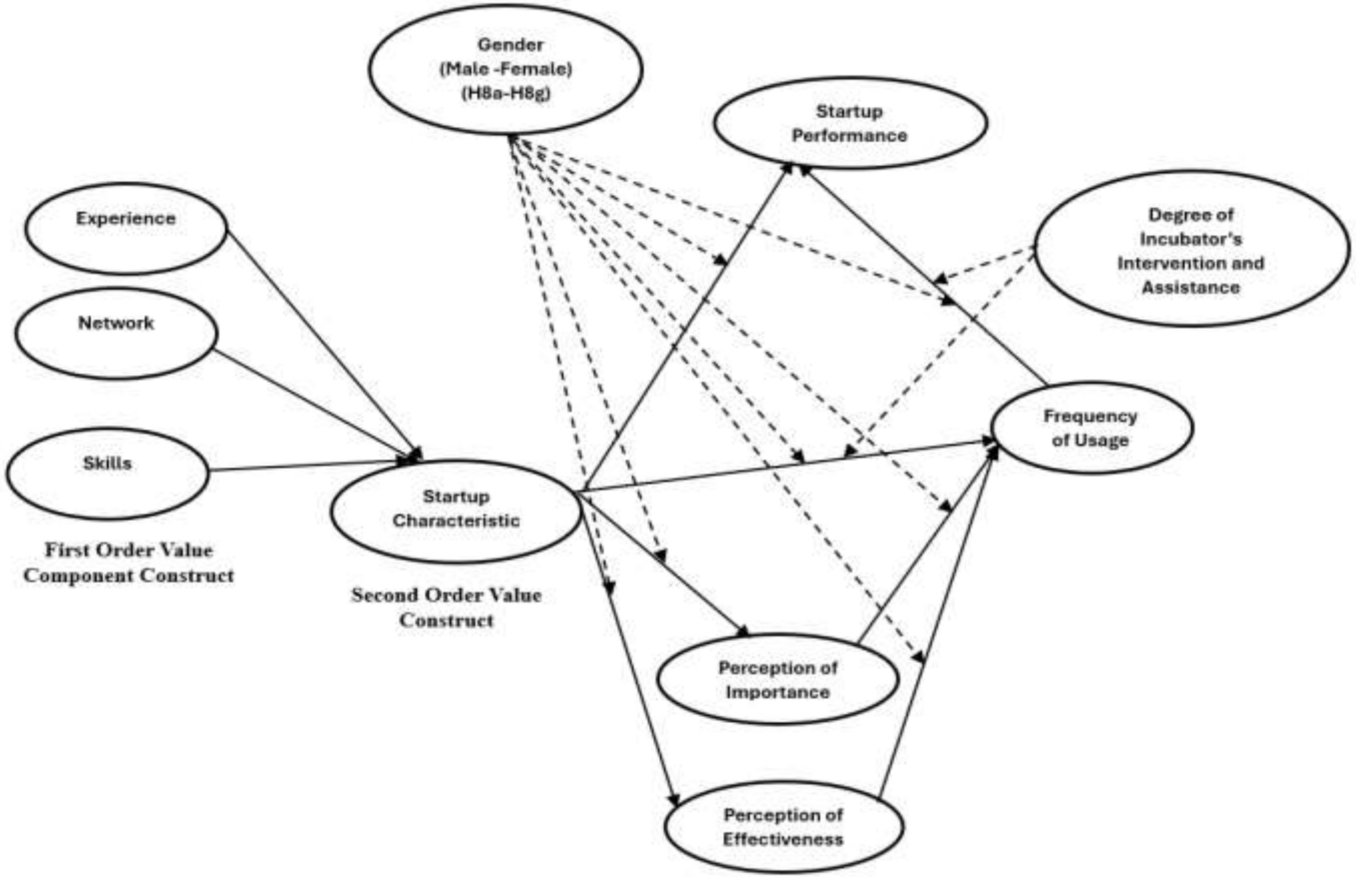
This study is particularly significant as it examines how startup characteristics such as experience, skills, networks influence the perception of the importance and effectiveness of incubator support services. By analysing how these characteristics shape startups' views on incubation, the study aims to understand how such perceptions influence the frequency of incubator service usage and, consequently, the performance of startups. This perspective provides a more nuanced understanding of the incubation process, highlighting that not all startups benefit equally from the same support services.

The findings of this research will be of significant relevance to various stakeholders:

- ***Entrepreneurs and Startup Founders:*** The results of this study will provide entrepreneurs with valuable insights into the performance of various incubator services, enabling them to make informed decisions about selecting incubators and their involvement with startups. Startups can maximise their use of incubation resources by determining the most effective support mechanisms. This allows them to improve their development, sustainability, and innovation potential.
- ***Incubator Managers:*** By identifying best practices and key success criteria within TBIs, the research will contribute to the enhancement of incubation techniques. To be more specific, incubator managers can utilise these insights to improve service offerings and ensure they align with the ever-changing requirements of startups.
- ***Policymakers:*** Policymakers can use the findings to establish evidence-based policies that foster a more effective entrepreneurial environment, hence increasing economic development through successful firm incubation in India. This, in turn, can contribute to the formulation of more effective policies that promote innovation and drive economic growth.
- ***Academics and Researchers:*** This research will provide a theoretical foundation for future studies on the effectiveness of incubation across various industries and economic contexts. This will be accomplished by conducting a systematic analysis of the role that incubation services play as mediating factors in the success of startups. As an additional benefit, the research will contribute to the development of interdisciplinary research in the fields of entrepreneurship and innovation management by helping to bridge the gap between theoretical incubation models and real applications. Additionally, this research will contribute to the academic literature by providing empirical evidence on the role of startup characteristics in shaping incubation outcomes**,** filling a critical gap in existing studies on business incubation.
- ***Venture capitalists and Investors:*** Understanding how incubator support services affect company growth, VCs can make better investment decisions and evaluate incubated startups more effectively. Investors can better assess risks and discover high-potential ventures that received structured backing using this research. These data can also help venture capital firms prioritise startups that have had effective incubation to improve portfolio management.

1.7 CONCEPTUAL MODEL

Figure 1.3: Proposed Conceptual Model



Source: Authors' own compilation based on earlier works

1.8 CHAPTERISATION SCHEME

The thesis is structured into five comprehensive chapters, each serving a distinct purpose in addressing the research objectives.

Chapter 1: The **Introduction** establishes the foundational context of the study by presenting the background and rationale, articulating the research problem, and clearly outlining the objectives and research questions. It underscores the significance of the study for key stakeholders and defines the scope and boundaries of the research. The chapter concludes with a concise overview of the overall structure of the thesis, providing a clear roadmap for the subsequent chapters.

Chapter 2: The **Review of Literature** provides the theoretical and empirical foundation of the study by tracing the evolution of research on business incubation and startup development. It critically examines prior studies to identify key constructs, conceptual linkages, and methodological approaches relevant to the present research. The chapter adopts a systematic two-phase review comprising bibliometric analysis and the Input–Mediator–Outcome (IMO) framework to map existing scholarship, identify research gaps, and establish the basis for the proposed conceptual model that guides the empirical investigation in subsequent chapters.

Chapter 3: Research Methodology outlines the research design and methodological choices adopted in the study. It describes the use of a structured questionnaire based on insights from in-depth interviews and validated through pilot testing. The chapter outlines the sampling technique, justifies the sample size, describes data collection procedures (both online and offline), and addresses ethical considerations. It also provides a rationale for using PLS-SEM as the primary analytical technique and introduces the SmartPLS software used for data analysis.

Chapter 4: Data Analysis and Interpretation presents the study's findings through a detailed statistical analysis. This includes descriptive statistics of the sample, measurement model assessment (reliability and validity), and structural model evaluation (path coefficients, R^2, Q^2, f^2). The chapter also reports results from bootstrapping, mediation and moderation analysis, Multi-Group Analysis (MGA), and advanced techniques such as Importance-Performance Map

Analysis (IPMA) and Necessary Condition Analysis (NCA). Interpretations are provided to align the findings with the research objectives and existing literature.

Chapter 5: Summary, Findings, Conclusions, and Suggestions for Further Research summarises the research process and significant findings, discusses their theoretical and practical implications, and draws meaningful conclusions. It outlines the study's contributions to the fields of entrepreneurship and business incubation. The chapter also acknowledges limitations and proposes directions for future research that can build upon the insights generated by this study

CHAPTER 2
REVIEW OF LITERATURE

This chapter presents a comprehensive review of the literature related to Technology Business Incubators (TBIs) and their influence on startup development and performance. It explores theoretical foundations and empirical evidence concerning constructs such as startup characteristics, perception of incubator services, frequency of usage, and performance outcomes. The review synthesizes prior research using the Input–Mediator–Outcome (IMO) framework to trace how incubators transform startup inputs into measurable outcomes through mediating mechanisms. By identifying key themes, methodological trends, and research gaps, this chapter provides the conceptual foundation for the subsequent analysis and formulation of hypotheses in the present study.

2.1 LITERATURE REVIEW METHODOLOGY

A literature review is a systematic compilation, classification, and assessment of the existing research on a specific subject. Its objective is to present each work in the context of its contribution to the subject, describe the relationship between various studies, and identify new interpretations while highlighting gaps in previous research. In addition, it attempts to resolve conflicts between seemingly contradictory findings, prevent duplication by acknowledging prior scholarship, and direct future research.

Ultimately, a literature review establishes the relevance and contribution of an original piece of research to the existing body of knowledge by situating it within the broader academic discourse. This chapter explores relevant scholarly contributions, critically analysing prior work in the domains of entrepreneurship, startup development, business incubation, and innovation ecosystems. The complete process of the literature search is illustrated in Figure 2.1.

In the initial stage, the literature review was conducted by exploring a wide range of scholarly sources, including research articles, theses, conference proceedings, dissertations, and working papers, all of which were aligned with the study's objectives. These sources were accessed through reputable databases, including Web of Science, Emerald, JSTOR, J-Gate Next, SpringerLink, Taylor & Francis, ScienceDirect (Elsevier), Wiley, and Google Scholar. To ensure a focused and comprehensive search, relevant keywords related to entrepreneurship, startup development, and business incubation were used instead of whole phrases, facilitating the identification of specific yet highly relevant resources.

In the next stage, all the collected literature was mapped and filtered to ensure alignment with the research domain and objectives. This process reduced the number of sources to approximately 500 documents. In the second and final filtering stage, papers were screened based on their abstracts and content, with a focus on their relevance to the research objectives—specifically, incubator interventions and the measurement of business incubation's impact on startup performance. Further refinement narrowed the focus exclusively to studies that assess startup performance measurement within the context of business incubation and its associated criteria.

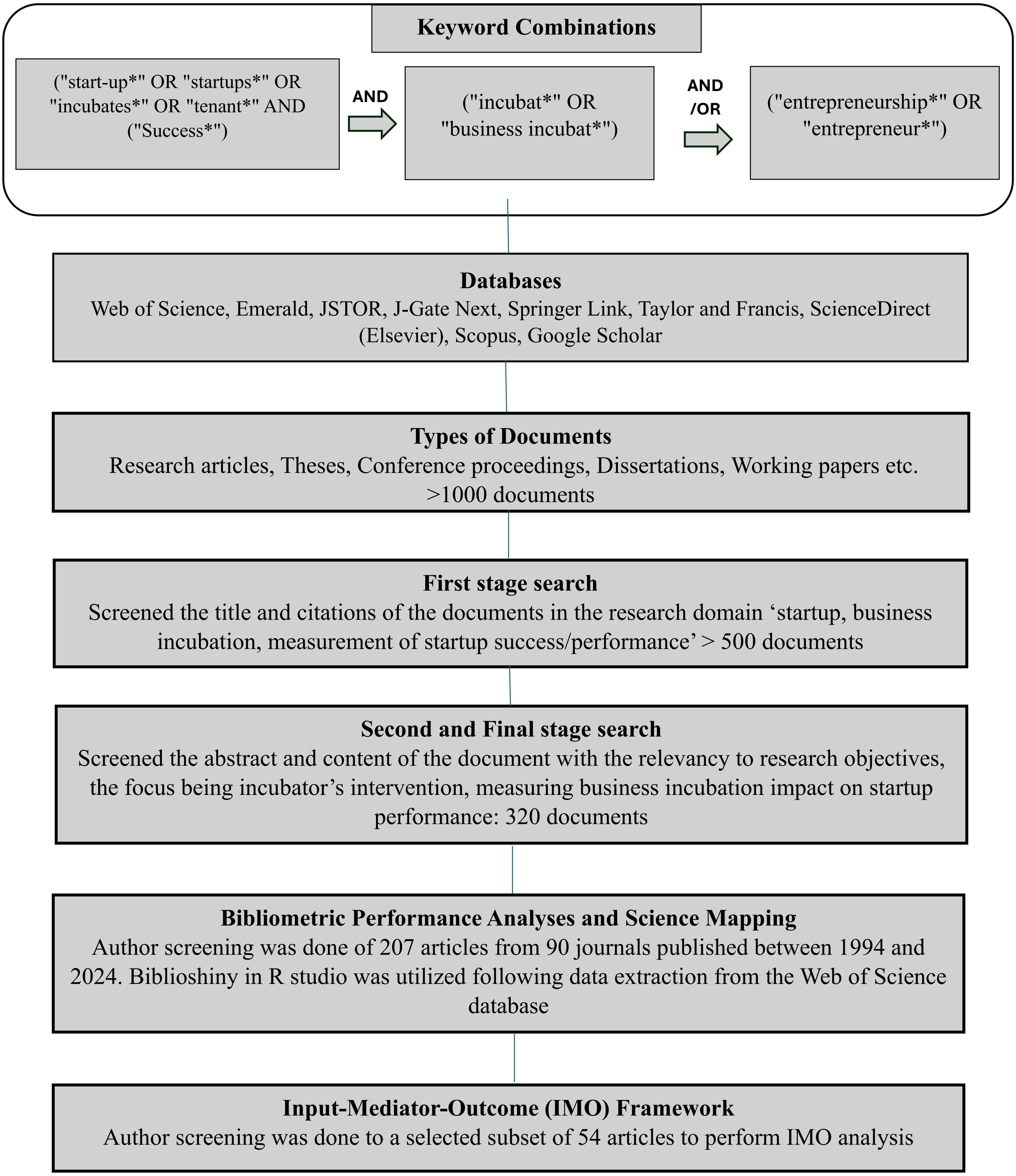
A few core documents were identified, which were then leveraged in a backward and forward snowballing process to uncover additional relevant references from other publishers and sources. This approach ensured a more comprehensive review by tracing influential studies and identifying key contributions in the field. Finally, all the collected resources were synthesised to refine the initial conceptual model and develop the questionnaire, ensuring alignment with the study's objectives.

2.2 SYSTEMATIC LITERATURE REVIEW

We have designed our Systematic Literature Review (SLR) using a two-step process: firstly, we conducted a bibliometric analysis, which included a performance analysis and a scientific mapping analysis.

Bibliometric analysis is much more reliable than peer review (Abramo & D'Angelo, 2011). Next, we conducted an SLR, employing the Input-Mediator-Outcome (IMO) Framework, proposed initially by Lecluyse et al. (2019), to gain a deeper understanding of the detailed processes and contextual factors that influence the effectiveness of Technology Business Incubators (TBIs). The IMO framework was applied to a refined selection of 54 articles, drawn from the second and final stages of the search process (Figure 2.1), where abstracts and content were screened. The focus was specifically on incubator interventions and assessing the impact of business incubation on the performance of startups.

Fig 2.1: The literature search process



Source: Compiled by author

2.2.1 BIBLIOMETRIC ANALYSIS

Bibliometric indicators help develop research policies and monitor technological activities (Costas et al., 2010). It also provides a retrospective window on a selected group of scholarly works, based on the assertion that citations can be used as indicators of current and past activities in scientific work (Garfield et al., 1964, 1983; Schildt & Sillanpää, 2004; Small, 1999).

2.2.1.1 *Performance analysis*

We performed a bibliometric analysis using Biblioshiny in RStudio. Table 2.1 presents the main features of the records collected for the bibliometric study. The data collected between 1994 and 2024 consists of 207 documents associated with 90 journal sources authored by 486 researchers with 36 single authors only; furthermore, there are about three co-authors per document, showing a good collaborative trend among the researchers; also the international co-authorship is approximately 33.82% signifying a positive influence in this area of research (Khor & Yu, 2016). The annual growth rate of documents is 8.62%, indicating a steady increase in output over the years. The average number of citations per document is approximately 27, indicating an increasing research interest in this area.

Table 2.1: Main features of the data

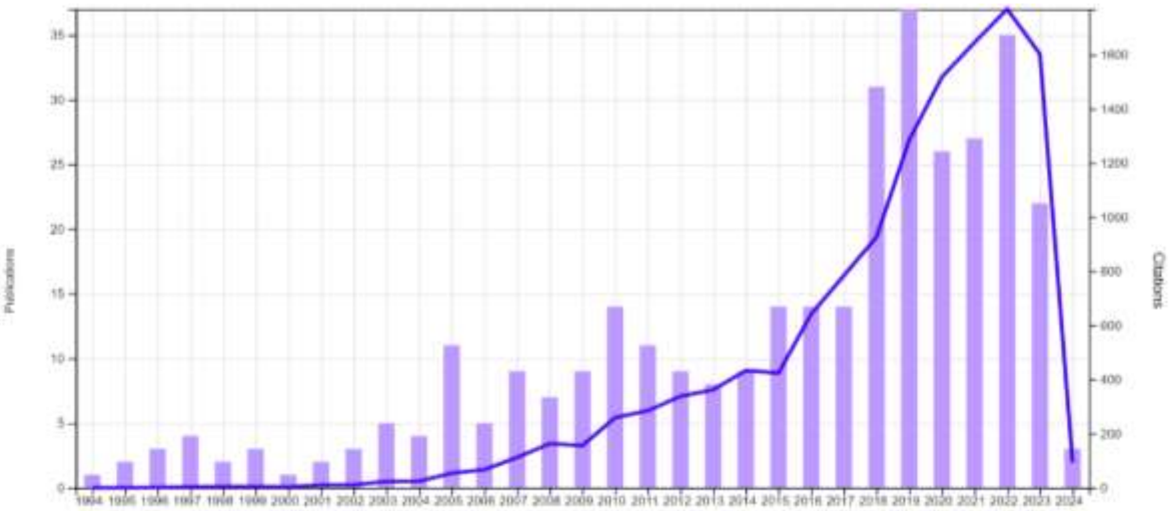
Description	Results
Timespan	1994:2024
Documents	207
Annual Growth Rate %	8.62
Average citations per doc	26.61
Authors	486
Authors of single-authored docs	36
Single-authored docs	38
Co-Authors per Doc	2.68
International co-authorships %	33.82

Source: Biblioshiny

Academic research on startups and incubation has appeared since the early 1990s (Mian, 1997, 1994, 1996a, 1996b). Figure 2.3 illustrates the combination of publications and citations for research involving startups and incubators. Examining the trend in Figure 2.3, the evolution of publications can be classified into three distinct periods. The first period spans from 1992 to 2005 (Sherman & Chapell, 1998; Lalkaka, 1996; Bøllingtoft & Ulhøi, 2005a; Pena, 2004; Löfsten & Lindelöf, 2004), during which research in this area is stable at a low level, indicating the early emergence of research in this area. The research grew moderately from 2006, marking the start of the second stage up to 2016 (Bergek & Norrman, 2008a; Aerts et al., 2007; Patton, 2014; Patton et al., 2009; Patton & Marlow, 2011; Vanderstraeten et al., 2016). This phase followed variations with very few publications during 2009. The third phase represents a steep increase in publications from 2017 to date, with the highest point in publication and citation in 2022(Van Rijnsoever et al., 2017; van Weele et al., 2020; Xiao & North, 2017; Klingbeil & Semrau, 2017; Lopes et al., 2018; Tang et al., 2021).

Similarly, the first phase is marked with a meagre citation count. However, post-2000, the distribution of citations began to increase(Chan & Lau, 2005; Moray & Clarysse, 2005; Etzkowitz et al., 2005; Markman et al., 2005), and there was a steep increase in citations during the second(Bergek & Norrman, 2008; McAdam & McAdam, 2008; Mian et al., 2016; Aerts et al., 2007; D. P. Soetanto & Jack, 2013) and third phases(Gorączkowska, 2020; van Rijnsoever, 2020; Tang et al., 2021; Ahmed et al., 2020; Karahan, 2024), with the highest point in 2023. Since WoS is a citation index, the records in the database contain information on citations made in that publication, allowing one to identify which publications have been cited and the number of times they have been mentioned. Publication and citation metrics are best when used in combination. Since the data was collected in February 2024, there has been a drop in publications and citations, indicating that the output for only part of 2024 is reflected.

Fig 2.2: Number of Publications and citations per year



Source: Biblioshiny

Table 2.2 lists the top ten Journals with at least five publications involving TBIs and startups. *The Journal of Technology Transfer and Sustainability is positioned first in this analysis, as it has* 17 publications each. These journals consistently emphasise the subject of technology business incubation and startups, as evidenced by the articles that explore the field's rapid expansion over the past two decades observed in this review. *Technovation* is similarly consistent, ranking second with 14 publications, followed by *Technological Forecasting and Social Change, which has* 11 publications. The investigation conducted by Mian (1996) in the journal *Research Policy,* which explored the effects of University Technology Business Incubators (UTBIs) on new technology-based tenant firms, sparked further research in this field.

Table 2.2 Top ten most relevant sources (>5 publications)

Rank	Sources	#Articles
1	Journal of Technology Transfer	17
2	Sustainability	17
3	Technovation	14
4	Technological Forecasting and Social Change	11
5	IEEE Transactions on Engineering Management	6
6	International Journal of Entrepreneurial Behaviour & Research	6
7	Research Policy	6
8	European Journal of Innovation Management	5
9	International Small Business Journal-Researching Entrepreneurship	5
10	Technology Analysis &/or Strategic Management	5

Source: Biblioshiny

Table 2.3 highlights the impact of publications involving business incubation and startups. Recently, the h-index has been used as an alternative to the Impact Factor (IF), as the IF is a short-term measure that only considers citations over a two-year period to assess journal quality (Mingers et al., 2012).

The h-index is defined as: "a scientist has index h if h of his / her papers have at least h citations each and the others (N-h) papers have no more than h citations each" (J.E.Hirsh, 2005). The g-index is used as an improvement of the h-index, wherein when the set of articles is ranked in decreasing order of the number of citations that they received, the g-index is the (unique) most significant number such that the top g articles received (together) at least g^2 citations (Egghe, 2006). Meanwhile, the m-index displays the h-index per year since the first publication. The h-index tends to increase with career length, and the m-index is used in situations where this is a shortcoming, such as comparing researchers within a field but with very different career lengths (Elsevier, 2018). *The Journal of Technology Transfer* tops the h-index (13), g-index (17), and m-index (1.083) with 17 publications cited 675 times, followed by Technovation, which has an h-index of 10, g-index of 14, and m-index of 0.333, with 14 publications cited 856 times. The table below uses TC, NP, and PY_start to mean Total Citations, Number of Publications, and Start of Publication (Year), respectively.

Table 2.3: Impact of the research publications

Journals	*h_index*	*g_index*	*m_index*	*TC*	*NP*	*PY_start*
Journal Of Technology Transfer	13	17	1.083	675	17	2012
Technovation	10	14	0.333	856	14	1994
Technological Forecasting and Social Change	9	11	0.5	341	11	2006
Research Policy	6	6	0.25	455	6	2000
Sustainability	6	11	1.2	138	17	2019
European Journal of Innovation Management	4	5	0.571	235	5	2017
International Journal of Entrepreneurial Behaviour &/or Research	4	6	0.571	81	6	2017
International Small Business Journal-Researching Entrepreneurship	4	5	0.222	252	5	2006
Entrepreneurship And Regional Development	3	4	0.13	155	4	2001
IEEE Transactions on Engineering Management	3	6	0.188	97	6	2008

Source: Biblioshiny

Table 2.4: Most productive authors (≥ 3 publications)

Authors	**Articles**	**Articles Fractionalized**
Van Rijnsoever FJ	11	5.00
Eveleens CP	5	1.67
Klofsten M	4	1.25
Lofsten H	3	0.87
Nicholls-Nixon CL	3	1.03
Valliere D	3	1.03
Zhang Y	3	0.87

Source: Biblioshiny

From the total of 455 authors analysed, fewer than ten have published at least three publications, 443 of them have published one article, and seven authors have published two. Table 2.4 shows the most productive authors, where *Van Rijnsover FJ* is among the most influential authors with 11 publications (Eveleens et al., 2017b; van Rijnsoever, 2022; Van Rijnsoever et al., 2017; van Rijnsoever & Eveleens, 2021; van Stijn et al., 2018; M. van Weele et al., 2017, 2018; M. A. van Weele et al., 2020). This author has also received the highest number of citations, as shown in Table 2.5, followed by McAdam M (McAdam & Marlow, 2007, 2011) and McAdam R(Galbraith et al., 2021; McAdam et al., 2006; McAdam & McAdam, 2008) with 21 citations each.

Table 2.5: Most locally cited authors

Author	Local citations
Van Rijnsoever FJ	44
McAdam M	21
McAdam R	21
Nauta F	20
Van Weele M	20
Rothaermel FT	19
Thursby M	19
Cohen S	14
Fehder DC	14
Hochberg YV	14

Source: Biblioshiny

Table 2.6: Authors' impact

Element	h-index	g-index	m-index	TC	NP	PY-start
Van Rijnsover FJ	10	11	1.429	338	11	2017
Eveleens CP	5	5	0.714	143	5	2017
Klofsten M	4	4	0.222	129	4	2006
Aaboen L	2	2	0.4	25	2	2019
Bandera C	2	2	0.333	70	2	2018
Bank N	2	2	0.286	57	2	2017
Baskaran A	2	2	0.182	23	2	2013
Blomquist T	2	2	0.4	25	2	2019
Bose SC	2	2	0.333	7	2	2018
Cantu C	2	2	0.222	32	2	2015

Source: Biblioshiny

Table 2.6 highlights the impact of the top ten researchers in business incubation and startups. *Van Rijnsover FJ* tops the list with the highest h-index of 10, which shows that 10 of his publications have at least ten citations, and 1 (11-10) has at least ten citations. His g-index is 11, and m-index is 1.429, respectively. It is evident from Table 5 that the publication years are recent. Therefore, the total citation (TC) counts are increasing, while the number of publications (NP) remains negligible in this area. Hence, there is good scope for researchers to explore this area further.

Out of the 47 countries analysed, the most productive countries in the scientific production of research articles in business incubation and startup research are represented in Table 2.7.

Table 2.7: Scientific Production of the countries

Rank	Region	#Articles
1	*USA*	83
2	*China*	62
3	*Italy*	53
3	*Spain*	50
4	*Sweden*	46
5	*UK*	46
6	*Netherlands*	31
7	*Canada*	24
8	*Germany*	21
9	*India*	17

Source: Biblioshiny

On the other hand, Table 2.8 shows countries with the highest citations and average citations. The USA has the highest number of articles (83) published, as well as the highest total citations (1,693) and the highest average article citations (70.50) (Rothaermel & Thursby, 2005b; Woolley & MacGregor, 2022; Smilor, 1986). China is the second highest (Kotabe et al., 2011; Liu et al., 2018; Motohashi, 2013; Yuan et al., 2022), followed by Italy (Bonini & Capizzi, 2019; Del Sarto et al., 2020; Lukeš et al., 2019). In terms of countries with the highest total citations, followed by the USA, are Italy (TC=80 and AAC=30) and the Netherlands (TC=340 and AAC=30)

Table 2.8: Most cited countries

Country	TC	Average Article Citations
USA	1693	70.50
Italy	480	30.00
Netherlands	340	28.30
Ireland	288	96.00
Switzerland	284	56.80
Sweden	231	17.80
United Kingdom	212	17.70
Spain	206	20.60
China	173	11.50
Canada	146	14.60

Source: Biblioshiny

2.2.1.2 ***Science Mapping analysis***

Under the science mapping analysis, we presented trends in topics and keywords, citation structures, and patterns of country collaboration.

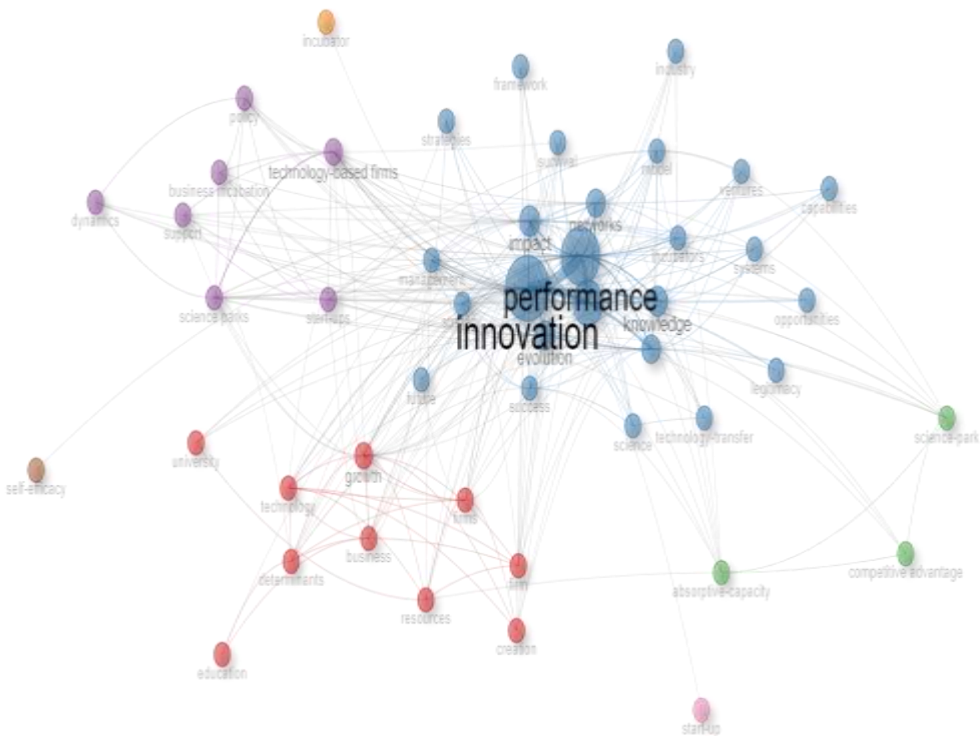
Topic and Keyword Trend

Biblioshiny presents topic and keyword trends (Aria & Cuccurullo, 2017). Fig.2.3 depicts the ***keyword co-occurrence network*** created using two or more keywords in the same research work. It examines the frequency of occurrence and the strength of the link between specific keywords. The co-occurrence analysis in this dataset reveals 6 clusters, each represented by a different colour. The clusters can be described as follows: The blue cluster indicates "Innovation of start-ups incubated and their performance." The blue colour cluster is denser, with the keywords "Innovation" and "performance" acting as a bridge between other clusters. The red and purple cluster shows close interconnections with the blue cluster by linking keywords such as "technology-based firms", "Science parks", "business incubation", "Start-ups", "growth", "technology", "business" which suggests focus on topics like innovation and technology-driven businesses, development and expansion of startups, indicating a trend where technology plays a crucial role in shaping and driving business activities, environments fostering collaboration, research, and the growth of technology-driven enterprises. The close interconnections between red, purple, and blue clusters suggest a collaborative environment where technology, business and innovation are intertwined. The green cluster represents a dynamic ecosystem where concepts such as absorptive capacity, competitive advantage, and the strategic role of science parks converge. In the orange cluster, the focal point revolves around the concept of incubation, signifying its central role in nurturing startups and fostering innovation within an ecosystem. Conversely, the brown cluster emphasises 'self-efficacy', underscoring the individual's belief in their ability to execute tasks and overcome challenges autonomously.

A thematic evolution in the literature of business incubation and startups was further performed based on a thematic map (Fig.2.4) using co-word analysis and author keyword cluster formations as performed by Cobo et al., 2011. The thematic map visualises the themes into four quadrants based on their centrality and density, represented along the two axes. The position of the keywords in the thematic map is based on the number of publications, their citations, and the strength of the tie with other themes.

Centrality indicates the importance of a theme relative to other themes on the map. At the same time, density measures the development of the internal links within a cluster represented by a theme. The size of the cluster corresponds to the number of occurrences of the keywords it contains, and the position of the cluster is determined by its centrality and density (Cobo et al., 2011).

Figure 2.3: Co-occurrence Network

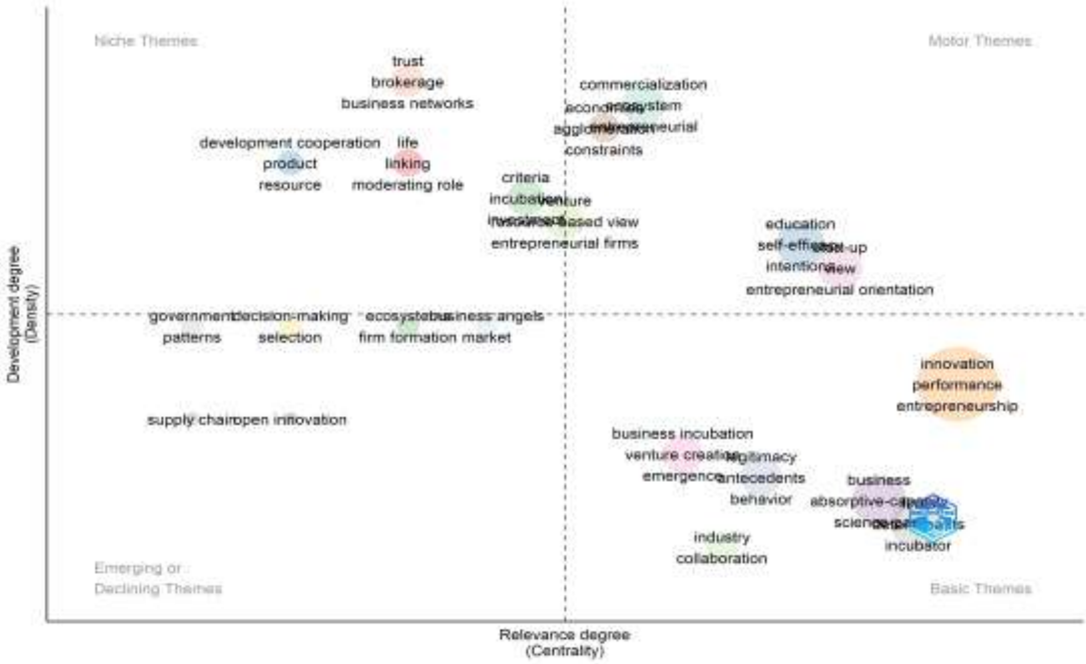


Source: Biblioshiny

The four quadrants are divided by theme into niche, motor, basic, and emerging themes. The niche theme clusters, such as 'trust, brokerage, and business networks' and 'development cooperation, product, resource', are located in the top-left quadrant and signify high density and low centrality, indicating that the topics are well-researched but have marginal importance in this area. The result is shown in Figure 2.4.

The themes in the top right quadrant are motor themes, such as 'entrepreneurial ecosystem and commercialisation', 'education, self-efficacy, intention', etc. (Becker & Endenich, 2023; Fuerlinger et al., 2015; Jha, 2018; Mack & Mayer, 2016; Malecki, 2018; Mujahid et al., 2019; Neumeyer et al., 2019; Prokop, 2021; Ratten, 2021; Santos, 2022; Spigel, 2017; Szczukiewicz & Makowiec, 2021; Xiao & North, 2018) which have high centrality and high density and imply that these topics are well-researched and highly important. We also notice that some clusters, such as 'venture, resource-based views, and entrepreneurial firms', overlap in the niche and motor themes. The clusters in the lower-right quadrant, such as 'innovation, performance, entrepreneurship', 'business, absorptive-capacity, science-parks', signify that the topics have high centrality and low density and are thus considered promising and not yet developed for the research field. Finally, the declining and emerging themes in the lower-left quadrant, such as 'government, patterns ', decision-making, selection', etc., signify declining or emerging themes with low centrality and density and hence are considered not well-developed with marginal importance.

Fig 2.4: Thematic Map



Source: Biblioshiny

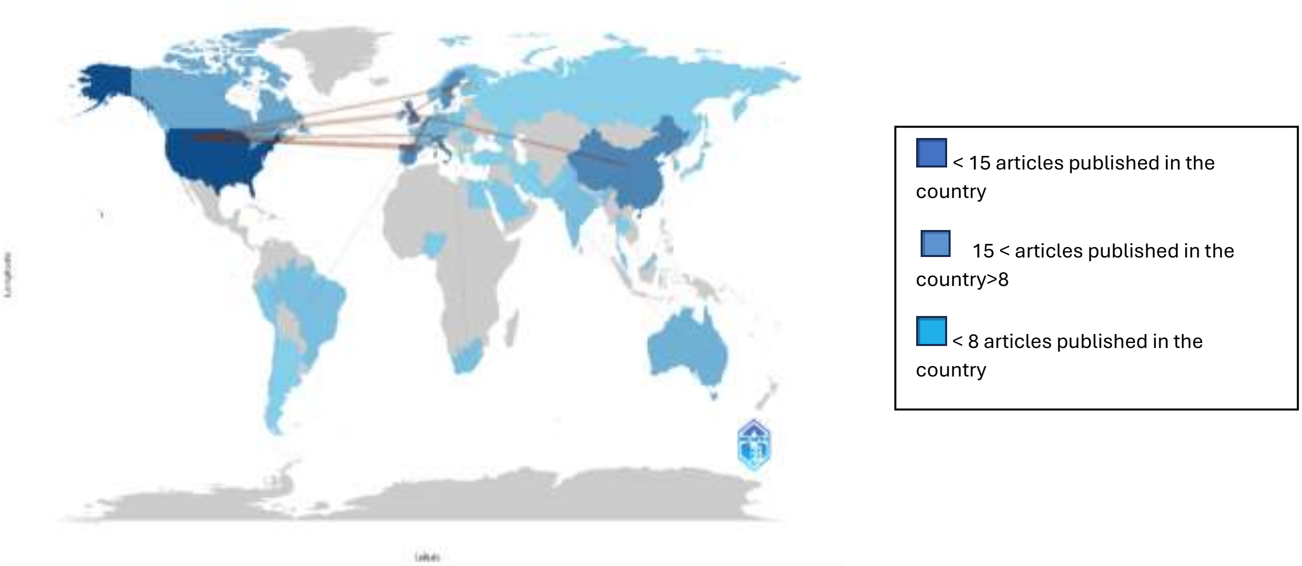
Analysis of Country Collaboration

Figure 2.5 depicts the global collaborations. The different shades of blue represent the various levels of research cooperation among nations. The thickness of the linking lines indicates the extent of collaboration between the authors. The USA collaborates most with the United Kingdom, Switzerland, Sweden, Italy, and France (Bonini & Capizzi, 2019; Feldman et al., 2022). Furthermore, strong collaborations are observed between the United Kingdom and Belgium, France, Sweden, Canada, and the Netherlands (Guerrero et al., 2023; Breznitz et al., 2018; Lemaire et al., 2023). It is evident that Western countries have high internal collaboration links.

2.2.2 INPUT-MEDIATOR-OUTCOME (IMO) FRAMEWORK

Employing the IMO methodology in a systematic literature review provided significant advantages by facilitating improved data structuring and analysis.

Fig 2.5: Country Collaboration Map



Source: Biblioshiny

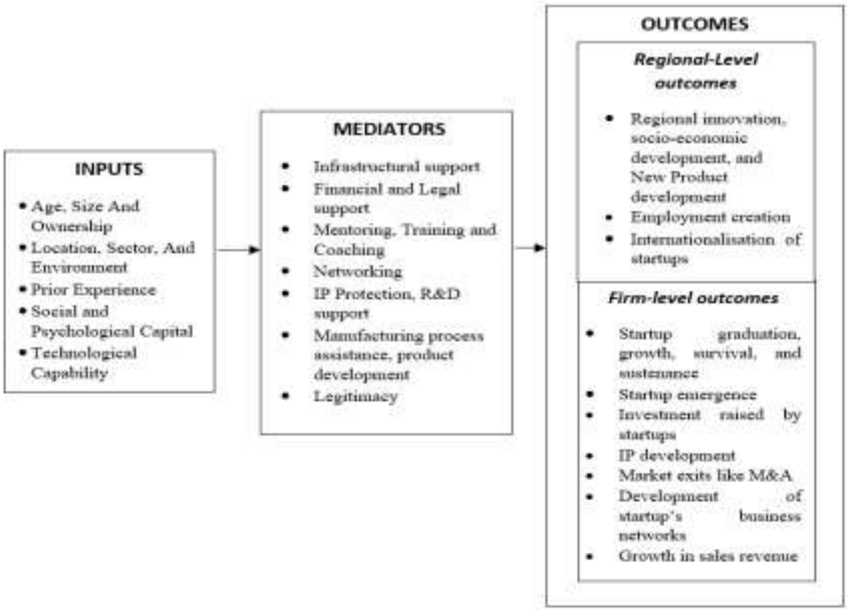
It aided in the development of a more comprehensive comprehension of the *inputs*, which encompass the diverse characteristics and attributes that either affect or limit the impact of TBIs on startup performance outcomes. Furthermore, it provided a comprehensive understanding of the mechanisms, or mediators, that represent the processes by which TBIs initiate these links between inputs and outcomes. These *outcomes* served as indicators for assessing the impact of TBIs on the development and performance of startups.

2.2.2.1 INPUTS

The initial inputs of startups are recognised as essential components in the development of successful ventures. Startups are perceived as both teams and individual entrepreneurs. Our synthesis of empirical research (summarised in Annexure E) investigates the relationship between these inputs and the development and performance of startups, as demonstrated in the framework depicted in Figure 2.6. Factors such as experience, ownership, psychological, social, and technological skills, as well as startup age, have been the primary focus of research. Younger startups, particularly those with limited industry experience, frequently encounter challenges in attracting investors and collaborators. According to Lukeš et al. (2019), incubation may initially have a detrimental influence on innovative startups that are one to two years old; however, its impact becomes beneficial as the startups mature to three to four years old.

The future performance and survival prospects of a startup are also significantly influenced by its size (Del Sarto et al., 2020). Fritsch et al. (2006) conducted research that demonstrated that larger businesses exhibit higher survival rates and are generally more resilient than their smaller counterparts. Moreover, the degree of specialisation within a startup is influenced by the size of the team, while the distribution of equity and governance control is influenced by ownership structures (Van Rijnsoever et al., 2017)

Figure 2.6 Input-Mediators-Outcomes (IMO) Framework (Noronha & Pillai, 2025)



Source: Authors' Compilation

The prospects of a startup are further enhanced by prior entrepreneurial experience. In comparison to first-time founders, entrepreneurs with such experience have more extensive professional networks and a broader business acumen (Colombo & Grilli, 2005; Van Rijnsoever et al., 2017b). Del Sarto et al. (2020) observed that entrepreneurs who have been in the business for a while possess a more profound understanding of the entrepreneurial voyage and the distinct phases of startup development. Similarly, Pena (2004) underscored the significance of human capital, particularly advanced education and managerial expertise, which significantly contribute to the survival and growth of new ventures. Entrepreneurs who possess these qualities have been observed to achieve superior performance outcomes. External contextual factors are also underscored by empirical research. The location of a venture provides access to critical resources, skilled labour pools, and potential collaborators and customers. The competitive landscape, regulatory barriers, and demand for the startup's innovations are influenced by the sector and broader business environment. Social capital, which is facilitated by networks and professional relationships, is essential for establishing connections with mentors, investors, and strategic partners. Psychological capital, which encompasses qualities such as optimism and resilience, is crucial for navigating entrepreneurial risks and uncertainties. Formal in-house collaborations through direct contracts and more informal networking activities were the two primary forms of internal business networks identified by Bøllingtoft & Ulhøi (2005). Lastly, the technological capabilities of a startup, such as its domain expertise and the uniqueness of its technological offerings, contribute to its competitive advantage by improving its market positioning and value proposition (Löfsten & Lindelöf, 2004).

Table 2.9: Startup Inputs

Startup inputs	Some Ideal References
Startups' age, size, and ownership	(Lukeš et al., 2019 ; Del Sarto et al., 2020 ; D. P. Soetanto & Jack, 2013a)
Startup's location, sector, and environment	(Paoloni & Modaffari, 2022; Pena, 2004 ; Fernandes et al., 2017)
Startups prior experience	(Li et al., 2020; Blank, 2023;Clausen & Korneliussen, 2012)
Startup's social and psychological capital	(Wang et al., 2020),(Bøllingtoft, 2012)(McAdam et al., 2006)
Technological capability	(Del Sarto et al., 2020; Chen et al., 2023 ; Van Rijnsoever et al., 2017b)

Source: Authors' Compilation

2.2.2.2 MEDIATORS/MECHANISMS

The mechanisms in the context of TBIs refer to the processes or factors that facilitate the transformation of a startup's initial inputs into purposeful outcomes. TBIs act as catalysts in this transformation by offering essential intermediary services, resources, and capabilities that support and accelerate startups. The literature identifies the following mechanisms (Table 2.10):

Infrastructural support

The most commonly provided support by incubators is the provision of shared facilities, such as subsidised spaces, offices, administrative staff, a shared canteen and reception, access to laboratories and other research facilities, etc.

According to Dourado Freire et al. (2022), resources bridge the gap between startups and TBIs, facilitating growth and sustainability. Among these resources, physical resources are significant in the early stages of startups. Such facilities enable startups to swiftly organise and initiate their trading activities, as incubators effectively mitigate numerous challenges associated with the practical aspects of forming a new business venture (McAdam & McAdam, 2008). New venture founders are provided with access to resources to help them learn how to commercialise technological ideas (Patton & Marlow, 2011). Xiao & North (2018) have emphasised both investing in an incubator's shared research facilities and equipment at lower-order innovation activity, as well as investing in more specialised facilities by some TBIs, which play a significant role in fostering advanced, R&D-intensive innovations across China.

Mentoring, training and coaching

Similarly, Xiao & North (2017) in the Chinese context have emphasised that the technical support and entrepreneurial mentoring provided by TBIs significantly benefit Tier 1 cities, which are affluent economic hubs with advanced infrastructure and high foreign investment, but have diminishing effects in Tier 2 and Tier 3 cities due to fewer resources and smaller markets. These services also impact graduation performance in government and university TBIs, respectively. Blank's (2021) study, based on 59 student startups operating in an academic incubator, elucidates how diverse prior experiences shape the interplay between the incubator's mentoring program and the startup's chances of survival in its first year.

Financial and legal support

Sung's (2007) research shows that Korean entrepreneurs prioritise financial services from incubators. This mismatch between expectations and outcomes highlights the ineffectiveness of government incubation policies. Sung suggests that to enhance results, incubators should shift to providing customised financial services by following the development process of technology firms (Chan & Lau, 2005), departing from the one-size-fits-all approach. Khodaei et al. (2022) likewise confirmed the subpar quality of incubator resources and the misalignment between startup needs and incubator resource offerings. Additionally, they identified another misalignment, specifically, a disconnect between the requirements of spin-offs and the support provided during their growth stages. Vanderstraeten & Matthyssens (2012) argue that the manner in which services are delivered warrants further consideration in studies on business incubators. They have hypothesised that the survival and growth of incubates largely depend on the extent of service customisation. There is a direct correlation between higher financial capacity and higher innovation performance among startups. With secured financial backing, they can acquire advanced technology or hire technical experts specialised in product research and development (Wang et al., 2020). The financial investments come from multiple entities such as financial institutions, government and enterprises (Bruneel et al., 2012; Dourado Freire et al., 2022); however, they are not immediately channelised through incubators without stable financing channels.

IP Protection, R&D support, Manufacturing process assistance, Product development

Gorączkowska (2020) investigates the impact of technology and university business incubators on innovation in industrial enterprises in Poland's Pomeranian and Kuyavian-Pomeranian regions. The study finds that incubators significantly enhance R&D activities and product innovations, with technology incubators being particularly effective in driving process innovations. While Corrocher et al.(2019) state that innovation is primarily boosted for already innovative firms through research collaborations and knowledge spillovers, it is less effective for firms without prior R&D capabilities.

Networking

Bøllingtoft (2012) has revealed two significant categories of networking activities, i.e. (i) providing business support activities by sharing knowledge and experiences related to running or developing a business, and (ii) rendering support services by using incubator networks, which is the necessity for nascent entities. Incubators act as institutional intermediaries between startups and market actors, such as investors and customers, connections to potential corporate partners, venture capitalists, and IP guidance (Rothaermel & Thursby, 2005a); otherwise, these connections and resources are costly to acquire in the open market (Rothaermel & Thursby, 2005b). Functioning as intermediaries within the institutional framework, business incubators leverage their wealth of knowledge and network-related resources to act as replacements for the inadequate market structures commonly found in emerging economies (Aernoudt, 2004). Xiao & North (2017) discovered that the most influential incubator service in accelerating the early development of resident firms is investing in the technical support platform by providing shared laboratory and research technical facilities, followed by entrepreneurial mentoring.

Legitimacy

The image of the incubator and the associated credibility it conveys give the tenant firm a significant advantage in its development and enhance its visibility (McAdam & McAdam, 2008). Vanderstraeten et al. (2016) and Vanderstraeten & Matthyssens (2012) have revealed that incubators with a focused approach provide business support services tailored to specific industries (e.g. IT, biotechnology, creative sector, etc.), aiming to generate enhanced value for their incubatees, thereby establishing a unique differentiation and service customisation for incubatees' survival and growth. McAdam & McAdam's (2008) study indicated that incubate firms are more likely to effectively utilise the resources and support provided by the incubator as the company advances through its lifecycle and seeks greater independence and autonomy.

Table 2.10: Mechanisms for purposeful outcomes

Mechanisms	Some Ideal References
Infrastructural support	(McAdam & McAdam, 2008;Schwartz, 2010; Pato & Teixeira, 2020)
Financial and Legal support	(Wang et al., 2020;Kwiotkowska & Gębczyńska, 2019 ; Khodaei et al., 2022)
Mentoring, Training and Coaching	(Del Sarto et al., 2020; Pena, 2004 ;Chan & Lau, 2005)
Networking	(Harper-Anderson & Lewis, 2018;Rothaermel & Thursby, 2005b ;Shih & Aaboen, 2019)
IP Protection, R&D support, Manufacturing process assistance, product development	(Gorączkowska, 2020; Corrocher et al., 2019;Bacalan et al., 2019, Xiao & North, 2017 ;Patton & Marlow, 2011; Lopes et al., 2018)
Legitimacy	(McAdam & McAdam, 2008; Schwartz, 2010)
Others	(Bøllingtoft, 2012;Gao et al., 2021;Löfsten et al., 2022)

Source: Authors' Compilation

2.2.2.3 OUTCOMES

In IMO analysis, the "outcome" pertains to the literature stream that explores the impact of the mechanisms introduced during the incubation process. In IMO analysis, the "outcome" pertains to the literature stream that explores the impact of the mechanisms introduced during the incubation process. The outcomes are divided into regional-level and firm-level (Table 2.11).

Table 2.11: Outcomes

Outcomes	Some Ideal References
Regional-Level outcomes	
Regional innovation, socio-economic development, and New Product development	Chen et al., 2023 **;** Xiao & North, 2017;Studdard, 2006; Lopes et al., 2018)
Employment creation	(Pena, 2004; D. P. Soetanto & Jack, 2013a; H. Zhang & Sonobe, 2011)
Internationalisation of startups	(Gao et al., 2021)
Firm-level outcomes	
Startup graduation, growth in sales revenue, survival, and sustenance	(Khodaei et al., 2022), (Dourado Freire et al., 2022), (L. Zhang et al., 2019), (Klingbeil & Semrau, 2017, Vanderstraeten et al., 2016, Pato & Teixeira, 2020, Sung, 2007)
Startup emergence	(Chan & Lau, 2005)
Investment raised by startups	(Van Rijnsoever et al., 2017)
IP development	(Chen et al., 2023), (Löfsten, 2016)
Development of the startup's business networks	(Shih & Aaboen, 2019), (van Rijnsoever, 2020), (Smilor, 1987a)

Source: Authors' Compilation

Regional-level outcomes

Studies examining regional-level outcomes often take a case-based approach or concentrate on specific contexts (Lecluyse et al., 2019). TBIs facilitate regional innovation by transferring technology and knowledge from research institutions and universities to startups (Wang et al., 2020; Loganathan & Subrahmanya, 2021), thus leading to innovative product and service development (Corrocher et al., 2019; Sedita et al., 2019b; Lopes et al., 2018; Redondo et al., 2022). In the regions that Gorączkowska (2020) studied, incubators promoted product innovation and R&D activities, with more robust support for innovation observed when technology incubators were involved. TBIs collaborate with the local community, startups, researchers, and industry players, coaching international clients through networking in global markets (Gao et al., 2021) and fostering an ecosystem for sharing and developing ideas (Colombo & Delmastro, 2002b; Sá & Lee, 2012). The incubator's primary goal is to efficiently connect talent, technology, capital, and expertise to harness entrepreneurial potential, expedite the commercialisation of technology, and foster the growth of new businesses (Smilor, 1987a). The first explanatory research of Paoloni & Modaffari (2022) confirmed the crucial role of business incubation in the firms' development process. Particularly in the early stage, knowledge transfer from the incubation centre enabled the startup to overcome its primary challenges, such as organisational aspects and financial capacity.

A significant outcome of incubation is the global expansion of startup clients, wherein incubators establish connections between networks that generate knowledge and those that apply internationally. Gao et al. (2021) have empirically investigated the significant role played by incubators in facilitating *internationalisation* from emerging markets where startups have limited access to international networks and knowledge resources.

Our sample represents 27 countries (Refer to Annexure E). Table 2.12 illustrates the top eight countries' contributions, featuring empirical research that examines the influence of regional innovation and socio-economic development on developed nations, including China as an emerging economy. However, the contributions of moulding and other emerging countries have been significantly underrepresented, especially those from South-East Asia. The table below shows that research on the impact of incubation has mainly centred on innovation-driven countries.

Table 2.12: Top 8 countries to study the influence of incubation empirically

Country	No. of studies
USA	**6**
China	**6**
Italy	**5**
Sweden	**4**
UK	**3**
Brazil	**3**
Netherlands	**3**
Spain	**3**

Source: Authors' Compilation

However, using different evaluation methods for efficiency-driven or transitioning nations is crucial. We suggest that this framework offers a new approach to analysing tech incubators and can be applied to other developing countries (Özdemir & Şehitoğlu, 2013).

Xiao & North (2017) revealed the noteworthy positive impact of technical and entrepreneurial support offered by Chinese TBIs on the early development and graduation of technology-based firms. These empirical findings have significant policy implications for national and provincial governments, as well as incubator management teams.

Furthermore, successful startups incubated by TBIs often expand, hire additional employees, and contribute positively to local employment, while stimulating job creation (Harper-Anderson & Lewis, 2018; Sung, 2007). Chen et al. (2023) have revealed that the digital economy enhances employment and entrepreneurship opportunities, creating a talent-friendly environment for the incubation industry. This enables incubators to attract high-quality talent, including recent college graduates and assists companies in recruiting top-notch professionals, leading to a talent clustering effect.

Firm-level outcomes

Most researchers have considered firm-level outcomes to directly reflect the effectiveness of TBI. Indeed, the most commonly used outcome variables in the studies reviewed are graduation, growth in sales revenue (Bacalan et al., 2019), startup survival and sustenance (S. Mian, 1997; Özdemir & Şehitoğlu, 2013; Löfsten, 2016). In many countries, recording the number of graduating firms is a crucial success metric that provincial and local governments use to measure their effectiveness. However, meeting graduation criteria (e.g., sales, profitability) doesn't guarantee long-term success (Rothaermel & Thursby, 2005a). Schwartz's (2010) research in East Germany revealed a high-risk period lasting up to 3 years after incubation, with evidence indicating that nearly one-third of firms were unlikely to survive beyond six years post-graduation. Nair & Blomquist (2019) have demonstrated that incubator processes are crucial for preventing and managing failures at various stages of development. They have adopted a process-oriented approach to failure prevention and management within business incubation by examining how these processes enhance business model scalability.

Schwartz's (2010) control group study, however, revealed no statistically significant benefits in terms of higher survival probabilities for firms within incubators compared to those outside. Surprisingly, startups that received incubator support even had lower survival rates in three out of five incubator locations. Thus, contrary to common beliefs among policymakers and incubator stakeholders, the location of incubators did not improve long-term business survival prospects. Alvarez Salazar's (2021) study in Peru posits that startup survival hinges on four conditions: break-even, accelerated growth, cash reserves, and continuous operations, influenced by five essential resources: human capital, social capital, entrepreneurial capital, organisational capital, and incubation. However, rather than solely assessing firm survival, which can be problematic due to closures with varying performance outcomes, Woolley & MacGregor (2022) focused on specific milestones that are crucial for technology entrepreneurs, like avoiding negative closures(such as bankruptcy or asset sales), obtaining government grants, and securing venture capital(VC).

Further, H. Zhang & Sonobe (2011) have found that while the number of firms graduating from a TBI is closely correlated with the infrastructure as well as the human and financial resources at the TBI's disposal, the graduates' firm sizes, in terms of employment and value-added, as well as their labour productivity, are unrelated to such resource outputs.

Another firm-level outcome is the development of the startup's business networks. Through the incubator, access to collective social capital generates various social and economic opportunities(Bøllingtoft & Ulhøi, 2005; Shih & Aaboen, 2019; van Rijnsoever, 2020) and provides reputation benefits (Studdard, 2006) which are invaluable for market access, collaboration and growth. TBI strategies emphasise knowledge assets, including partnerships with universities and research centres. In contrast, relationship assets involve technology-sharing networks among incubated companies, science park occupants, and various stakeholders, including universities, research centres, funding agencies, development banks, investors, and large companies (Fernandes et al., 2017). L. Zhang et al. (2019) affirm that network involvement amplifies the impact of entrepreneurial experience on the successful graduation of tenants. Soetanto & Jack (2018) have discussed how small technology firms acquire external slack resources from organisations like incubators. These resources, including access to research facilities, engagement with researchers and students, and leveraging university knowledge, provide valuable support for these firms in exploring new technologies. Löfsten et al. (2022) found that proximity to regional business partners, incubator networks, and universities has a positive impact on growth. Additionally, professional and consultative networks play a significant role in the development of emerging firms by helping them expand their business opportunities.

Furthermore, Van Rijnsoever et al. (2017) examined two mechanisms to clarify the link between incubation and the level of investment secured by early-stage startups as a performance metric: 'hit maker' and 'network broker'. Their findings revealed that incubators have a positive impact on the funding levels acquired by startups and their capacity to attract funding from formal investors and banks.

Pato & Teixeira (2020) found that, when compared to new ventures in rural and urban settings in Portuguese business incubators, certain institutional factors had a more pronounced positive impact on rural ventures. These factors included European Union support, financial backing from non-bank sources, business advisory services for startups, ongoing activities, and collaborative efforts to access new markets. This influence was particularly significant in terms of enhancing export performance.

2.3 THEORETICAL BACKGROUND

The theoretical background provides the conceptual foundation upon which this study is built, offering a framework to understand how different constructs interact within the entrepreneurial ecosystem.

2.3.1 TECHNO-ENTREPRENEURIAL THEORY

Entrepreneurship is the process by which an entrepreneur initiates the creation or establishment of a new venture (Paul et al., 2015). Entrepreneurs are at the centre of this change; they are key to creating new business sectors and accelerating the growth of startups, which in turn helps create dynamic entrepreneurial environments (Roja & Marian, 2014). Schumpeter (1976) highlighted entrepreneurs as individuals who, in contrast to conventional capitalists, launch novel businesses or activities that were previously nonexistent, engaging in innovative and creative undertakings.

Technological entrepreneurship has been described as a style of business leadership that focuses on identifying and capitalising on high-potential human resources, pursuing technology-intensive opportunities, managing rapid growth, and undertaking significant risks (Byers et al., 2005). Similarly, Shane & Venkataraman (2003) define it as the process by which entrepreneurial ventures assemble resources, technical systems, and strategies to pursue emerging opportunities. Together, these perspectives emphasise that technological entrepreneurship combines opportunity recognition with the effective mobilization of resources to drive innovation and growth.

Globalisation, knowledge-driven economies, the growing importance of innovation in regional innovation systems, and the key role of technological entrepreneurship in wealth creation have all changed the economic landscape, leading to the creation of new types of entrepreneurial ecosystems (Camagni, 1995; Feldman, 1994). Technology entrepreneurship serves as a catalyst for prosperity among individuals, enterprises, regions, and nations (Bailetti, 2012). Some areas are ahead of others because they are better at using new technologies and encouraging people to become tech businesses. This is happening in an economy that is undergoing change due to globalisation, the rise of knowledge-based economies, and the emergence of new ideas in regional systems. According to Raghavendra & Subrahmanya (2006), the competitiveness of a nation and the economic performance of its industries are dictated by technological capabilities.

According to Gartner (1985), the creation of a new venture can be understood through four key dimensions. First, the *individual's characteristics* play a crucial role, as they initiate and drive the establishment of the organisation. Second, the *organisation* refers to the type and structure of the firm being created. Third, the *environment* encompasses external factors and conditions that influence the new venture. Ultimately, the latest venture process includes the actions taken by the individual(s) to launch and develop the business. Together, these dimensions form the foundation of a successful entrepreneurial endeavour. Based on these key dimensions, Cooper (1993) established a framework that links the main elements—individual characteristics, organisation, environment, and the new venture process—to startup performance, highlighting how these factors collectively influence entrepreneurial success. As referred to by Afriana (2018), in our study, the Cooper model also serves as the foundational framework for developing a relational model of factors influencing startup performance within business incubation programs. The study focuses on startups as the unit of analysis, integrating the entrepreneur as an individual and the startup company as an organisation into a single construct, referred to as startup characteristics.

We have adapted the framework proposed by Cooper (1993), shown in Figure 2.2, which initially examined the relationships among entrepreneurs' characteristics, founding processes, initial firm characteristics, environment, and firm performance. Recognising the evolving nature of startup ecosystems and the critical role of external support systems, the framework is modified to suit the context of startups incubated within Technology Business Incubators (TBIs). Specifically, *Founding Processes* are replaced by "Incubator Support Services," reflecting the various forms of assistance provided by incubators, such as mentorship, funding facilitation, infrastructure support, and network development. *Initial Firm Characteristics* are reinterpreted as the resource base and capability development outcomes that startups achieve through incubation. Furthermore, the "Entrepreneurs' or Startup Characteristics", such as prior experience, Skills, their network connections, educational background, technical expertise, and psychological traits, continue to play a foundational role. "Startup performance" is evaluated through key success indicators, including revenue growth, market expansion, survival rate, and innovation outcomes. This adapted framework guides the investigation into how startup characteristics and incubator interventions collectively influence startup success.

Building upon the adapted framework, this study further incorporates two perceptual factors - "Perception of Importance (PoI)" and "Perception of Effectiveness (PoE)" (Abduh et al., 2007; Ayatse et al., 2017)—reflecting how startup founders evaluate the support services provided by incubators. These perceptions are posited as mediators that influence how incubator services translate into tangible resources for startups. Abduh et al. (2007) emphasise the varying perspectives on incubation programs. Additionally, the "Degree of Incubators' Intervention and Assistance (DIIA)" is introduced as a moderating variable that conditions the strength of the relationship between incubator services, startup resource development, and startup performance. Higher degrees of intervention are expected to amplify the positive impact of incubation support on resource building and performance outcomes. While it is evident that the resources provided by incubators are identified as being important to startups, incubators can only help startups when the startups actually use these resources (M. van Weele et al., 2017). Being nascent, startups do not have unlimited means to fill all resource gaps simultaneously; hence, they need to prioritise which resources to develop first. Here, the incubators may decide to intervene in this process by stimulating or even forcing the startups to use their resources. Bergek & Norrman (2008), in their research exploring incubators' intervention in the incubation process, distinguish between 'strong intervention' and 'laissez-faire' incubators. They consider these two as opposite ends of a scale. Van Stijn et al.(2018) refer to this scale as incubators' assertiveness: the more assertive incubators take a strong intervention approach, while less assertive incubators take a laissez-faire approach.

Strong intervention incubators have a large interdisciplinary team staff who are closely involved in the Startup's development (Clarysse et al., 2005). For example, incubators can engage in 'intense-aggressive coaching' (Rice, 2002) that may be mandatory for the entrepreneurs to participate in (Patton et al., 2009). Incubators may subject startups to an ongoing review process, with the incubator setting milestones that start-ups are required to achieve. Through the strong intervention approach, startups become aware of their resource gaps and are stimulated to develop the missing resources.

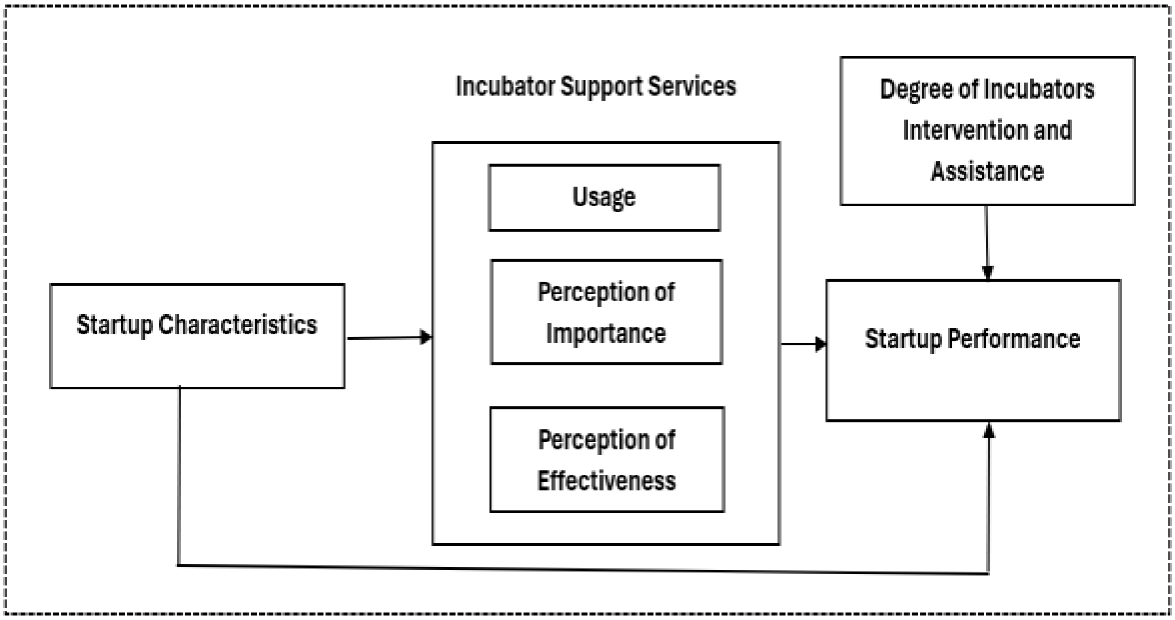
In contrast, Laissez-Faire incubators take a demand-driven approach and may only provide limited resources unless the entrepreneur explicitly requests assistance. Hence, ad-hoc support is provided on an as-needed basis to help entrepreneurs tackle a particular problem. Here, the incubator staff may only consist of the incubator manager (Rice, 2002).

Incubator governance involves managing relationships among startups, boards, clients, and stakeholders, while also ensuring visibility of progress, enhancing productivity and competitiveness, and mitigating risks during incubation (Mian et al., 2016). A comprehensive performance measurement system for incubated startups helps diagnose performance gaps and supports strategic decision-making for continuous improvement (Casado et al., 2020). In this study, startup performance, the primary construct, is operationalised through the sub-constructs of financial performance, operational performance, human capital and team development, networking and market position, innovation and sustainability, prototype development, and graduation. These sub-constructs were selected as they are widely recognized in prior research as comprehensive indicators of how incubators influence the growth, competitiveness, and long-term sustainability of startups (Zhou, 2023; Fuschi & Galiyeva, 2022; Sutrisno et al., 2024; Sedita et al., 2019; Nicholls-Nixon & Valliere, 2021; Jimainal et al., 2022)

Under Financial Performance, a critical measure of startup performance, it reflects the startup's ability to generate revenue and manage expenses effectively. The incubator often facilitates this process by reducing information asymmetry and agency costs, thereby improving access to funding (Zhou, 2023). Operational performance can be assessed through metrics and Key Performance Indicators (KPIs) that measure the efficiency and effectiveness of the incubator's processes, ensuring that startups meet their operational goals and manage resources effectively (Fuschi & Galiyeva, 2022). Human capital and team development are essential, as incubators enhance Human Resource competence through training programs and mentoring, which are crucial for the growth and success of startups, particularly among young entrepreneurs (Sutrisno et al., 2024). Networking and market position are also vital, as incubators provide a conducive environment for startups to develop innovative ideas and connect with various elements of the entrepreneurship ecosystem, thereby improving their market position and fostering growth (Sutrisno et al., 2024).

Furthermore, Innovation and sustainability are essential parameters, as incubators support the development of new technological platforms and sustainable business practices, which are crucial for the long-term success of startups (Sutrisno et al., 2024). Prototype development serves as a tangible indicator of progress and innovation, enhancing performance and leading to new-to-market innovations that drive sales and growth, particularly in manufacturing and knowledge-intensive sectors (Sedita et al., 2019a). The performance of startups, including their ability to develop prototypes, is influenced by the fit between the incubation process and the entrepreneurial opportunities they pursue. This fit is crucial for maximising the value created by the incubation process (Nicholls-Nixon & Valliere, 2021). Graduation reflects the startup's readiness to operate independently in the market, and this measure of startup performance is influenced by various factors, including the incubator's policies, the social capital of the tenants, and the support services provided. Jimainal et al., (2022) suggests that structured graduation criteria can help startups achieve a level of maturity necessary for independent operation.

Figure 2.7: Initial Model of main research elements



Source : Authors' own compilation based on earlier works

The choice to adopt a more comprehensive model for evaluating startup performance within the business incubation system is further reinforced by Chrisman et al. (1998), who emphasised that multiple factors influence startup performance and that various key elements should be incorporated into the model. Accordingly, the constructs illustrated in Figure 2.2 served as the foundation for the initial conceptual framework and effectively guided the development of the literature review.

2.4 BUSINESS INCUBATION

The term *incubation* originates from the Latin word *incubatio*, historically associated with the Roman practice of nurturing rudimentary ideas and gradually transforming them into visionary concepts over time. It is currently associated with the medical treatment of premature infants under controlled circumstances. Drawing from this medical analogy, the idea of business incubation has been adapted to describe institutions that provide critical developmental support during the fragile, early stages of new venture creation. The first incubators supporting startups were established in the USA. The world's oldest incubator, Student Agencies Inc., was founded in Ithaca, New York, in 1942 to support student entrepreneurial initiatives. The first official business incubator, the Batavia Industrial Centre, was started by Joseph Mancuso in 1959 in Batavia, New York (O'Neal, 2005; Thérin, 2007).

Business incubators provide physical infrastructure, communication facilities, access to networks and funding, enhanced credibility through association with the incubator, and techno-managerial assistance through in-house expertise and external networks to support startups during their fragile early stages, drawing from this medical analogy (Smilor & Gill, 1986; Bøllingtoft & Ulhøi, 2005). It is a dynamic process of enterprise development worldwide that enhances the success rate of start-up companies by creating a supportive environment that fosters growth, innovation, and sustainability (Stefanović et al., 2008). Smilor (1987) describes a business incubator as an innovative framework designed to assist entrepreneurs, especially in technological domains, in launching new enterprises. Incubators effectively connect talent, technology, capital, and expertise by offering a range of services and resources to startups and emerging enterprises. This integration facilitates the utilisation of entrepreneurial potential, accelerates the development of new ventures, and expedites the commercialisation of technological advances. The fundamental concept of business incubation involves maintaining controlled conditions for fledgling startup companies, which includes various support systems and external networks that foster their growth and development, providing them with the necessary support to enhance their chances of success (Kim & Ames, 2006; Smilor, 1987b). According to NBIA (2008), a business incubator is an economic development tool designed to foster the growth and success of entrepreneurial ventures. It achieves this by providing a range of business support resources and services, nurturing startups, and helping them survive and expand during their most vulnerable early stages.

The business incubator model has undergone significant evolution since its inception in the 1980s. The earliest business incubators (BIs) emerged in the United States during the 1950s(Adkins, 2002). The concept gained broader popularity in the 1980s and subsequently expanded internationally, taking various forms such as business centres, innovation hubs, and similar initiatives (Barrow, 2001; Lalkaka & Bishop, 1996). The first generation focused primarily on offering affordable space and shared administrative services (Bruneel et al., 2012; Pauwels et al., 2016). In the 1990s, the second generation expanded to include professional business development services, such as coaching, training and advisory support (Smilor & Gill, 1986; Clarysse & Bruneel, 2007; Hansen et al., 2000; Scillitoe & Chakrabarti, 2010). Following the dot-com crash of the early 2000s, third-generation incubators shifted their focus toward knowledge- and technology-intensive ventures, emphasising proactive mentoring, coaching, networking, and seed funding (Hansen et al., 2000). These early generations largely confined their support to resident startups within physical incubation spaces for 2–5 years (Scillitoe & Chakrabarti, 2010; Bøllingtoft & Ulhøi, 2005; McAdam & McAdam, 2008). Since 2005, fourth-generation incubators have expanded their services, strengthened external and international networking, and contributed to the rise of e-incubators. Leveraging web-based platforms, these incubators expanded access, reduced geographic barriers, and delivered cost-effective services to a broader range of startups (Bruneel et al., 2012; Pauwels et al., 2016; Ratinho & Henriques, 2010).

Aernoudt (2004) categorises U.S. incubators into five types based on their primary objectives: *mixed incubators, economic development incubators, technology incubators, social incubators, and basic research incubators*. Mixed incubators address multiple objectives, focusing on startup creation and employment generation across all sectors. Economic development incubators aim to reduce regional or local disparities by promoting business growth. In contrast, technology incubators focus on fostering technology-driven ventures to enhance the technical competencies of society, particularly in sectors like IT, biotechnology, and speech technology. Social incubators aim to bridge social and economic inequalities by fostering entrepreneurship among marginalised groups, primarily serving the nonprofit sector. Basic research incubators focus on developing new knowledge and creating high-tech spin-offs through innovative, blue-sky research initiatives. Performance data, available primarily for mixed, economic development, and technology incubators, reveals that technology incubators tend to outperform others across most performance dimensions.

Carayannis & von Zedtwitz (2005) classify incubation systems into five basic archetypes by analysing their competitive scope (industry, region, or population segment served) and strategic objective (profit orientation). These include: (1) university incubators, (2) virtual incubators, (3) regional business incubators, (4) company-internal incubators, and (5) independent commercial incubators.

Sohail et al. (2023) identified eight distinct types of business incubators based on the focus and nature of support provided to startups. These include general business incubators, university business incubators, accelerators, technology business incubators, science parks, corporate incubators, social incubators, and virtual incubators. General business incubators, the most widely studied type, primarily assist startups across various sectors (Aernoudt, 2004; Brun, 2019). University business incubators, closely linked to academic institutions, foster innovation and entrepreneurship among students and researchers (Breznitz & Zhang, 2019). Accelerators focus on rapid business scaling through intensive mentoring and investment opportunities (Bliemel et al., 2019; Pauwels et al., 2016). Technology business incubators specialise in supporting technology-driven startups (Lalkaka, 2002; Rathore & Agrawal, 2021), while science parks create a conducive environment for research-based companies (Chan & Lau, 2005; Martinez-Canas et al., 2021). Large firms establish corporate incubators to foster internal innovation and support startups (Connolly et al., 2018). Social incubators aim to support enterprises with a social mission (Casasnovas & Bruno, 2013), and virtual incubators deliver support services remotely, leveraging digital platforms (Arif & Sonobe, 2012).

Incubators play a significant role in economic and social development by supporting new ventures in multiple ways. Eshun Jr, (2005) identifies five key roles: *community development*, through job creation, business retention, and economic diversification; *advocacy*, by promoting entrepreneurship via training, networking, and policy engagement (NBIA, 2008); *brokering*, by linking start-ups with critical resources and service providers; *mediation*, by bridging macro-level policy and micro-level implementation, thereby strengthening government–community relations (OECD, 1997) and serving as a *one-stop shop*, where entrepreneurs gain access to a wide range of affordable services, from administrative support to advanced training in business, technology, and finance(NBIA, 2008).

The National Business Incubation Association (NBIA), which operates in over 60 countries, has demonstrated that business incubators create up to twenty times more jobs than traditional community projects. The cost of creating a job through incubators is also significantly lower, at approximately US$144–216 per job, compared to US$2,920–6,872 for infrastructure projects. In 2001, North American incubators alone supported over 35,000 start-ups, providing jobs for nearly 82,000 people and generating more than $ 7 billion in annual revenue (NBIA, 2009). Since our study focuses specifically on Technology Business Incubators (TBIs), a more detailed discussion on TBIs will follow in the next section.

2.4.1 TECHNOLOGY BUSINESS INCUBATORS (TBIS)

Technology-based enterprises (TBEs) have increasingly attracted the attention of policymakers due to their relatively higher capacity for job creation, wealth generation through business expansion, and lower failure rates compared to non-technology ventures. Given that new technologies often originate within R&D institutions, it was these institutions in Western countries that initially pioneered incubation facilities as a mechanism for transferring innovations from laboratories to the marketplace(Manimala & Vijay, 2012). Over time, the model was adapted and expanded by both public and private organisations to support the development of technology for emerging ventures. Such initiatives, now widely recognised as Technology Business Incubators (TBIs), vary in their emphasis, with some primarily facilitating technology transfer. In contrast, others focus on fostering technology development for nascent enterprises (Manimala & Vijay, 2012).

TBIs, also known as Technology Incubators (TIs), are offshoots of business incubators. A TBI is an organisational setup that aims to nurture technology-based and knowledge-driven companies during their initial startup phase, which typically lasts around two to three years. TBIs are a collaborative venture among universities, public research institutes, local governments, and private players to promote and bolster a new, innovative, technology-oriented, knowledge-intensive enterprise (Sunil Abraham et al., 2015). They are designed to facilitate the transfer and commercialisation of innovations originating from universities or research laboratories. They offer scientists or inventors transitioning into entrepreneurship a structured environment to refine the scientific and technical elements of their technology, while gaining essential experience in key business areas such as management, marketing, finance, and product design —all of which are crucial for successful business growth (Johnsrud, 2004).

TBIs are by design characterised by ‘institutionalised links’ to research institutions and R&D Centres such as universities, technology-transfer agencies, research centres, and national laboratories are located in specific industrial clusters near these institutions (OECD, 1997). While there are cases where TBIs are interspersed in multi-tenant buildings alongside other types of establishments, the key disadvantages of such a location are higher costs and reduced exposure to similar companies. The proximity to R&D institutions is a key design feature of TBIs, as their primary objective is to facilitate technology commercialisation while fostering economic development through property ventures and real estate development, alongside the promotion of entrepreneurship, particularly among researchers and academics (OECD, 1997).

Technology incubators primarily seek to connect academia with industry, foster innovation within small and medium-sized enterprises, and stimulate investment in technology-driven start-ups (Cooper, 2006). Higher education and research institutions increasingly engage with the production sector and broader society through activities such as conducting R&D for industry, establishing spin-off companies, and participating in capital formation initiatives. TBIs' facilities support this integration by offering entrepreneurial training and encouraging students to convert research outcomes into viable businesses (Juma, 2006).

Since the goals of Technology Business Incubators (TBIs) differ from those of general incubators, their requirements and services are also more extensive. They provide their 'clients' with an array of targeted resources usually orchestrated by the incubator management. These services are offered both within the business incubator and through its network of contacts, providing invaluable mentorship and financial support to nurture startups by accessing critical services (NSTEDB, 2020).TBIs offer a wide range of support to startups, extending beyond basic facilities and amenities. These include physical infrastructure such as office space, equipment, meeting rooms, and clerical support; R&D-related resources like access to laboratories, research publications, advanced equipment, and computers; financial support through grants, subsidies, and connections to investors and venture capitalists; and administrative services such as legal and patent support, accounting and tax help, trade assistance, government contract guidance, and training or employment support(Phillips, 2002; Tamásy, 2007).

While technology incubators align with the primary objectives of business incubators, they prioritise the commercialisation and dissemination of technology by emerging enterprises. These incubators specifically assist high-tech entrepreneurs, functioning as a technology-oriented variation of conventional business incubators(Bubou & Okrigwe, 2011; Stefanović et al., 2008). They assume the role of an implementing agency for diverse government schemes and programs, acting as an autonomous entity to effectively support startups with commercialisation and marketing assistance.

TBIs implement strict control mechanisms, such as selective admission and interim evaluations, to maximise the potential returns from their incubatees (Bergek & Norrman, 2008). Selection processes, based on factors such as team composition, technology, and ambition, help identify the most promising startups early (Bergek & Norrman, 2008). Interim evaluations, however, are more complex, as technology-based startups require time for product and business development before demonstrating commercial viability (Kazanjian & Drazin, 1990). Typically, incubators provide support for two to three years, during which startups are assessed based on milestone achievements rather than immediate turnover (Schwartz, 2009). These milestones are crucial indicators of a path toward commercial growth. For startups that meet specified performance thresholds, such as achieving a particular turnover or reaching a specific firm size, incubators offer subsequent growth programs to accelerate their development further (Kakati, 2003; McGee & Dowling, 1994; Mian, 1996).

Knopp (2006) summarises that the concept of business incubation, whether technology-focused or otherwise, was developed to address various economic and socioeconomic policy needs. These include job and wealth creation, fostering an entrepreneurial culture within communities, promoting the commercialisation of technology, and diversifying local economies. Additionally, incubators contribute to the development and growth of regional industry clusters, supporting business creation and retention, and fostering entrepreneurship among women and minority groups. They also help identify potential spin-in or spin-out business opportunities and play a role in community revitalisation.

2.4.2 HISTORICAL PERSPECTIVE OF TBIs

Business incubation systems in India, like those in other developed and developing countries, have become an integral part of national economic development initiatives by providing a variety of support services to the entrepreneurial community. The rise of Technology Business Incubators (TBIs) across the globe during the 1980s and 1990s is closely linked to scientific breakthroughs in biomedical technologies and the rapid spread of the Internet and the World Wide Web (Phan et al., 2005b). In India, TBIs have existed since the 1980s, under the Government of India, and since the late 1990s, under the private sector. They have played a critical role in encouraging risk-taking and public research in the information technology industry. Before 1980, most research on technology transfer focused on cross-national transfer from industrialised to developing nations (Bozeman, 2000). However, Bubou & Okrigwe (2011) have stated that TBIs have helped reverse this trend by fostering innovation and entrepreneurship, leading to the development of new technologies, enhanced national competitiveness, and local economic development. Incubators and accelerators are the growth boosters of the startup ecosystem in India. The Government of India (GoI) initiated TBIs in the 1980s, whereas they were established privately in the 1990s. Various government and non-government agencies have actively promoted entrepreneurship. In particular, the Government of India has made significant efforts to support techno-entrepreneurship through multiple agencies under the Department of Science and Technology (DST). It has also established the National Science and Technology Entrepreneurship Development Board (NSTEDB) under DST to drive sustained industrial development, regional growth, and employment generation.

Business incubation in a commercial setting has been a development that coincided with the growth of the IT industry in the late 1990s. The dot-com boom and the development of the venture capital industry in India also contributed to the emergence of business incubation in India.

Tiruchi Regional Engineering College-Science and Technology Entrepreneurs Park was the first Technology business incubator in India. It was launched in 1985 and became fully operational by 1989, equipped with 15 nursery incubators. India's first incubator, jointly funded by the private and public sectors, is Start-up Village; its promoters include the Department of Science and Technology, Government of India, Technopark Trivandrum, and MobME Wireless. Kris Gopalakrishnan, co-founder of Infosys and one of the most successful IT entrepreneurs from Kerala, served as the chief mentor. They targeted student start-ups from college campuses, and their focus was to provide direct industry links, business support services to enhance and develop their business; upgrade skills and techniques; provide technological advice and assistance with intellectual property protection; financial resources for R&D, initial marketing expenses; and access to potential private investors and strategic partners.

India's technology business incubation ecosystem has grown steadily through a series of government-led and collaborative initiatives aimed at fostering technological entrepreneurship (TE). The Department of Science and Technology (DST) has played a central role in these efforts. Its joint venture with the NSTEDB and FICCI, the Technology Innovation Management and Entrepreneurship Information Service (TIME IS), provides technopreneurs with access to projects, funding opportunities, policy frameworks, and industrial infrastructure while tapping local talent pools.

To support the conversion of innovations into viable businesses, the government has established 14 Science and Technology Entrepreneurship Parks (STEPs) and around 24 Technology Business Incubators (TBIs). Universities have also contributed by developing entrepreneurship centres and incubators, such as the Society for Innovation & Entrepreneurship (SINE) at IIT Bombay. The Technopreneur Promotion Programme (TePP), launched by the Ministry of Science & Technology, further supports individual innovators in commercialising their technologies. Additionally, the Home-Grown Technology Programme (HGTP), initiated in 1993, funds the commercialisation of indigenous research and development (R&D) through soft loans, repayable in flexible instalments after project completion. These initiatives have collectively laid a strong foundation for technology business incubators in India, fostering innovation, entrepreneurship, and the effective commercialisation of homegrown technologies.

2.4.3 CURRENT INDIAN SCENARIO

According to the NASSCOM Start-up Catalysts - Incubators & Accelerators 2020, there are approximately 520 incubators and accelerators in India. The Government of India has been playing an active role as a catalyst for economic growth by launching numerous schemes and initiatives aimed at promoting entrepreneurship. As part of the 'Start-up India' program launched by the Government of India, a Rs. 10,000 crore 'Fund of Funds' has been approved to support start-ups.

Although India is renowned for its technological dominance and phenomenal economic rise on a global scale, the country has regularly been plagued by disparities in economic status among its people. Globalisation has created opportunities for both skilled and unskilled Indian workforce. Since then, India has progressed from merely being a supplier of human resources to encouraging its talented individuals to start their own entrepreneurial ventures. Today, India has made significant strides in its scientific and technological culture. It has occupied a prominent place on the world map due to its significant contributions to knowledge-driven products and services, its emergence as a global R&D hub, and the high calibre of its professionals in science and technology. To sustain growth in a volatile, ever-challenging global business environment, speedy translation of innovative ideas into products, processes and services for the market is the need of the hour.

2.5 STARTUPS

Startups are entrepreneurial ventures initiated by individuals or teams that struggle for existence, aiming to transform innovative ideas into viable businesses and play a crucial role in the socio-economic transformation of any region. New innovative firms are widely regarded as key drivers of innovation and essential contributors to job creation (Colombo & Delmastro, 2002). Typically established within five years, these companies are characterised by their small size, limited resources, and innovative business models or products driven by passionate and energetic founding teams (Hu, 2024). While all businesses are influenced by their environment, new ventures face heightened risks due to their reliance on a limited range of products or services, a narrow market focus, and a few critical resources (A. C. Cooper, 1993). Overall, startups are vital for fostering innovation and economic growth, necessitating supportive policies and ecosystems to overcome inherent challenges and maximise their potential impact.

Startups frequently encounter a high rate of failure, with the majority of them collapsing during their initial phases and less than one-third of them becoming fully established companies (Vesper, 1990). This failure can be attributed to several challenges, including inadequate business knowledge, technological shortcomings, ineffective leadership, and insufficient funding (Gómez, 2007). Nevertheless, a significant number of these enterprises become effective and make a substantial contribution to economic development, despite overcoming the initial obstacles (Martinsons, 2002). The "valley of death" is a metaphorical term that refers to the uncertain and hazardous period between the initial startup and sustainable operation, which is a critical yet ambiguous phase in this journey (Hudson & Khazragui, 2013).

The "liability of newness" and the "smallness effect" are challenges that startups frequently encounter to survive. These challenges include limitations in resources, networks, reputation, credibility, innovation capacity, and marketing capabilities (Baum et al., 2000; Lasrado et al., 2016; Neyens et al., 2010). According to Salamzadeh & Kesim (2015), the "liability of newness" is indicative of a startup's lack of experience, standardised procedures, trust, credibility, necessary expertise, and established relationships with clients and partners. Conversely, the "smallness effect" highlights the limitations that entrepreneurs face due to restricted human, physical, and financial resources, which weaken their capacity to market and expand new products (Neyens et al., 2010).

The Startup Outlook Report 2019 identifies two primary elements that render India an appealing startup ecosystem: minimal business expenses due to the proximity of customers and vendors, and a substantial domestic market characterised by a large internet user population. India, with over 500 million internet users, has emerged as the world's second-largest consumer internet market, surpassing China in this regard. The cost-effectiveness and availability of digital innovation have simplified the development and launch of digital products and services. In the past decade, India’s startup ecosystem has undergone significant expansion. India has solidified its position as the world's third-largest startup ecosystem, with over 1.57 lakh startups recognised by the Department for Promotion of Industry and Internal Trade (DPIIT) as of December 31, 2024, as stated by the Ministry of Commerce and Industry, GoI. Driven by a thriving network of over 100 unicorns, the country's entrepreneurial landscape is reshaping innovation and generating opportunities across various industries. Leading hubs, such as Bengaluru, Hyderabad, Mumbai, and the Delhi-NCR region, have spearheaded this transformation, while smaller cities are playing an increasingly significant role, with more than 51% of startups emerging from Tier II and III cities. Government initiatives, such as Startup India, have been instrumental in fostering this growth and empowering the next wave of entrepreneurs (Press Information Bureau, 2025).

2.5.1 INFLUENCE OF STARTUP CHARACTERISTICS ON BUSINESS INCUBATION

Startups, driven by innovation and growth, often struggle with strategic decision-making, limited entrepreneurial skills, and a lack of legitimacy. To overcome these challenges and foster development, many turn to business incubation programs or other intermediary supports (Eveleens, 2019). Monsson & Jørgensen (2016) demonstrate that the characteristics of entrepreneurs significantly influence their benefits from business incubator programs. They found that entrepreneurial experience, development stage, and decision-making logic are the most influential traits shaping how startups engage with and utilise various incubator services. These characteristics help explain why some entrepreneurs gain more value from incubation than others. On the other hand, factors such as gender, education level, and market orientation did not show significant differences in the benefits received. The authors therefore suggest that incubation programs should be customised to match the unique needs and profiles of entrepreneurs, as tailored support can improve outcomes, enhance program effectiveness, and ensure better utilisation of resources (Monsson & Jørgensen,2016).

The performance of startups is influenced by numerous factors that span both individual and organisational dimensions. Chrisman et al. (1998) identified vital elements, such as the entrepreneur, business strategy, resources, organisational structure, process, and system employed to implement its chosen strategy, as critical to startup success. Integrating these elements into a unified construct of startup characteristics, research carried out by Afriana (2018) has further elucidated these factors. Since this research will consider a startup as a combination of its team and the company itself, the entrepreneurial features will be chosen based only on team-level variables. The Startup Characteristics construct captures the intrinsic attributes and capabilities of startup founders that influence how effectively they identify opportunities, utilise incubator support services, and drive venture performance (Afriana, 2018). Following prior entrepreneurship and incubation literature, three key dimensions, experience, skills, and networks, have been selected as representative indicators of startup characteristics.

2.5.1.1 EXPERIENCE

Earlier studies have consistently highlighted the significant impact of a founder's business experience on company behaviour, particularly within business incubation (Scillitoe &

Chakrabarti, 2010; McCarthy et al., 2023). Experience acts as an input variable that shapes the entrepreneur's absorptive capacity, learning orientation, and effectiveness in leveraging incubator support. Entrepreneurial experience refers to the cumulative managerial, industrial, and technical exposure that shapes a founder's ability to recognise opportunities, assess risks, and make informed strategic decisions. Prior entrepreneurial, managerial, or industry-specific experience equips founders with practical knowledge of business processes**,** organizational management**,** and resource allocation**,** thereby enhancing their capacity to understand incubator offerings and apply them effectively to their ventures.

Such experience can manifest in several complementary forms. Working experience in top managerial positions provides strategic insight, leadership capabilities, and exposure to complex decision-making environments. Experience in the same industry contributes to domain expertise, an understanding of market dynamics, and established professional networks that strengthen competitive advantage. Entrepreneurial or startup experience offers hands-on familiarity with venture creation, innovation, and risk management, fostering resilience and adaptability in uncertain environments. Finally, technical or subject-matter expertise enhances an entrepreneur's ability to innovate, solve complex problems, and engage with technology-driven or knowledge-intensive incubation programs.

Empirical research demonstrates that these diverse forms of experience significantly enhance entrepreneurs' absorptive capacity, which is the ability to identify, assimilate, and exploit external knowledge. This, in turn, improves the effectiveness of incubator support and venture performance. Studies by Colombo & Grilli (2005), Baum et al. (2000), and Unger et al. (2011) underscore that managerial, industry, and technical experience are critical predictors of startup growth, innovation, and survival. Similarly, Monsson & Jørgensen (2016) and Capelleras et al. (2019) highlight that founders' experience strongly influences how they perceive, utilise, and benefit from different elements of business incubator programs.

2.5.1.2 SKILL

Entrepreneurial skills encompass a combination of cognitive, behavioural, and functional competencies that enable founders to manage and grow their ventures effectively. These include opportunity recognition**,** innovation**,** strategic thinking**,** and leadership, which collectively determine how entrepreneurs make decisions, solve problems, and adapt to dynamic environments. In addition to these cognitive and behavioural abilities, functional expertise in areas such as marketing, sales and business development, finance and accounting, administration and human resource management, as well as engineering, technology, and research and development (R&D), plays a vital role in translating entrepreneurial vision into operational success. Together, these skills represent the practical and managerial capabilities that enhance the startup's capacity to utilise incubator support effectively, attract resources, and achieve sustainable growth.

Empirical research underscores that such a blend of entrepreneurial and functional skills constitutes the human capital foundation of successful new ventures. Mitchelmore & Rowley (2010) highlight the importance of managerial, entrepreneurial, human relations, and technical skills as essential components of entrepreneurial competence. Similarly, Hazlina Ahmad et al. (2010) identify personal and business competencies, including innovation, decision-making, marketing, and financial management, as critical to entrepreneurial performance. Rasmussen et al. (2011) emphasise that opportunity refinement, resource mobilisation, and team leadership are central to the development of entrepreneurial capability. In contrast, Unger et al. (2011) and Colombo & Grilli (2005) demonstrate that founders' accumulated skills significantly influence venture growth and innovation outcomes.

The success of a startup in acquiring essential knowledge from business incubation programs hinges on the entrepreneur's skills and abilities, particularly their capacity to absorb relevant knowledge and effectively utilise the provided resources, which are crucial in determining the overall effectiveness of the incubator programs for the startup's success (M. van Weele et al., 2017).

2.5.1.3 NETWORK

Another key characteristic of a startup is the size of the company's network. Entrepreneurial networks represent the social and relational capital available to startup founders through both formal and informal connections. These networks facilitate access to vital resources, knowledge, and opportunities that startups often lack in their early stages. Well-developed informal alliances, such as those with friends, family members, and acquaintances, provide emotional support, early-stage funding, and practical advice, which are particularly crucial during the early stages of venture formation. In addition, formal business partnerships with external institutions, government agencies, and research organisations enhance credibility and facilitate resource sharing, while technical project collaborations strengthen innovation capacity and drive technological development.

Networks also extend to trade and business associations, which provide access to industry information, advocacy, and collective market visibility. Further, maintaining contacts with potential or targeted customers and established suppliers ensures a stable value chain and continuous feedback on product–market fit. Ultimately, establishing connections with capital and funding sources, such as venture capitalists, angel investors, and financial institutions, is crucial for sustaining growth and scaling operations.

The literature consistently highlights that such multifaceted networks spanning social, professional, and institutional domains serve as strategic assets that enable entrepreneurs to acquire knowledge, build legitimacy, and mobilise resources (Hoang & Antoncic, 2003; Lockett et al., 2003; Bruneel et al., 2012; Grandgirard et al., 2002; Greve & Salaff, 2003; Stam et al., 2014). Within the incubation context, startups with stronger networks can integrate external and incubator-based support more effectively, thereby improving performance outcomes and enhancing their survival prospects. A more extensive network offers essential resources and knowledge, making it a crucial factor in determining the startup's potential for success (Ayatse et al., 2017; Soetanto & Jack, 2013). Lyons (2002) highlights the importance of both internal and external networks for incubatees. Internal networks foster social capital by sharing resources among organisations, while external networks connect tenants with potential partners, clients, and local businesses.

2.6 INCUBATION SUPPORT SERVICES

The scope and sophistication of incubator support services have evolved substantially over time, reflecting a shift from providing basic infrastructure to facilitating holistic, ecosystem-based growth of entrepreneurship and in the early phase of incubation—often referred to as the first generation of incubators during the 1980s and 1990s—the focus was primarily on providing *physical infrastructure*, such as affordable office space, administrative assistance, and shared utilities, to reduce operational costs and mitigate risks for nascent firms (OECD, 1997; Aernoudt, 2004). The emergence of second-generation incubators in the late 1990s expanded the service portfolio to include business advisory services, mentoring, and financial access, acknowledging that startups required more than just facilities—they needed knowledge, networks, and managerial competencies to survive and grow.

Subsequent third-generation and technology-based incubators (TBIs) have further transformed the incubation landscape by emphasising innovation, technology transfer, R&D support, and international linkages. These incubators integrate academic research, industry collaboration, and funding mechanisms to foster high-growth ventures (Grimaldi & Grandi, 2005; Carayannis & von Zedtwitz, 2005; Bruneel et al., 2012). This transition represents a paradigm shift from facility-based to competency-based and ultimately to ecosystem-based incubation models, where incubators function as strategic intermediaries connecting startups with diverse stakeholders across the entrepreneurial ecosystem (Phan et al., 2005a).

Importantly, incubation support has also become more stage-specific, aligning services with the evolving needs of startups at different phases of their lifecycle:

- **Creation Phase:** During the initial creation phase, non-market-oriented entities—such as universities, research institutions, and technology incubators—play a crucial role by providing early-stage R&D funding, technical assistance, and support for business model formulation. These services help entrepreneurs translate research ideas into viable business opportunities and reduce technological uncertainty (Etzkowitz & Leydesdorff, 2000; Phan et al., 2005).
- **Development Phase:** In the development phase, startups refine their products or services with the support of accelerators, investors, and early adopters, who contribute innovation resources for prototyping, validation, and market testing. This phase emphasises capability building, mentorship, and iterative product improvement to enhance market readiness (Clarysse et al., 2005; Pauwels et al., 2016)
- **Market Phase:** During the market or scaling phase, startups collaborate with market-oriented actors—including corporates, industry partners, and venture capitalists—to expand operations, optimise business models, and achieve organisational scalability. The incubator's role at this stage focuses on facilitating market access, investor connections, and internationalisation support, thereby enabling startups to sustain competitive advantage and growth (Aernoudt, 2004; Bruneel et al., 2012).

In parallel with this lifecycle-based evolution, Technology business incubators have expanded their service portfolios far beyond physical infrastructure and facilities. They now offer a comprehensive suite of business and skill development services—including coaching, training, consultancy, funding, and networking assistance—to address the multidimensional needs of startups (Hackett & Dilts, 2004; Hansen et al., 2000; Bøllingtoft & Ulhøi, 2005b; Bruneel et al., 2012).

2.6.1 RESOURCE-BASED VIEW (RBV) APPROACH TO INCUBATOR SUPPORT SERVICES

The Resource-Based View (RBV) provides a robust theoretical framework for understanding how incubation support services contribute to the competitiveness and survival of startups. According to RBV, a firm's performance and sustained competitive advantage stem from its access to and effective utilisation of valuable, rare, inimitable, and non-substitutable resources (Barney, 1991; Wernerfelt, 1984). Startups, unlike established firms, typically possess incomplete, underdeveloped, and evolving resource bases, which create what Stinchcombe (1965) termed the *"liability of newness."* This lack of essential tangible and intangible resources constrains their capacity for innovation, growth, and market entry (Amezcua et al., 2013; van Weele et al., 2017).

TBIs play a pivotal role by providing startups with access to critical resources and support systems that supplement their limited internal capabilities. Drawing from the RBV perspective, they are not merely providers of space but strategic resource intermediaries that enable startups to acquire, combine, and deploy resources more effectively (Barbero et al., 2012; C. P. Eveleens et al., 2017). Through this lens, incubators can be viewed as *resource orchestration mechanisms*, creating, structuring, and leveraging both tangible and intangible resources that enhance startups' ability to build sustainable competitive advantages (van Rijnsoever & Eveleens,2021).

Startups' incomplete resource base is an inherent characteristic of their early-stage development. Limited financial reserves, inadequate managerial expertise, and a lack of social and technological capital often hinder their competitiveness and growth potential (Bergek & Norrman, 2008). Consequently, they face significant challenges in acquiring key inputs necessary for innovation, scaling, and market penetration. Recognising these constraints, incubators provide a resource-rich environment that compensates for startups' deficiencies and helps mitigate early-stage vulnerabilities.

Incubators function as resource amplifiers, enhancing startups' access to both tangible and intangible assets. They provide these resources through direct provision, shared facilities, or by facilitating linkages with external networks, investors, and institutions. This hybrid model allows startups to acquire and combine complementary resources that would otherwise be inaccessible or prohibitively costly. By integrating internal capabilities with incubator-provided resources, startups enhance their competitive position and increase their chances of survival and success (Grimaldi & Grandi, 2005; Bruneel et al., 2012).

Understanding the resource needs of startups and the role of incubators in fulfilling them is crucial for optimising the incubation process. When incubators align their resource offerings with the evolving demands of startups, they create a comprehensive nurturing environment that accelerates entrepreneurial growth. The RBV thus provides a theoretical basis for evaluating how incubator services (as resource bundles) translate into improved performance outcomes for incubated firms. The Resource-Based View to incubation underscores that the effectiveness of incubators lies in their ability to identify, orchestrate, and deliver critical resources—both tangible and intangible—that startups lack. By strategically leveraging these resources, incubators transform resource scarcity into opportunity, fostering innovation and sustainability within the entrepreneurial ecosystem.

Following the theoretical approach of van Rijnsoever & Eveleens(2021) for resource-based incubation analysis, this study identifies five essential resources consistently emphasised in the literature (Amezcua et al., 2013; Bruneel et al., 2012; C. P. Eveleens et al., 2017; van Weele et al., 2017) as critical to startup success and frequently provided through incubators:

1. **Physical Capital** – Refers to access to technology, equipment, facilities, and infrastructure essential for production and innovation. Startups often struggle to acquire such resources due to financial constraints. Incubators mitigate this challenge by offering shared office spaces, laboratories, meeting rooms, and specialised equipment, thereby enhancing operational efficiency and productivity. University-affiliated incubators, in particular, provide access to **scientific libraries, laboratories, and technical expertise**, enabling technology-based startups to engage in research and

development (R&D) and prototype development (OECD, 1997; Etzkowitz & Leydesdorff, 2000).

2. **Financial Capital** – Startups are typically perceived as high-risk investments, making it difficult for them to obtain external financing. Incubators address this constraint by providing seed funding, micro-grants, or convertible equity investments**,** and by connecting startups with venture capitalists, angel investors, and government funding programs. Through such financial linkages, incubators help startups secure essential liquidity for early-stage survival and scaling (Hackett & Dilts, 2004; Barbero et al., 2012).
3. **Business Knowledge –** Incubators provide training, coaching, mentoring, and strategic guidance, enabling entrepreneurs to refine their business models, enhance managerial skills, and deepen their market understanding.
4. **Networks** – Through access to diverse stakeholders, such as mentors, investors, researchers, and customers, incubators help startups build social and professional capital that facilitates knowledge sharing and opportunity recognition (Bøllingtoft & Ulhøi, 2005b).
5. **Legitimacy** – Association with reputed incubators or universities enhances a startup's credibility and trustworthiness, improving its chances of attracting investment, customers, and partnerships (Amezcua et al., 2013; Bruneel et al., 2012).

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Thus, applying the Resource-Based View to incubation underscores that the effectiveness of incubators lies in their ability to identify, orchestrate, and deliver critical resources—both tangible and intangible—that startups lack. By strategically leveraging these resources, incubators transform resource scarcity into opportunity, fostering innovation and sustainability within the entrepreneurial ecosystem.

2.7 USAGE AND PERCEPTIONS OF SUPPORT SERVICES

Given the multifaceted nature of incubation support, assessing the quality and impact of these services requires capturing how startups perceive and utilise the resources provided by incubators. In this study, the mediating construct of Incubation Support Services is operationalised through three interrelated yet distinct dimensions- Perception of Importance (PoI), Perception of Effectiveness (PoE), and Frequency of Usage (FU)—adapted from Abduh et al. (2007) and refined through subsequent incubation research (Hsu et al., 2019; Messeghem et al., 2023).

2.7.1 PERCEPTION OF IMPORTANCE (PoI)

Perception of Importance reflects the degree to which startups value a particular incubator service in achieving their business objectives. It measures the subjective relevance or significance that startup founders attach to different types of support, such as access to finance, mentorship, R&D facilities, and networking opportunities. Startups differ in their priorities depending on their development phase, where early-stage ventures often attach higher importance to infrastructure and technical assistance, while scaling startups value market access and investor linkages. Hence, PoI captures how startups prioritise among the five critical resources, i.e Physical Capital, Financial Capital, Business Knowledge, Networks, and Legitimacy—identified in the literature (Amezcua et al., 2013; Bruneel et al., 2012; C. P. Eveleens et al., 2017; van Weele et al., 2017). A high PoI score indicates that a service is considered crucial for venture success, guiding incubator managers to allocate resources efficiently.

2.7.2 PERCEPTION OF EFFECTIVENESS (PoE)

Perception of Effectiveness refers to the extent to which startups believe that the incubator has successfully delivered or facilitated a given service, reflecting their evaluation of the success, quality, adequacy, and usefulness of incubator support based on their lived experience within the incubation environment. It represents the subjective assessment of how well an incubator performs in delivering the promised support, including mentorship, funding facilitation, networking, and technical assistance. This perception can vary depending on the type of resource provided, the startup's maturity level, and the entrepreneur's prior experience.

A service may be perceived as necessary but not necessarily effective if it lacks quality, customisation, or timely delivery. For instance, while mentorship and access to funding may be universally valued, their effectiveness depends on the mentor's expertise, network reach, and administrative efficiency. This construct thus evaluates how well incubator interventions translate into tangible outcomes, providing feedback for continuous program improvement (Abduh et al., 2007; Vanderstraeten & Matthyssens, 2012).

According to Gagliardo et al. (2017), the availability and quality of resources provided by incubators significantly affect how startups perceive their own effectiveness. When incubators deliver high-quality support through reliable infrastructure, timely financial linkages, and knowledgeable mentors, startups tend to perceive these services as highly effective. Similarly, Fithri et al. (2024) emphasise that understanding the value of incubation from the startup's perspective is critical, as perceived effectiveness determines satisfaction, engagement, and continued participation in incubator programs.

Furthermore, the perception of effectiveness is strengthened when incubators actively support disruptive innovation through interdisciplinary collaboration, technological integration, and financial support (Morrish et al., 2019). Thus, PoE reflects more than just service quality; it encompasses startups' cognitive and emotional evaluation of how well incubators facilitate opportunity realisation, competence building, and venture success. Measuring this perception allows incubators to understand which services yield the most tangible and psychological value to startups, thereby informing strategies for continuous improvement and customised service delivery (Abduh et al., 2007; Vanderstraeten & Matthyssens, 2012).

2.7.3 FREQUENCY OF USAGE (FU)

Frequency of Usage captures the extent and regularity with which startups actually utilise the available incubator services. While importance and effectiveness reflect perceptions, FU reflects behavioural engagement—how often and how consistently startups access various forms of support. Regular usage indicates a stronger integration between startups and the incubator ecosystem, reflecting higher absorptive capacity and more substantial perceived value of services (Bergek & Norrman, 2008). Startups that actively engage in mentoring sessions, networking events, funding programs, and training workshops tend to achieve better performance outcomes due to continuous learning and participation in the ecosystem. Thus, FU complements PoI and PoE by capturing the actual degree of service utilisation, which mediates the link between incubator provision and startup performance outcomes (Hsu et al., 2019; Bruneel et al., 2012).

Together, these three dimensions — PoI, PoE, and FU — offer a comprehensive lens to assess both the perceived and behavioural aspects of incubation support utilisation. They also provide an evidence-based foundation for understanding how the availability, quality, and engagement level of incubation services collectively influence startup growth and performance. This triadic approach aligns with the Input–Mediator–Outcome (IMO) framework of the study, where *Startup Characteristics* represent the input conditions, *Incubation Support Services* (via PoI, PoE, and FU) serve as mediating mechanisms, and *Startup Performance* constitutes the outcome of the incubation process.

2.8 INCUBATORS' INTERVENTION AND ASSISTANCE

The effectiveness of business incubation is understood as a function of interactive and relational dynamics rather than as a static set of institutional provisions. According to Nair & Blomquist (2021), the incubation process primarily evolves through ongoing, personalis*ed interactions* between incubation managers (or coaches) and incubatees, underscoring the central role of relational, experiential, and social learning. This approach reframes incubation from a purely structural or service-based model to one that emphasises human engagement, mentorship, and active facilitation as critical elements for fostering entrepreneurial capability and venture growth.

The Degree of Incubator's Intervention and Assistance (DIIA) refers to the extent, intensity, and depth of direct support and engagement provided by incubators to startups throughout the incubation lifecycle. It captures both the *breadth of services delivered* (e.g., mentoring, networking, financial advisory, training, legal and IP support) and the *depth of involvement*—that is, the degree of personalised guidance, monitoring, and feedback provided by incubation managers. DIIA embodies the hands-on, facilitative role that incubators play in guiding startups from idea validation through scaling. Unlike passive support models, where incubators act merely as infrastructure providers, high-intervention incubators engage proactively with startups, tailoring their assistance to meet the specific developmental needs of each startup. Such active involvement promotes entrepreneurial learning, strengthens the startup's ability to access and integrate external resources, and accelerates capability formation (Nair & Blomquist, 2019; Scillitoe & Chakrabarti, 2010).

The level of intervention and assistance varies across the three main phases of the incubation process (Nair & Blomquist, 2019; Bergek & Norrman, 2008)

- **Selection Phase:** During this phase, incubators screen and evaluate applicants based on entrepreneurial potential, business feasibility, and alignment with available resources (Aerts et al., 2007; Merrifield, 1987). The intervention here is *selective and strategic*—aimed at ensuring that limited incubator resources are allocated to ventures most likely to succeed.

- **Support and Development Phase:** Once startups are admitted, the level of intervention intensifies. Incubators offer comprehensive business support, including individualised coaching, entrepreneurial training, and access to critical services such as office infrastructure, legal and financial advice, accounting, marketing, and IP management. Incubators also play a boundary-spanning role, linking startups with external networks, investors, and institutional partners that enhance their access to resources and markets (Bruneel et al., 2012; Lynn et al., 1996; C. Cooper et al., 2012). At this stage, incubator managers function as mentors and facilitators who nurture the entrepreneurial mindset and ensure strategic alignment between startups' goals and ecosystem opportunities.
- **Exit and Post-Incubation Phase:** The level of assistance typically tapers as startups reach maturity or outgrow the incubator's support ecosystem, often within three to five years (Bøllingtoft, 2012). The intervention at this stage focuses on ensuring smooth graduation, market access, and post-incubation linkages. Some incubators continue to offer limited advisory or alumni support networks to maintain relational continuity and enhance reputation effects.

Drawing from prior literature (Bruneel et al., 2012; Nair & Blomquist, 2019; C. Cooper et al., 2012) and the items included in this study's measurement instrument, incubator intervention and assistance encompass several interrelated dimensions:

1. **Personalised Managerial Guidance:** The incubation manager or team provides ongoing, customised coaching and mentorship to help startups navigate business challenges and make strategic decisions.
2. **Facilitation of Resource Access:** Incubators actively connect startups to key resources, including funding opportunities, specialised equipment, and expert services.
3. **Networking and Collaboration Opportunities:** Through organised events, investor introductions, and networking sessions, incubators expand startups' social capital and market reach.
4. **Professional and Skill Development:** Incubators conduct training workshops and entrepreneurial development programs to build managerial, technical, and leadership competencies.
5. **Financial and Strategic Advisory Support:** Guidance in financial planning, cost management, and investment readiness enhances startups' decision-making and sustainability.
6. **Market Access and Customer Acquisition Support:** Incubators help startups identify markets, connect with early customers, and refine go-to-market strategies.
7. **Intellectual Property (IP) and Legal Assistance:** Specialised support in IP protection, patent filing, and legal compliance strengthens startups' innovation potential and safeguards intellectual assets.

In this study, the Degree of Incubator's Intervention and Assistance (DIIA) is conceptualised as a continuous moderating variable. Treating DIIA as a continuous moderator allows for an examination of how incremental differences in the intensity of incubator involvement influence the relationships among key constructs—specifically, between *Startup Characteristics*, *Frequency of Service Usage (FU)*, and *Startup Performance (SP)*.

High levels of incubator intervention are expected to amplify the positive effects of startup characteristics and resource utilisation by enhancing knowledge transfer, motivation, and strategic alignment (Nair & Blomquist, 2021). Conversely, minimal intervention may lead to weak engagement and limited learning outcomes. This approach provides a nuanced understanding of how tailored, interactive, and resource-integrated assistance contributes to more effective incubation outcomes.

2.9 STARTUP PERFORMANCE

Startup Performance (SP) represents the extent of growth, development, and sustainability achieved by incubated startups as a result of their participation in business incubation programs. It reflects how effectively startups convert incubator support, resources, and interventions into measurable organisational outcomes. As noted by Casado et al. (2020), a comprehensive performance measurement system enables the diagnosis of performance gaps, guides strategic improvement, and demonstrates the impact of incubation on entrepreneurial success.

From the Resource-Based View (RBV) and learning perspectives, incubated startups are expected to outperform non-incubated firms due to enhanced access to tangible and intangible resources, knowledge transfer, and network-based learning. Empirical studies have shown that incubated firms generally exhibit higher survival rates and faster growth trajectories than their non-incubated counterparts, with the age, maturity, and accumulated knowledge of the incubator playing a crucial role in shaping these outcomes (C. Eveleens, 2019; Zhou, 2023)

In this study, Startup Performance is conceptualised as a multidimensional construct capturing the holistic outcomes of incubation across seven key dimensions:
(1) Financial Performance, (2) Operational Performance, (3) Human Capital and Team Development, (4) Networking and Market Position, (5) Innovation and Sustainability, (6) Prototype Development, and (7) Graduation.
Together, these dimensions provide a comprehensive understanding of how incubation translates into economic, organisational, and innovative performance gains.

Financial Performance: Financial performance is a critical indicator of startup success, reflecting the venture's ability to generate revenues, manage costs, and achieve profitability. Participation in an incubator can enhance financial outcomes by reducing information asymmetry, improving investment readiness, and lowering agency costs (Zhou, 2023). Access to incubator-facilitated funding networks, investor connections, and financial mentoring improves startups' liquidity and financial management practices. In this study, financial performance encompasses startups' ability to achieve revenue growth, maintain profit margins, secure external funding, and ensure financial sustainability—all of which represent core entrepreneurial milestones.

Operational Performance: Operational performance captures the efficiency and effectiveness with which startups manage production, service delivery, and market operations. Incubators help enhance operational performance by providing management support, process optimisation training, and access to operational infrastructure, thereby enabling startups to manage resources efficiently and achieve their strategic goals (Fuschi & Galiyeva, 2022). Key operational indicators include product development progress, market penetration, productivity improvement, and cost optimisation. This dimension reflects how incubator-enabled startups translate learning and access to resources into tangible process improvements.

Human Capital and Team Development: Human capital is a pivotal driver of innovation and adaptability in startups. Incubators play a crucial role in enhancing team competencies, offering mentorship, and organising skill-building and leadership development programs. According to Sutrisno et al. (2024), incubators significantly contribute to the development of HR competence, particularly among young and inexperienced entrepreneurs, by creating learning environments that encourage continuous capability growth. This study measures this dimension through indicators such as team expansion, skill enhancement, employee retention, and professional development—factors that collectively strengthen organisational resilience and learning capacity.

Networking and Market Position: Networking and market positioning represent the external relational and reputational outcomes of incubation. Incubators serve as boundary-spanning intermediaries that integrate startups into entrepreneurial ecosystems, facilitating strategic partnerships, customer linkages, and brand-building opportunities (Sutrisno et al., 2024). These networks enhance a startup's visibility, credibility, and access to markets, allowing it to compete effectively and scale efficiently. Indicators in this dimension include strategic partnerships, industry collaborations, enhanced brand reputation, customer engagement, and improved competitiveness.

Innovation and Sustainability: Innovation capability and sustainability orientation are central to long-term startup success. Incubators nurture innovation by providing technical expertise, access to research and development (R&D), facilitating interdisciplinary collaboration, and offering market feedback, thereby enabling startups to develop novel products, services, and business models (Sedita et al., 2019a). Sustainability further reflects a startup's commitment to social, environmental, and economic viability—factors increasingly valued in modern entrepreneurial ecosystems (Sutrisno et al., 2024). In this study, this dimension captures a startup's ability to launch innovative products, scale into new markets, and implement sustainable practices that contribute to both competitive advantage and societal impact.

Prototype Development: Prototype development serves as a tangible manifestation of innovation performance, reflecting a startup's capacity to transform ideas into market-ready solutions. Incubators facilitate prototype development by providing technical mentoring, R&D facilities, and access to prototyping equipment, thereby accelerating innovation cycles. According to Sedita et al. (2019), prototyping capability is a strong predictor of market success and venture scalability, particularly in technology-driven and manufacturing sectors. Moreover, the effectiveness of prototype development is shaped by the fit between incubation processes and entrepreneurial opportunity structures, underscoring the need for alignment between startup needs and incubator support (Nicholls-Nixon & Valliere, 2021).

Graduation and Post-Incubation Readiness: Graduation marks the culmination of the incubation process and signifies a startup's readiness to operate independently in the market. Successful graduation depends on the maturity of the venture, the intensity of support from the incubator, and the entrepreneur's network and resource base. Structured graduation policies enhance the likelihood of sustainable post-incubation performance by ensuring that startups have acquired sufficient market, financial, and managerial capabilities (Jimainal et al.,2022). This dimension reflects a startup's preparedness to transition from incubator dependence to market autonomy, showcasing the overall effectiveness of the incubation process.

A growing body of research confirms that the higher the frequency and quality of incubator service utilisation, the more significantly it enhances startup performance (Zhou, 2023; C. Eveleens, 2019; Zheng et al., 2019). Incubators provide structured environments that mitigate common startup challenges such as information asymmetry, resource scarcity, and strategic uncertainty. By offering multifaceted support ranging from infrastructure and access to funding to mentoring and networking, incubators enhance operational efficiency, innovation capacity, and organisational learning, ultimately leading to superior performance outcomes.

2.10 GENDER AS A MODERATOR

Gender has long been recognised as a crucial factor in shaping entrepreneurial attitudes, behaviours, and outcomes. In this study, Gender is incorporated as a categorical moderating variable to examine whether the relationships among Startup Characteristics, Incubator Support Service Usage (through Perceived Importance, Perceived Effectiveness, and Frequency of Usage), and Startup Performance differ across male and female entrepreneurs. This approach enables a nuanced understanding of how gender-based differences impact the entrepreneurial experience within the incubation ecosystem and whether the effectiveness of incubation support varies by gender.

The inclusion of gender as a moderator is grounded in *Social Role Theory* (Eagly, 1987) and *Institutional Theory* (Scott, 2015), which suggest that gendered social norms and institutional structures shape entrepreneurial behaviour, access to resources, and performance outcomes. Male and female entrepreneurs often operate under distinct socio-cultural expectations and institutional constraints that influence their risk-taking behaviour, resource acquisition strategies, and leadership styles (Brush et al., 2018).

Research indicates that female entrepreneurs frequently face systemic barriers**,** including limited access to funding networks, gender bias in investor relations, fewer mentorship opportunities, and restricted participation in high-growth sectors (Jennings & Brush, 2013; Díaz-garcía & Jiménez-moreno, 2010). In contrast, male entrepreneurs may benefit from greater social legitimacy and easier access to institutional support. These contextual disparities can shape not only how entrepreneurs utilise incubator services but also how they perceive their effectiveness and importance.

Business incubation environments are designed to provide neutral support to startups; however, several studies highlight that gendered experiences persist even within structured incubation programs. Female entrepreneurs often prioritise relational support, mentoring, and community-based learning, whereas male entrepreneurs tend to emphasise strategic networking, financial access, and market expansion (Manolava et al., 2007; Marlow et al., 2013).

Differences also emerge in how genders engage with incubator managers and networks. Female founders tend to value trust-based relationships, skill enhancement, and capacity-building programs. In contrast, male founders often leverage incubator networks more aggressively to pursue investment opportunities and scale their businesses (Marlow et al., 2013). These behavioural distinctions may lead to different patterns in the frequency of service usage and perceived value of incubation support.

Moreover, cultural and institutional settings in emerging economies can intensify these disparities. In contexts where entrepreneurship remains male-dominated, female entrepreneurs often encounter institutional voids and social biases, making incubator support mechanisms—especially mentoring, networking, and legitimacy-building—more critical to their success (Fernandez-guadaño et al., 2023).

Empirical evidence shows that gender moderates the relationship between incubation support and performance outcomes. For example, studies have reported that incubation programs incorporating gender-sensitive policies and inclusive mentoring frameworks yield better engagement and performance outcomes among women-led startups (Brush et al., 2018; García & Welter, 2011). Likewise, differences in perceptions of service quality and importance across genders highlight the need for differentiated service delivery models (Messeghem et al., 2018).

By examining gender-based moderation, this study aims to determine whether male and female entrepreneurs differ in how they leverage startup characteristics and incubation services to achieve performance outcomes. Gender is treated as a categorical moderator, distinguishing between male and female founders or co-founders. Multi-group analysis (MGA) in SmartPLS 4 is used to test whether the path coefficients differ significantly across these two groups. This analytical approach enables the identification of whether the magnitude and direction of relationships between constructs differ statistically based on gender (Henseler et al., 2009). This method also aligns with recent calls for inclusive and diversity-aware entrepreneurship research, emphasising that understanding gender dynamics can help incubators design more equitable support programs, enhance participation among women entrepreneurs, and reduce gender disparities in entrepreneurial ecosystems (Henry & Foss, 2015).

2.11 RESEARCH GAP

A review of existing literature on business incubation and startup development reveals significant progress in understanding how incubators contribute to entrepreneurial success. However, several conceptual, methodological, and contextual gaps persist that restrict a holistic understanding of the incubation process, particularly in the context of emerging economies such as India.

Early incubation research primarily focused on institutional and structural factors, emphasising the provision of infrastructure, administrative support, and policy mechanisms (OECD, 1997; Aernoudt, 2004). Subsequent studies shifted toward a service-based perspective, highlighting the range of services incubators offer, such as mentoring, funding facilitation, and networking (Hackett & Dilts, 2004; Bruneel et al., 2012). However, these studies typically adopted an incubator-centric viewpoint, evaluating the role and efficiency of incubators rather than how startups themselves perceive and engage with incubation support. Limited research has specifically examined the startup perspective, including how startups perceive the importance and effectiveness of incubation services and how these perceptions influence their usage patterns and overall outcomes (Grigorian, 2010).

Moreover, despite the broad application of the Resource-Based View (RBV) as a theoretical foundation, few studies have operationalised it in the incubation context to map specific resource dimensions- physical, financial, knowledge, network, and legitimacy that drive startup competitiveness (Amezcua et al., 2013; van Weele et al., 2017; van Rijnsoever & Eveleens, 2021). Many works also remain qualitative or descriptive, relying on case studies or subjective assessments, with limited adoption of quantitative, data-driven methodologies capable of measuring the strength and direction of relationships between startup characteristics, perceptions of support, usage patterns, and performance outcomes.

Existing research also neglects the behavioural and cognitive dimensions of incubation. While prior studies have explored incubator functionality, few have examined how startup founders perceive, interpret, and decide which services to use and how frequently. These cognitive perceptions, i.e Perceived Importance and Perceived Effectiveness, are crucial for understanding the behavioural link between incubator offerings and actual service utilisation. There is limited empirical evidence explaining how startup characteristics (experience, skills, and networks) shape these perceptions and how they, in turn, affect the frequency of service usage and startup performance.

Furthermore, although incubator effectiveness depends on the quality of human engagement, the degree of incubator intervention and assistance (DIIA), which reflects the level of personalised mentoring, networking facilitation, and strategic guidance, remains underexplored as a moderating factor. The relational and interactive dynamics between incubators and startups, as well as the extent to which varying levels of intervention influence performance outcomes, are insufficiently studied (Nair & Blomquist, 2021).

In addition, many studies assess incubation outcomes narrowly through financial performance, overlooking broader and multi-dimensional indicators such as operational efficiency, team development, innovation capacity, sustainability, prototype creation, and graduation readiness (Casado et al., 2020; Sutrisno et al., 2024). There is a pressing need to integrate these into a unified performance model that captures both tangible and intangible outcomes of incubation.

From a contextual standpoint, much of the existing incubation research adopts a generalised or global perspective, with minimal attention to regional and industry-specific variations in developing economies. In India, startups face diverse regional ecosystems—ranging from mature hubs in Maharashtra and Karnataka to emerging centres like Goa—each with its own distinct challenges and institutional support mechanisms. Comparative empirical evidence examining the effectiveness of incubation across various contexts remains limited *(DPIIT, 2024)*.

Finally, the gender dimension of incubation remains underexplored. Despite increasing emphasis on inclusive entrepreneurship, most studies continue to treat incubation support as gender-neutral. However, male and female entrepreneurs may perceive, access, and utilise incubation services differently due to socio-cultural and institutional factors (McAdam & Marlow, 2011; Brush et al., 2018). There is scant empirical work analysing gender as a moderating factor influencing the pathways between startup characteristics, incubation support, and performance, particularly within the Technology Business Incubator (TBI) environment in India.

The identified gaps collectively justify the need for a comprehensive, empirically validated framework that integrates startup characteristics, incubation support services, incubator intervention, and gender to explain startup performance outcomes. Each of the following research questions directly addresses one or more of these gaps:

1. How do startup characteristics influence the frequency of usage of support services provided by Technology Business Incubators (TBIs)?
   -Addresses the startup perspective gap by exploring how founders' attributes shape their engagement with incubation support.
2. What is the impact of startup characteristics on the perception of importance and effectiveness of incubators' support services?
   -Responds to the cognitive-behavioural gap by investigating how experience, skills, and networks influence perception formation
3. How are these usage patterns affected by startups' perceptions of the importance and effectiveness of these services?
   -Fills the quantitative and perceptual gap by linking perceived value to actual behaviour (usage frequency).
4. To what extent does the frequency of usage of incubators' support services influence the performance of startups?
   -Addresses the performance measurement gap by connecting behavioural engagement to multidimensional performance outcomes.
5. Does the Degree of Incubator's Intervention and Assistance strengthen or weaken the impact of Frequency of Usage on Startup Performance, and between Startup Characteristics and Frequency of Usage?
   -Fills the relational–intervention gap by examining IIA as a moderating construct affecting the strength of relationships.
6. Do the characteristics of a startup directly impact its overall performance, independent of intermediary factors?
   -Tests the direct-effect pathway, responding to the need for a holistic model that captures both mediated and direct effects.
7. How does gender moderate the relationship between startup characteristics, incubator service usage, perceived service value, and startup performance?
   -Addresses the gender gap by examining gender-based differences in perception, usage, and outcomes within TBIs.

2.12 PROPOSED MODEL

Based on the research gaps identified in Section 2.11, this study proposes a comprehensive Input–Mediator–Moderator–Outcome (IMMO) framework to examine how startup characteristics, incubation support services, and incubator interventions influence the performance of startups operating within Technology Business Incubators (TBIs) in India. The proposed research model (Figure 2.8) identifies seven key constructs**,** namely: Startup Characteristics (SC) – a higher-order construct composed of Experience (EXP)**,** Skills (SKL)**,** and Network (NET) as its lower-order dimensions; Degree of Incubator's Intervention and Assistance (DIIA); Perceived Importance (PoI); Perceived Effectiveness (PoE)**;** Frequency of Usage (FU)**;** and Startup Performance (SP)**.** Based on insights from the literature review, the proposed conceptual model (Figure 2.8) integrates the key constructs examined in this study. To provide clarity and logical flow, the model is explained through an objective-wise discussion, wherein each research objective is linked to its underlying theoretical rationale and associated hypotheses.

Objective 1: To examine the influence of startup characteristics on the frequency of usage of support services offered by Technology Business Incubators (TBIs).

Startup Characteristics (SC) represent the internal inputs that define how a startup interacts with its incubation environment. These characteristics reflect the *human* and *social capital* embodied within the founding team and serve as critical determinants of how effectively entrepreneurs identify, access, and utilize the resources provided by TBIs. In the proposed model, SC is conceptualized as a *Higher-Order Construct (HOC)* consisting of three *Lower-Order Constructs (LOCs)* namely Experience, Skills, and Networks which together explain the heterogeneity among incubated startups.

- **Experience** (EXP) captures the prior entrepreneurial, managerial, or industry-specific exposure of founders that enhances their cognitive ability to recognize opportunities and apply incubator resources strategically. Entrepreneurs with higher experience tend to understand business dynamics better and are more likely to engage actively with incubator services to accelerate venture growth (Colombo & Grilli, 2005; Unger et al., 2011; Monsson & Jørgensen, 2016).

- **Skills** (SKL) denote the entrepreneurial competencies—such as innovation, opportunity recognition, financial planning, problem-solving, and leadership—that enable founders to absorb and implement the knowledge and support offered by incubators effectively. These capabilities determine the extent to which startups can transform incubator interventions into tangible business outcomes (Hazlina Ahmad et al.,2010;Mitchelmore & Rowley, 2010; C. P. Eveleens et al., 2017).
- **Networks** (NET) represent the breadth and strength of a startup's relational ties with mentors, peers, customers, suppliers, investors, and institutional partners. Strong social and professional networks provide informational advantages, enhance trust, and ease access to external resources, thereby motivating startups to participate more frequently in TBI programs and collaborative activities (Hoang & Antoncic, 2003; Lockett et al., 2003; Bruneel et al., 2012; Grandgirard et al., 2002; Greve & Salaff, 2003; Stam et al., 2014).

Collectively, these dimensions of Startup Characteristics are expected to shape how entrepreneurs perceive the relevance and value of incubator offerings. Startups with greater experience, well-developed skills, and richer networks are hypothesized to display higher engagement levels and more frequent utilization of TBI support services. Hence, the following hypotheses are proposed under this objective:

Startup Characteristics and First-order components

H1a(i): Experience has a positive contribution towards Startup Characteristics.

H1a(ii): Network has a positive contribution towards Startup Characteristics.

H1a(iii): Skills have a positive contribution towards Startup Characteristics.

H1b: Startup Characteristics have a significant direct impact on Frequency of Usage.

Objective 2: To assess the impact of startup characteristics on startups' perception of the importance and effectiveness of incubator support services.

Startup Characteristics (SC) fundamentally shape how entrepreneurs interpret, value, and evaluate the incubation support ecosystem. Founders' prior experiences, skills, and networks influence their cognitive and behavioral responses toward the range of services provided by Technology Business Incubators (TBIs). These characteristics determine not only what entrepreneurs deem *important* for their venture's growth but also how they perceive the *effectiveness* of the services they actually receive.

Startups led by entrepreneurs with substantial experience possess enhanced business acumen and situational awareness, enabling them to recognize the strategic relevance of incubation services such as mentoring, funding facilitation, and networking (Colombo & Grilli, 2005; Monsson & Jørgensen, 2016). Similarly, founders equipped with strong entrepreneurial skills are more capable of assessing the practical value of incubator interventions, as their managerial and innovative competencies help translate abstract support into actionable benefits (Hazlina Ahmad et al.,2010;Mitchelmore & Rowley, 2010). Moreover, well-established networks broaden access to information, role models, and peer learning, thereby enhancing the entrepreneur's ability to judge which incubator services are most valuable or impactful for their venture's stage of development (Hoang & Antoncic, 2003; Bruneel et al., 2012).

Consequently, startups with richer experience, stronger skills, and denser networks are likely to perceive incubator services as both more *important* for their business objectives and more *effective* in meeting those objectives. These perceptual differences explain the heterogeneity observed among incubatees in terms of their engagement and satisfaction with incubation programs. Therefore, the following hypotheses are proposed under this objective:
H2a: SC have a significant positive impact on PoI.
H2b: SC have a significant positive impact on PoE.

Objective 3: To analyse how startups' perceptions of the importance and effectiveness of incubator services influence their frequency of usage.

The way incubatees perceive the importance and effectiveness of the services offered by Technology Business Incubators (TBIs) plays a crucial role in determining their engagement behaviour and the extent to which they utilize those services. Perceptions act as cognitive filters through which entrepreneurs interpret the relevance and value of incubator interventions, shaping their motivation and commitment to participate in incubation activities.

Startups that attach high importance to specific incubator services—such as mentoring, investor connections, training programs, or networking events—are more likely to prioritize and frequently use these services, viewing them as strategic tools for business growth (Autio

& Klofsten, 2017;Bruneel et al., 2012). On the other hand, the perceived effectiveness of incubator services, defined as the degree to which entrepreneurs believe these offerings contribute to achieving their business goals, reinforces continued participation and sustained engagement (Hackett & Dilts, 2004; Vanderstraeten & Matthyssens, 2012). When incubatees experience tangible benefits from services—such as improved product development, funding access, or market visibility—they are more inclined to re-engage with the incubator's programs at higher frequencies.

Empirical studies emphasize that the perceived relevance and demonstrated impact of support mechanisms are key behavioural drivers in determining how entrepreneurs allocate time and effort toward incubation activities (Patton, 2014; van Weele et al., 2017). Hence, positive perceptions of importance and effectiveness are expected to translate into higher frequency of usage, indicating stronger incubator–incubatee alignment. Accordingly, the following hypotheses are proposed under this objective:
H3a: PoI has a significant positive impact on FU.
H3b: PoE has a significant positive impact on FU.

Objective 4: To examine the mediating role of Perception of Importance (PoI) and Perception of Effectiveness (PoE) in the relationship between Startup Characteristics (SC) and Frequency of Usage (FU) of incubator services.

While startup characteristics define the internal capacity and predisposition of entrepreneurs to engage with incubation programs, their actual participation and intensity of usage depend largely on the perceptions they form about the relevance and impact of the services provided. In other words, the influence of Startup Characteristics (SC) on Frequency of Usage (FU) may not be entirely direct but may operate through cognitive and attitudinal mechanisms captured by Perception of Importance (PoI) and Perception of Effectiveness (PoE).

Entrepreneurs with higher levels of experience, skills, and networks tend to be more discerning about which incubation services are most valuable to their ventures (Colombo & Grilli, 2005; Monsson & Jørgensen, 2016). These startups are more likely to perceive incubator offerings as strategically *important* to their business development and operational success. Similarly, when founders possess stronger managerial and relational capabilities, they are better positioned to evaluate and appreciate the *effectiveness* of incubation interventions (Hazlina Ahmad et al.,2010; Bruneel et al., 2012). Such positive perceptions, in turn, motivate entrepreneurs to engage more frequently with the incubator's programs and resources.

Empirical studies indicate that perception-based constructs often mediate the relationship between firm characteristics and behavioural outcomes, as they shape the motivational pathways leading to action (Patton, 2014; van Weele et al., 2017). Therefore, it is theorized that both PoI and PoE serve as mediating mechanisms through which startup characteristics influence the frequency with which startups access and utilize incubator services.Accordingly, the following hypotheses are proposed under this objective:
H4a: PoI has a significant mediating role between SC and FU.
H4b: PoE has a significant mediating role between SC and FU.

Objective 5: To investigate whether the Degree of Incubator's Intervention and Assistance (DIIA) moderates (a) the relationship between Frequency of Usage (FU) and Startup Performance (SP), and (b) the relationship between Startup Characteristics (SC) and Frequency of Usage (FU).

The impact of incubation on startup outcomes often depends not only on how startups engage with incubator services but also on the intensity and quality of support extended by the incubator itself. The Degree of Incubator's Intervention and Assistance (DIIA) captures the depth, consistency, and responsiveness of incubator involvement in assisting startups through mentoring, technical support, financial linkages, networking, and strategic guidance. It represents the external contextual strength of the incubation process, which can amplify or weaken the effects of internal startup attributes and behavioural factors on performance outcomes.

When incubators provide high levels of intervention and assistance, they are better equipped to tailor their offerings to the unique needs of startups, thereby enhancing the efficiency with which incubatees convert resource utilization into tangible business outcomes (Grimaldi & Grandi, 2005; Patton, 2014). This suggests that DIIA may moderate the relationship between Frequency of Usage (FU) and Startup Performance (SP)—such that startups that frequently use incubator services achieve higher performance only when the quality and depth of incubator intervention are strong. Conversely, under weak or generic intervention conditions, even frequent usage may not translate into substantial performance gains.

Similarly, the relationship between Startup Characteristics (SC) and Frequency of Usage (FU) may also be moderated by DIIA. Startups with greater experience, skills, or networks are more likely to engage with incubation activities when the incubator demonstrates proactive, customized, and resource-rich support (Bruneel et al., 2012; Hausberg & Korreck, 2020). However, in incubators with limited interaction or low support intensity, such startups may rely more on their own resources and external networks, resulting in lower usage of incubator services. Accordingly, the following hypotheses are proposed under this objective:
H5a: DIIA moderates the relationship between Startup Characteristics and Startup Performance.
H5b: DIIA moderates the relationship between Frequency of Usage and Startup Performance.

Objective 6: To evaluate the extent to which the frequency of usage of incubator support services affects startup performance.

The Frequency of Usage (FU) of incubator support services reflects the degree of engagement and participation of startups within the incubation ecosystem. It represents how consistently and extensively incubatees utilize the various forms of assistance offered—such as mentoring, training, infrastructure, networking, funding access, and business development programs. Higher frequency of usage indicates deeper involvement with the incubation process, greater exposure to learning opportunities, and sustained interaction with mentors and peers, all of which are expected to contribute positively to startup growth and performance outcomes.

Empirical research has shown that the benefits derived from business incubation are not automatic but depend on the extent and intensity of engagement between the incubator and the incubatee (Barbero et al., 2014; Patton, 2014; van Weele et al., 2017). Startups that regularly attend incubation activities, actively seek mentorship, and apply acquired knowledge are more likely to achieve improved market performance, innovation capability, and sustainability. In contrast, low engagement levels or infrequent participation can limit the potential advantages of incubation, as startups fail to fully absorb or operationalize the resources provided (Mian et al., 2016 ; Scillitoe & Chakrabarti, 2010).

In the proposed framework, Frequency of Usage functions as a behavioral pathway through which startups translate incubation opportunities into measurable outcomes. By actively engaging with incubator support services, startups can enhance their learning curve, expand their networks, and strengthen business viability—thereby improving overall Startup Performance (SP). Accordingly, the following hypothesis is proposed under this objective:

H6: Frequency of Usage (FU) has a significant positive impact on Startup Performance (SP).

Objective 7: To determine whether Startup Characteristics (SC) have a direct effect on Startup Performance (SP), independent of any mediating constructs.

While incubation programs provide crucial external support, the intrinsic characteristics of startups remain fundamental determinants of venture success. Startup Characteristics (SC)—encompassing the founder's experience, entrepreneurial and managerial skills, and the breadth of social and professional networks—constitute the internal capital base that influences performance regardless of the incubation context. These characteristics shape how effectively entrepreneurs recognize opportunities, mobilize resources, and respond to market dynamics, thereby driving growth and competitiveness even in the absence of mediating factors such as perception or frequency of usage.

Empirical studies in entrepreneurship consistently highlight that founders with rich experience possess superior problem-solving and decision-making capabilities, allowing them to steer their ventures toward sustainable outcomes (Colombo & Grilli, 2005;Unger et al., 2011). Similarly, strong entrepreneurial and managerial skills enhance operational efficiency, innovation capacity, and adaptability—core ingredients of performance excellence (Mitchelmore & Rowley, 2010;Hazlina Ahmad et al.,2010). Extensive networks provide informational, financial, and reputational resources that improve access to opportunities and strengthen market positioning (Hoang & Antoncic, 2003; Greve & Salaff, 2003; Stam et al., 2014).

Building on this foundation, the proposed model posits that these internal competencies exert a direct influence on Startup Performance (SP), beyond the indirect pathways mediated through perceptions or engagement behaviours. Thus, even when incubator support mechanisms are accounted for, the inherent strength of the startup's human and social capital is expected to significantly predict its success. Accordingly, the following hypothesis is proposed under this objective:

H7: Startup Characteristics (SC) have a significant direct impact on Startup Performance (SP).

Objective 8: To explore the moderating role of gender in the relationships among Startup Characteristics, Perceptions of Incubator Support, Frequency of Usage, and Startup Performance.

Gender has been increasingly recognized as an important contextual factor influencing entrepreneurial behaviour, opportunity perception, and resource utilization. Within the incubation ecosystem, gender differences may affect how entrepreneurs interpret, access, and benefit from incubator support services. The moderating role of gender is thus critical in understanding whether the relationships among key constructs—such as Startup Characteristics (SC), Perception of Importance (PoI), Perception of Effectiveness (PoE), Frequency of Usage (FU), and Startup Performance (SP)—operate uniformly across male- and female-led startups.

Research suggests that male and female entrepreneurs often differ in their entrepreneurial motivations, social capital structures, risk orientation, and access to resources (Brush et al., 2018; Jennings & Brush, 2013). These variations may influence how startup characteristics—like experience, skills, and networks—translate into perceived importance and effectiveness of incubation services. For instance, female entrepreneurs may value certain incubation supports (e.g., mentoring, networking, training) more highly, but structural and social barriers might limit their ability to use them as frequently or effectively as their male counterparts (Díaz-garcía & Jiménez-moreno, 2010).

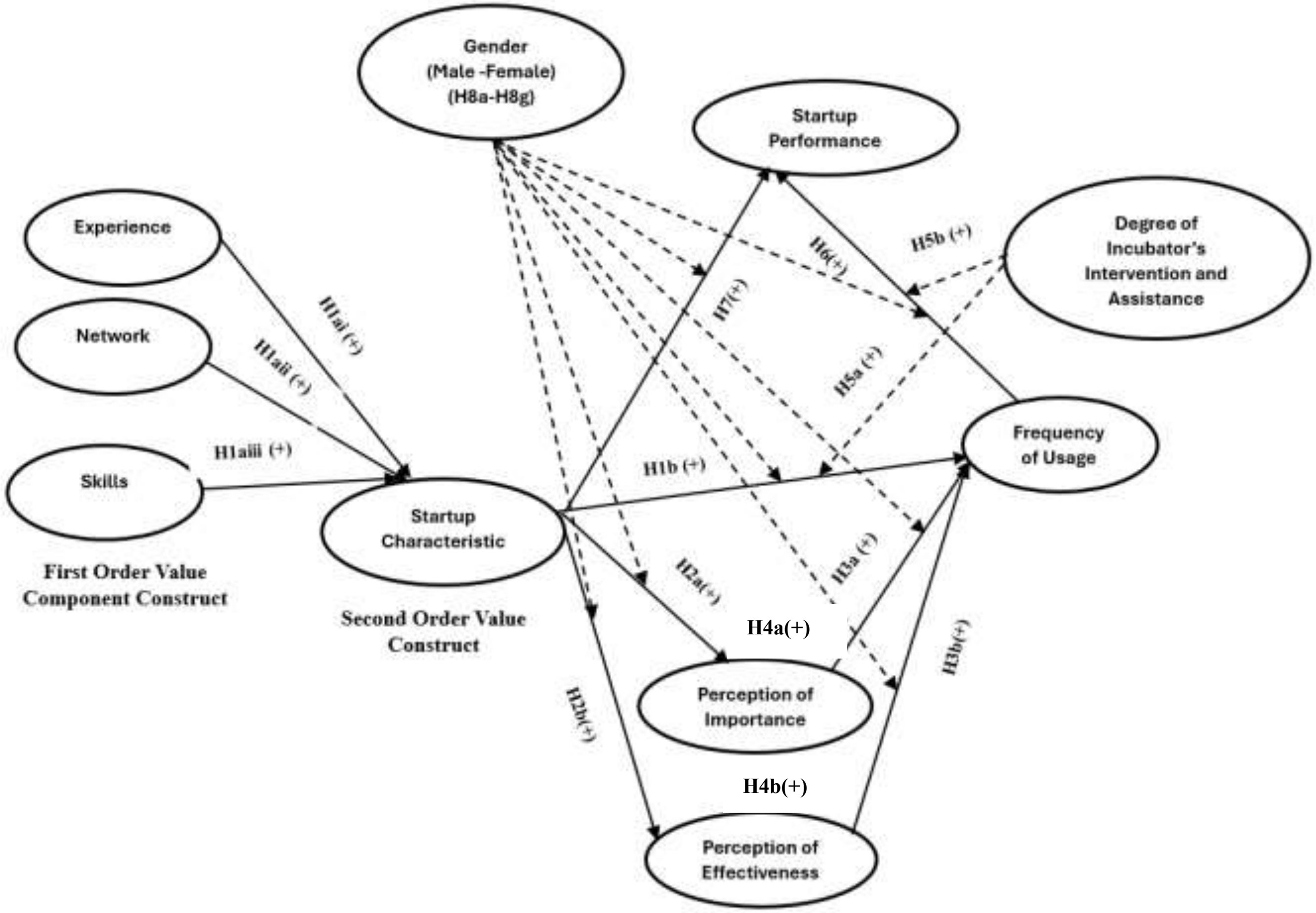
Moreover, gendered experiences within the incubation process can moderate behavioural engagement and performance outcomes. Studies have found that male founders often report greater access to funding and networks, whereas female founders exhibit stronger relational and community-oriented approaches that influence perception and satisfaction levels differently (Marlow et al., 2013 ;Henry & Foss, 2015). Consequently, gender may moderate how perceptions of incubator effectiveness and importance translate into actual service usage and subsequent performance.

Exploring gender as a moderator thus provides valuable insights into whether incubation impacts are equitably distributed and whether interventions should be tailored to address gender-specific needs.

Accordingly, the following hypotheses are proposed under this objective:

- **H8a:** Gender moderates the relationship between Startup Characteristics (SC) and Frequency of Usage (FU).
- **H8b:** Gender moderates the relationship between Perception of Effectiveness (PoE) and Frequency of Usage (FU).
- **H8c:** Gender moderates the relationship between Startup Characteristics (SC) and Perception of Effectiveness (PoE).
- **H8d:** Gender moderates the relationship between Perception of Effectiveness (PoE) and Frequency of Usage (FU).
- **H8e:** Gender moderates the relationship between Perception of Importance (PoI) and Frequency of Usage (FU).
- **H8f:** Gender moderates the relationship between Frequency of Usage (FU) and Startup Performance (SP).
- **H8g:** Gender moderates the relationship between Startup Characteristics (SC) and Startup Performance (SP).

Fig 2.8 Research Model for the study



Source: Authors' own compilation

2.13 SUMMARY

This chapter presented a comprehensive review of the literature through a two-phase systematic approach**.** In the first phase, a bibliometric analysis was conducted encompassing both *performance analysis* and *scientific mapping* to identify key publication trends, prolific authors, influential journals, and evolving research themes within the domain of technology business incubation and startup performance. This quantitative overview provided a macro-level understanding of the field's intellectual structure and research dynamics. In the second phase, the Input–Mediator–Outcome (IMO) framework was employed to synthesise and interpret the existing studies systematically. This framework facilitated the logical organisation of prior findings by linking startup inputs, incubation processes, and performance outcomes, thereby highlighting how different constructs interact to shape entrepreneurial success within incubator settings. The chapter also discussed the theoretical underpinnings that form the conceptual foundation of the research.

Building upon the insights derived from the literature, a research gap was identified concerning the limited empirical understanding of how startup characteristics, perceptions of incubator support, and engagement behaviours collectively influence startup performance in the Indian incubation ecosystem. To address this gap, a proposed conceptual model was developed, as illustrated in Figure 2.8, linking the key constructs under study through clearly defined objectives and hypotheses. The model integrates both direct and indirect pathways capturing the mediating roles of perception and frequency of usage and the moderating effects of the degree of incubator intervention and gender within the broader Input–Mediator–Outcome framework. This integrative model serves as the theoretical and analytical foundation for the subsequent chapters, guiding the empirical examination of relationships among startup characteristics, incubator mechanisms, and performance outcomes.

CHAPTER 3
RESEARCH METHODOLOGY

This chapter outlines the methodological framework and research process adopted to achieve the study's objectives and validate the proposed conceptual model. It explains the overall research design, data collection methods, and analytical techniques employed to ensure rigour and reliability. The chapter is structured around two main stages: Stage A – Model Development**,** which focuses on constructing the conceptual framework based on theoretical foundations, and Stage B – Model Estimation, which involves empirical data collection, preparation, and statistical analysis. Together, these stages provide a systematic approach for examining the influence of incubator support services on startup performance.

3.1 INTRODUCTION

This chapter presents a comprehensive overview of the research process, outlining the methodological and statistical approaches adopted to structure and conduct the study. It describes the overall research design, data collection procedures, analytical techniques, and the interpretation of results, ensuring a systematic approach to achieving the study's objectives.

The chapter details the selection of appropriate research methods, the formulation of objectives and hypotheses, and the process of gathering, processing, and analysing data using advanced statistical tools. A structured and rigorous methodology has been adopted to ensure the reliability, validity, and credibility of the findings. The research design integrates both conceptual development and empirical testing, thereby enabling a comprehensive evaluation of the relationships among the key constructs.

The primary purpose of this chapter is to present a systematic framework for developing and validating the proposed conceptual model that examines the influence of incubation support services on startup performance. The chosen methodological and statistical approaches—aligned with the study's nature and objectives—facilitate robust empirical analysis and provide meaningful insights for both academic research and practical decision-making in the field of technology business incubation. To provide a clear understanding, the rest of this chapter is organised as follows:

- **Research Process (Section 3.2):** This section presents the overall research design and the systematic process followed in conducting the study—from defining the research problem to developing and validating the conceptual framework. It comprises two key subsections:
    - **Stage A Model Development (Section 3.3)**
    - **Stage B Model Estimation (Section 3.4)**

3.2 RESEARCH PROCESS

Research is a systematic process of gathering data and uncovering facts to advance knowledge in a particular field (Mark Saunders & Thornhill, 2019). The research methodology defines how a study is conducted, based on its nature, and guides data collection through methods such as surveys and interviews (Flick, 2011; Morgan, 2014). The collected data is then processed and analysed to test theories, ideas, or hypotheses (Morgan, 2014; Mouton, 2001). The research process involves a sequence of essential actions or steps that must be systematically followed to conduct the study effectively, ensuring that each phase is executed in a logical and structured manner. This study followed a two-stage research process to conduct the research systematically. The Stage A, **Model Development**, focuses on constructing the conceptual framework, defining key variables, and establishing relationships based on existing literature and theoretical foundations. The Stage B, **Model Estimation**, is dedicated to validating the proposed model and empirically testing its effectiveness. To enhance the robustness of the study, Stage B is further divided into two sub-stages:

- **Stage B(i): Empirical Data Collection and Preparation**, involving the design and administration of a structured questionnaire to gather quantitative data from incubated startups across Maharashtra, Karnataka, and Goa, followed by data screening and preparation; and
- **Stage B(ii): Statistical Analysis**, which applied advanced analytical techniques such as Partial Least Squares–Structural Equation Modelling (PLS-SEM)**,** Multi-Group Analysis (MGA)**,** Importance-Performance Map Analysis (IPMA)**,** and **Necessary** Condition Analysis (NCA) to test hypotheses and validate the conceptual model.

3.3 STAGE A: MODEL DEVELOPMENT

Stage A focuses on constructing the conceptual framework that serves as the foundation of the research. This stage involved an extensive review of existing literature and relevant theoretical perspectives to identify key variables and define their interrelationships. Drawing upon the Input–Mediator–Outcome (IMO) framework, the model conceptualises how startup inputs (e.g., characteristics and resources) are transformed through mediating mechanisms (perceptions and usage of incubator support services) into performance outcomes.

The major constructs incorporated in the framework include Startup Characteristics, Perceptions of Importance and Effectiveness, Frequency of Usage, Degree of Incubator's Intervention and Assistance, Gender, and Startup Performance**.** These constructs were operationalised based on prior empirical evidence and adapted to the context of technology business incubation. The conceptual model was anchored in the Resource-Based View (RBV)**,** Human and Social Capital Theory**,** and the Incubation Process Model, ensuring strong theoretical coherence and relevance. Hypotheses were formulated to represent the proposed relationships among the constructs, providing a basis for empirical validation in the subsequent stage.

3.4 STAGE B: MODEL ESTIMATION

Stage B focuses on empirically validating the proposed model and testing its effectiveness using quantitative data. A structured questionnaire was developed to collect primary data from incubated startups across Maharashtra, Karnataka, and Goa, ensuring representation across sectors and incubation stages. The data collection process included instrument design, pilot testing, sampling, and ethical compliance to ensure the reliability and validity of the dataset.

The methodological approach therefore links theory and evidence, moving from conceptual model development (Stage A) to empirical testing (Stage B). This structured design establishes a robust foundation for the Statistical Approach presented in the following section, where the collected data are analysed and the hypotheses are empirically tested.

Stage B is comprised of two interconnected components. Stage B(i): Empirical Data Collection and Preparation involved the design and administration of a structured questionnaire to collect quantitative data from incubated startups.The process included the construction and refinement of the questionnaire based on expert feedback, assessment of face and content validity, and the conduct of a pilot study to ensure clarity and reliability. Appropriate sampling techniques were applied to determine a representative sample size, and data were systematically screened and prepared for analysis. Stage B(ii): Statistical Approach entailed the application of advanced statistical techniques to analyse the collected data, test hypotheses, and validate the conceptual model.

3.4.1 STAGE B(i): EMPIRICAL DATA COLLECTION AND PREPARATION

A survey serves as a structured method for gathering data essential to empirical research. This approach is particularly beneficial as it enables researchers to systematically collect information from a broad and diverse group of participants. By utilising well-designed questionnaires or interviews, surveys help capture various perspectives, opinions, and behaviours relevant to the study (Sue & Ritter, 2012; Walter, 2019). The primary reason for choosing a survey for this research is its ability to facilitate the examination of patterns, trends, and relationships within a given population. Additionally, surveys provide a reliable means to predict specific behavioural aspects based on the responses obtained. This systematic data collection technique ensures that the study gains valuable insights, leading to well-supported conclusions about the characteristics and tendencies of the population of interest. (Mouton, 2001).

In the survey methodology, developing a well-structured questionnaire requires an extensive literature review to ensure the accuracy, relevance, and reliability of the data collected. This process is particularly crucial in empirical research, where the goal is to obtain meaningful insights based on established theoretical frameworks and prior empirical findings.

For this study, which focuses on startup founders as participants, a comprehensive literature review was conducted to identify and analyse the key factors influencing the performance of incubated startups. By examining existing studies, theoretical models, and industry best practices, the research aimed to ensure that all the variables considered were well-grounded in academic and practical knowledge. The questionnaire was designed by carefully selecting measurement items that align with the factors identified in the literature. This approach not only strengthens the validity of the research but also ensures that the data collected can effectively capture the impact of these factors on startup performance. The development of the questionnaire was guided by established theories, previous empirical findings, and logical reasoning, ensuring that it adequately reflects the constructs under investigation. A detailed description and literature review of the questionnaire development for the survey are presented in this the chapter.

By basing the questionnaire items on existing literature and theoretical foundations, the study ensures consistency with prior research while also contributing to the broader understanding of startup incubation dynamics. This systematic approach enhances the reliability of the study and allows for meaningful comparisons with other research in the field.

3.4.1.1 QUESTIONNAIRE CONSTRUCTION

The questionnaire is meticulously designed by adhering to established principles of survey design outlined by Sekaran & Bougie (2017) and the scaling methodology proposed by Krosnick & Fabrigar (1997). These frameworks ensure the development of a robust and reliable instrument for data collection, enhancing the validity and accuracy of the research findings. The questionnaire is carefully designed to comprehensively address all the research hypotheses and questions while also capturing demographic information to categorise and describe the characteristics of the sample population.

Each section of the questionnaire is structured to ensure that the data collected aligns with the study's objectives. The questions related to hypotheses and research questions are formulated to measure key variables, assess relationships, and validate theoretical assumptions. These items are designed based on prior literature and empirical studies to ensure relevance and reliability in capturing meaningful insights. Additionally, demographic data such as age, education, industry experience, business sector, nature, and stage of the startup, as well as other relevant characteristics, are included in the questionnaire. This demographic information plays a crucial role in segmenting the respondents and understanding the sample's composition. It helps in identifying patterns, making comparisons, and ensuring that the analysis accounts for potential variations among different groups within the study.

The questionnaire employs a 7-point Likert scale, a widely used tool in social research for capturing subjective perceptions, attitudes, and beliefs (Krosnick & Fabrigar, 1997; Sekaran &

Bougie, 2017; Hackett & Dilts, 2008). The 7-scale format is chosen to enhance sensitivity, minimise measurement errors, and maximise information collection, allowing respondents to express opinions with greater precision. It improves reliability and validity while reducing central tendency bias. The questionnaire incorporates different but familiar measurement scales, such as experience (Totally inexperienced to Extremely experienced) and importance (Not Important to Very Important), ensuring clarity and relevance. Given that the study focuses on subjective evaluations from startup founders, this approach enables a detailed and comprehensive assessment of the factors influencing the performance of incubated startups.

The questionnaire is structured into five distinct parts to ensure a systematic and comprehensive data collection process. It begins with a title and confidentiality statement, assuring respondents of data privacy. The first section gathers basic startup demographic information, including the startup's name, its product or service offerings, market nature, segment, team size, startup's location, and stage, as well as the founder's age, gender, and education. The second section focuses on startup characteristics, capturing variables such as entrepreneurial experience, skills, and networking capabilities. The third section assesses the intervention and support provided by the Technology Business Incubator (TBI), including assistance from the incubation manager and their team. The fourth section evaluates the business incubation process, examining the startup's participation, perceived importance, and effectiveness of incubation programs. Lastly, the fifth section measures the impact of business incubation on startup performance, analysing outcomes resulting from the incubation experience. This structured approach ensures a precise alignment with the study's research objectives.

3.4.1.2 REFINEMENT OF QUESTIONNAIRE AFTER SEEKING EXPERT OPINION AND TEST FOR FACE AND CONTENT VALIDITY

The questionnaire was tested for face and content validity through an in-depth interview and expert opinion survey involving a diverse panel of experts.

This validation process included:

- **Two Academicians**:
  Prof. M. H. Balasubramanya - Professor- Department of Management Studies, IISc, Bangalore

Dr Mathivanan Periasamy - Associate Professor - Decision Sciences, NSB Academy, Bangalore

- **Two incubation managers**:
  Mr Kiran Mehta - Head Incubation & Innovation at FiiRE , Goa
  Dr Srinivas Madhusudan Kandada- Operation Head, CPDMED TBI-A Medtech & Geriatric Healthcare Technology Business Incubator, IISC, Bangalore
- **Two startup founders**
  Balachandran Elayath- Yaguar Raptors, FiiRE, Goa
  Siddhartha Nair – Zeuron.ai, DERBI Foundations, Bangalore

The primary objective of this step was to ensure that the questionnaire items accurately captured the intended sub-constructs. To establish face validity, the researcher sought to confirm that each item appeared, on the surface, to measure what it was intended to measure. For this purpose, the questionnaire was reviewed by a panel of domain experts, including academicians and practitioners familiar with Technology Business Incubation and startup development. The researcher personally interviewed each expert to obtain qualitative feedback on the clarity, wording, and relevance of the items.

In addition, content validity was ensured by verifying the comprehensiveness and representativeness of the items with respect to the conceptual framework and constructs under study. The experts evaluated whether the questionnaire adequately covered all dimensions of the latent variables. Based on their suggestions, several items were refined, reworded, or repositioned to improve precision and contextual relevance. This iterative expert validation process helped enhance both the face and content validity of the instrument before its final administration to startup founders.

3.4.1.3 PILOT STUDY

A pilot study is a preliminary, small-scale investigation conducted before the main study to assess the feasibility of the research design and methodology. It helps identify potential issues in data collection, ensuring the study's effectiveness. Additionally, the pilot study is instrumental in pretesting the questionnaire, allowing researchers to evaluate the clarity, reliability, and validity of the survey items. It also helps estimate the time required for respondents to complete the questionnaire, ensuring a smooth and efficient data collection process. By conducting a pilot study, necessary refinements can be made to enhance the accuracy and effectiveness of the final research instrument.

Data from 34 entrepreneurs was collected and analysed as part of the pilot study. To ensure construct validity**,** Cronbach's alpha was computed and examined for all variables, assessing the internal consistency and reliability of the measurement items. The Cronbach Alpha values are represented in Table 3.1. Additionally, the total time required to complete the questionnaire was recorded, with respondents taking an average of 25 to 30 minutes to finish. This assessment helped refine the questionnaire by identifying potential improvements in clarity, structure, and respondent burden before the full-scale study.

Table 3.1 Reliability Statistics

Code	**Sub-dimension**	**Cronbach's Alpha**	**N of Items**
SC	Startup Characteristics		
EXP	Startup Experience	0.804	4
NET	Startup Network	0.872	7
SKL	Startup Skill	0.763	5
DIIA	Degree of Incubators' Intervention and Assistance	0.975	7
FU	Frequency of Usage	0.659	5
PoI	Perception of Importance	0.689	5
PoE	Perception of Effectiveness	0.821	5
SP	Startup Performance	0.876	7

Source: Compiled from Primary Data

The analysis of the pilot study showed that, except for FU and PoI, all other sub-dimensions had Cronbach's alpha values above 0.7**,** which is considered acceptable for internal consistency (Nunnally & Bernstein, 1994). In exploratory research, an alpha value of 0.6 and above is also deemed tolerable (Kline, 2000), hence FU and PoI were retained. The final questionnaire consisted of 45 items**,** none of which were modified based on the pilot study findings.

3.4.1.4 SAMPLE SIZE

Israel (1992) outlined four strategies for determining sample size: (1) using the entire population when it is small, (2) selecting a sample size based on similar past studies**,** (3) referring to published tables that consider precision, confidence intervals, and variability, and

(4) applying pre-determined formulae to calculate the required sample size. For this study, the second and third strategies were employed. Following the conventional approach**,** an average sample size was derived from previous studies, revealing that a sample size of more than 500 was the most commonly used among researchers. Additionally, a content analysis of 56 research papers confirmed that the majority of studies utilised a sample size of approximately 500, supporting the selection of this benchmark for this study.

A quantitative methodology is used to collect data from 612 incubatee startups across 20 TBIs in Maharashtra, Karnataka, and Goa, where most TBIs are clustered in India's West and South Zones. We used convenience sampling to select startups from the incubation centres. The sampling framework consists of the startup founders incubated at any of the chosen incubation centres, as represented in Table 3.2. A total of 720 questionnaires were conveniently distributed in the following places in India: Mumbai, Hubli, Bangalore, and Goa. Out of these, 31 were not returned, 659 (91.52%) responses were received, with 47 being incomplete, and 30 respondents were identified as unengaged. The remaining 612 responses were retained, comprising the usable response rate of 85% for statistical analysis.

Table 3.2 List of TBIs for data collection

Sr. No	Name of the TBI	Population*	No. of respondents
Goa			
1	FiiRE - Forum for Innovation Incubation Research and Entrepreneurship	128	82
2	CIBA- Centre for Incubation and Business Acceleration	21	17
3	AIC- Atal Incubation Centre, GIMS	11	11
4	BGIIES- BITS Goa Innovation, Incubation & Entrepreneurship Society	07	05
Mumbai			
5	SINE, IIT Bombay- Society for innovation & entrepreneurship	146	94
6	Riidl - Research Innovation Incubation Design Labs	153	89
7	CIBA- Centre for Incubation and Business Acceleration	82	46
8	AIC- NMIMS Incubation Centre	32	20
9	Zone Startups India	58	47
Bangalore			
10	CPDMED	26	24
11	Bangalore Bioinnovation Centre	38	27
12	Ginserve- Global Incubation Services	24	20

13	DERBI Foundation	**65**	**30**
14	IIITB Innovation Centre	**42**	**30**
15	InCeNSE Technology Business Incubator	**07**	**06**
16	NSRCEL	**105**	**65**
17	M S Ramaiah TBI	**14**	**08**
18	Ramaiah Evolute	**11**	**07**
19	Social Alpha	**67**	**57**
Hubli			
20	Deshpande Foundation	**48**	**35**
	Total	**1085**	**720**

**at the time of data collection* *Source: Compiled from primary data*

The study utilised a structured questionnaire as the primary research instrument, with 45% of responses collected online and 55% offline**.** Before this, in-depth semi-structured interviews were conducted with startup founders, incubation managers, and academicians specialising in similar research areas to refine the questionnaire. The online survey was necessary due to the unavailability of incubated founders for in-person discussions, as some were too busy to respond immediately. In contrast, others preferred to complete the questionnaire at their convenience without any guidance. The data collection period was from May 2023 to May 2024. Finally, the survey data were analysed using statistical methods to examine the statistical significance of the proposed conceptual model as part of Stage B(ii). The analysis aimed to validate the relationships between variables and assess the robustness of the model, ensuring that the findings were empirically supported and statistically reliable**.**

3.4.2 STAGE B(ii):STATISTICAL APPROACH

SmartPLS 4.0 was used as the principal analytical software for model estimation(Ringle et al., 2024). SmartPLS is a user-friendly, variance-based structural equation modelling (SEM) application that implements the Partial Least Squares (PLS) path-modelling approach (J. F. Hair et al., 2017). PLS-SEM is particularly suitable for studies involving complex theoretical frameworks, latent variables, and both mediating and moderating relationships. It is a prediction-oriented, non-parametric technique that places fewer restrictions on data normality and sample size, making it appropriate for exploratory and theory-building research such as this study.

PLS-SEM allows the simultaneous assessment of the measurement model—which examines the reliability and validity of the latent constructs—and the structural model, which tests the hypothesised causal relationships among constructs. Measurement model evaluation includes indicator reliability, internal consistency, convergent validity (using average variance extracted, AVE), and discriminant validity (using the Fornell–Larcker criterion and HTMT ratio). The structural model is then assessed using path coefficients, R^2 (explained variance), Q^2 (predictive relevance), f^2 (effect size), and SRMR (model fit) as recommended by J. F. Hair et al. (2017)) and Ramayah et al. (2016).

To test the statistical significance of relationships, the bootstrapping procedure was employed, which resamples the data thousands of times to generate robust standard errors and confidence intervals. This method enhances the reliability of parameter estimates and significance testing. Blindfolding was used to assess the model's predictive relevance (Q^2), offering an additional measure of how well the exogenous constructs predict the endogenous variables.

Further, Multi-Group Analysis (MGA) was applied to examine gender-based differences in the structural relationships, identifying whether the model operates equivalently across male- and female-led startups. This analysis provides valuable insight into potential heterogeneity within the dataset and validates the moderating role of gender.

The Importance-Performance Map Analysis (IPMA) was used to supplement the PLS-SEM results by combining the importance (total effect) and performance (average latent variable score) of each construct (Ringle & Sarstedt, 2016; J. F. Hair et al., 2022). IPMA helps to identify high-impact constructs that most strongly influence startup performance, offering practical implications for incubator managers and policymakers regarding which support services require prioritisation or improvement (Sarstedt et al., 2019).

Finally, Necessary Condition Analysis (NCA) (Sarstedt et al., 2019) was conducted to identify essential conditions that must be present for achieving specific levels of startup performance. Unlike PLS-SEM, which captures sufficiency relationships (how much X contributes to Y), NCA identifies the minimum thresholds of certain variables that are indispensable for an outcome to occur. The combined use of PLS-SEM and NCA thus provides a comprehensive analytical perspective, addressing both sufficiency and necessity logic.

The integration of these techniques—PLS-SEM, bootstrapping, blindfolding, MGA, IPMA, and NCA ensures analytical rigour and multidimensional interpretation of the results. Together, they enable a nuanced understanding of the relationships among startup characteristics, incubator mechanisms, and performance outcomes, while enhancing the robustness, predictive accuracy, and practical relevance of the study's findings.

3.5 SUMMARY

This chapter presented a comprehensive overview of the research process adopted to achieve the study's objectives and empirically validate the proposed conceptual model. The research methodology was organised under a structured methodological approach**,** comprising two key stages Stage A and Stage B.

Stage A – Model Development focused on constructing the conceptual framework based on an extensive review of existing literature and relevant theoretical foundations. Drawing from the Input–Mediator–Outcome (IMO) framework, the model identified and defined the key constructs—Startup Characteristics, Perceptions of Importance and Effectiveness, Frequency of Usage, Degree of Incubator's Intervention and Assistance, Gender, and Startup Performance—and established hypothesised relationships among them. The conceptual model was grounded in the Resource-Based View (RBV), Human and Social Capital Theory, and the Incubation Process Model, providing a strong theoretical foundation for empirical testing.

Stage B – Model Estimation concentrated on empirically testing and evaluating the proposed model. It comprised two interconnected components. Stage B(i): Empirical Data Collection and Preparation involved the design and administration of a structured questionnaire to collect quantitative data from incubated startups across Maharashtra, Karnataka, and Goa. The process included the construction and refinement of the questionnaire based on expert feedback, assessment of face and content validity, and the conduct of a pilot study to ensure clarity and reliability. Appropriate sampling techniques were applied to determine a representative sample size, and data were systematically screened and prepared for analysis.

Stage B(ii): Statistical Approach entailed the application of advanced statistical techniques to analyse the collected data, test hypotheses, and validate the conceptual model. The methodological framework incorporated Partial Least Squares–Structural Equation Modelling

(PLS-SEM) using SmartPLS 4, supported by SPSS for preliminary statistical analysis. Both the measurement and structural models were rigorously assessed for reliability, convergent validity, and discriminant validity. In addition, Mediation and Moderation Testing**,** Multi-Group Analysis (MGA) to examine group-wise (e.g., gender-based) differences, and Necessary Condition Analysis (NCA) to identify essential conditions influencing startup performance were conducted to enhance the robustness of the findings. Overall, the chapter demonstrated a systematic and integrated methodological design that combines conceptual development with empirical validation forming a solid foundation for the presentation and interpretation of findings in the subsequent chapter.

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION

This chapter presents the empirical analysis and results of the study. It details the procedures adopted for data screening, measurement model assessment, and structural model evaluation using PLS-SEM. The findings are interpreted in relation to the study's objectives and hypotheses. The results provide statistical evidence supporting the conceptual framework and form the basis for the discussion and conclusions presented in the next chapter.

4.1 INTRODUCTION

This chapter presents the analysis and interpretation of data collected for the study. It is structured into three sections. The first section addresses preliminary analysis, including the handling of missing values, identification of outliers, and assessment of data normality to ensure analytical accuracy. The second section presents the demographic profile of the respondent startups and their founders. The third section involves quantitative analysis using Partial Least Squares–Structural Equation Modelling (PLS-SEM) through *SmartPLS 4* to test the hypothesised relationships proposed in Chapter 2. The analysis follows a two-step approach: evaluation of the measurement model to establish reliability and validity, including the higher-order construct of *Startup Characteristics* and its lower-order dimensions, and assessment of the structural model to examine the hypothesised paths and the model's predictive power. Additionally, advanced analyses such as Multi-Group Analysis (MGA), Importance-Performance Map Analysis (IPMA), and Necessary Condition Analysis (NCA) are conducted to explore group differences, assess the importance and performance of constructs, and identify the essential conditions that influence startup performance.

4.2. SURVEY INSTRUMENT RESPONSE RATE AND DATA COLLECTION PROCESS

The collection of questionnaires spanned nearly 12 months, from May 2023 to May 2024. During this period, the researcher personally administered the questionnaires to respondents across three states: Maharashtra (Mumbai), Karnataka (Hubli and Bangalore), and Goa (North and South Goa). A total of 720 questionnaires were distributed both physically (55%) and electronically (45%). Out of the 720 questionnaires distributed, 31 were not returned, while

659 responses were received. Among these, 47 were found to be incomplete as nearly 50% of their questions were left incomplete by respondents, and 30 respondents were identified as unengaged. After excluding these, a total of 612 valid responses were retained for statistical analysis, yielding a final response rate of 85% as depicted in Table 4.1.

Table 4.1 The Response Rate for the Questionnaire

Responses	Total
Questionnaires distributed	720
Returned Questionnaires	659
Returned and excluded	77
Returned and usable	612
Questionnaires not returned	31
Response rate	91.72%
Usable response rate	85%

Source: Compiled from primary data

4.3 PRELIMINARY DATA SCREENING

A preliminary analysis was conducted on the dataset to verify its appropriateness for multivariate procedures. During this preliminary phase, the following steps were performed: identification of outliers, testing for normality, assessment of common method variance and non-response bias, and verification of multicollinearity. Additionally, missing values were addressed. These analyses were conducted using SPSS version 25. These stages are essential for verifying that the data aligns with the assumptions necessary for multivariate analysis and for gaining a more comprehensive understanding of the dataset (Hair, J et al., 2010). The procedure commenced with the coding of all usable questionnaires into SPSS 25. Following this, the data were inspected to identify and rectify any potential entry errors. The analysis continued with the treatment of missing values after the accurate coding was confirmed.

4.3.1 MISSING VALUES

Handling missing data is a critical aspect of research, as it can significantly impact the accuracy and reliability of the findings (Cavana et al., 2001). Missing values typically occur when respondents choose not to answer specific questions, either intentionally or unintentionally (Hair Jr et al.,2014). Several factors can contribute to missing data, including skipped items, incorrect responses, or data entry errors(Tabachnick & Fidell, 2007). To address this, Hair Jr et al. (2014) recommend using mean substitution, replacing missing values with the mean of surrounding data points, as a simple and effective method, especially when the proportion of missing data is 10% or less. This approach was adopted in the present study as shown in Table 4.2.

Specifically, only 16 out of a total of 27,540 data points were missing, representing a negligible percentage of 0.0005. Table 4.2 presents the percentage of missing values for all variables, with a more detailed distribution provided in Annexure D- Table 1***(refer page no.213)***.

Table 4.2 Total and Percentage of Missing Values

Variables	Number of missing values
Experience	3
Skills	3
Network	2
Degree of Incubator's Assistance and Intervention	1
Frequency of Usage	1
Perception of Importance	2
Perception of Effectiveness	2
Startup Performance	2
Total Missing values	16
Percentage of missing values	Missing Value out of 27540 data points x 100= 0.05%

Note: Percentage of missing values = (the total number of missing values / total number of data points) x 100

Source: Compiled from primary data

4.3.2 STRAIGHT LINING DETECTION

Straight-lining refers to a type of response bias where a participant provides the same response across a high proportion of items, typically on a Likert-type scale. This pattern of responding can indicate low engagement or inattentiveness, thereby compromising data quality.

To detect straight-lining, the standard deviation of responses to all measurement items on the seven-point Likert scale was calculated for each respondent. A standard deviation of zero indicates that a respondent selected the same option for all items, suggesting potential straight-lining behaviour. Using this criterion, four respondents (representing 0.5% of the total sample) were identified as straight-liners and flagged for further scrutiny. Further these four responses were excluded from the sample.

4.3.3 INCONSISTENT RESPONSES

Inconsistent responses occur when participants provide contradictory answers to questions that are intended to measure the same underlying criterion. In this study, inconsistency was assessed through two screening questions designed to capture respondents' frequency of usage of incubation services: (1) period of use, and (2) frequency of use.

For instance, a respondent who indicated having 'never' used a particular incubation service in the *period of use* question but reported using it 'frequently' in the *frequency of use* question was flagged for inconsistency. Based on this criterion, a total of 7 respondents (representing approximately 0.97% of the sample) were identified as having provided inconsistent responses and thereby excluded.

4.3.4 NORMALITY TEST

Assessing data normality is a crucial preliminary step in multivariate analysis. Normality implies a bell-shaped, symmetrical distribution, with most values centred and fewer at the extremes (Gravetter et al., 2015). While normality is essential for many statistical tests, especially covariance-based structural equation modelling (J. Hair et al., 2007), it is not a requirement for SmartPLS 4. Nonetheless, understanding the data distribution remains important before performing inferential statistics.

J. F. Hair et al. (2014) recommended using skewness and kurtosis to test for normality. Accordingly, this study analysed both, with all values falling within acceptable thresholds (±2 for skewness, ±7 for kurtosis), as supported by Hair, J. et al. (2010). These results are presented in Annexure D - Table 2 ***(refer page no.214)***.

4.3.5 COMMON METHOD VARIANCE

Common Method Variance (CMV) refers to the variance attributable to the measurement method rather than to the constructs the measures are intended to represent (Podsakoff et al., 2003). CMV can arise when data are collected from a single source, such as a survey or interview, leading to inflated or spurious correlations among variables (Richardson et al., 2009). This artificial internal consistency may lead to misleading conclusions about the relationships between constructs, thereby compromising the validity of the findings.

To assess the presence of CMV, the current study follows the recommendation by Podsakoff et al. (2003), which suggests that if a single factor does not account for more than 50% of the total variance in an unrotated principal components factor analysis, CMV is unlikely to be a serious issue.

Accordingly, principal component analysis (PCA) was conducted on all the items used in the study. The results, presented in Annexure D - Table 3 ***(refer page no.215)***, indicate that the factors collectively explained 67.621% of the total variance, while the first (largest) factor accounted for only 23.789% of the total variance. Since this is below the 50% threshold, it can be concluded that common method bias is not a significant concern in this study.

4.4 DEMOGRAPHIC PROFILE OF THE RESPONDENTS

This section provides a detailed overview of the demographic characteristics of the sample. Relevant graphs and charts have been included to illustrate the distribution of various demographic variables effectively.

Table 4.3: Demographic Profile of Startup Founders (N= 612)

Demography		#Respondents	%
Gender	Male	451	73.7
	Female	161	26.3
Age	Less than 20 years	3	0.55
	21 to 30 years	191	31.02
	31 to 40 years	290	47.4
	41 to 50 years	125	20.4
	51 years and more	3	0.55
Education	Graduation	204	33.3
	Post-Graduation	285	46.6
	Ph.D.	105	17.2
	Others	18	2.9
Stage	Ideation	44	7.2
	Validation	158	25.8
	Early Traction	255	41.7
	Scaling	155	25.3
Product/Service or both	Product	286	46.7
	Service	314	51.3
	Product and Service	12	2
Duration of Incubation	Less than 6 months	63	10.3
	Up to 1 year	284	46.4
	Up to 2 years	190	31
	Up to 3 years or more	75	12.3
Team-size	Self-owned	27	4.4
	1-3 members	152	24.8
	4-7 members	220	35.9
	More than seven members	213	34.8
Nature of the Market	B2B	165	27

	B2C	252	41.18
	B2G	52	8.49
	B2B/C/G	144	23.53
Segment of the startup	HealthTech	176	28.76
	IT services	69	11.27
	Agriculture	52	8.50
	Renewable Energy/Sustainability	70	11.44
	EdTech	68	11.11
	BioTech	60	9.80
	FinTech	40	6.54
	IoT	36	5.88
	Others	41	6.70

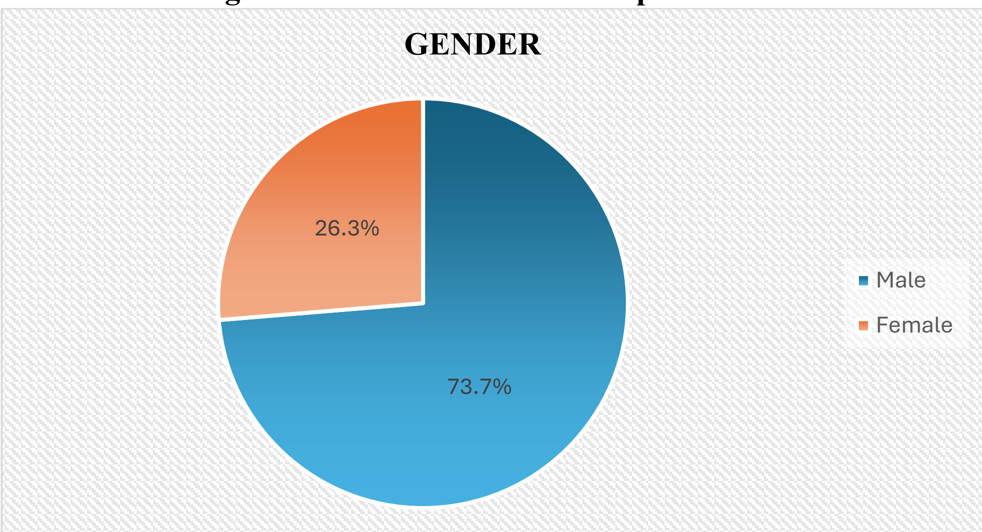
Source: Compiled from Primary Data

Based on Table 4.3, which presents the demographic profile of startup founders, each demographic variable is discussed in detail below:

4.4.1 GENDER

The data reveals a significant gender gap in starting a business as presented in Figure 4.1, with male founders comprising nearly three-fourths, 451 (73.7%) of the total startup founders. Female participation in startups is comparatively lower, at 161 (26.3%), indicating that entrepreneurship remains a male-dominated domain. However, the representation of women in startups is substantial, suggesting that efforts toward gender inclusivity in entrepreneurship may be showing progress.

Figure 4.1: Gender of the Startup Founders

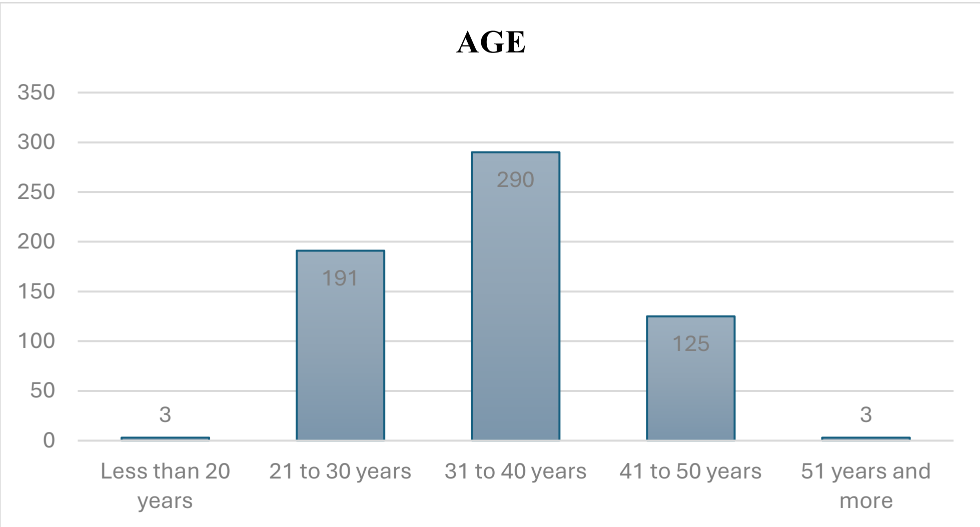


Source: Compiled from primary data

4.4.2 AGE

Figure 4.2 represents Age of the startup founders. It is evident that most startup founders fall within the 21 to 40-year age range, accounting for approximately 78.42% of the total respondents. The 31 to 40 years old age group has the highest representation (47.4%), indicating that many entrepreneurs begin their ventures after gaining work experience or achieving financial stability. The 21 to 30 age group (31.02%) consists of younger entrepreneurs, who are fresh graduates or those who have gained minimal work experience before venturing into startups. A significant portion of founders are between 41 and 50 years old (20.4%), indicating that some individuals enter entrepreneurship later in their careers. We also encountered returnee entrepreneurs in this category. Very few startup founders are under 20 years old (0.55%) or over 50 years old (0.55%), highlighting that entrepreneurship is generally not a preferred choice for either very young individuals or older professionals nearing retirement.

Figure 4.2: Age of the Startup Founders

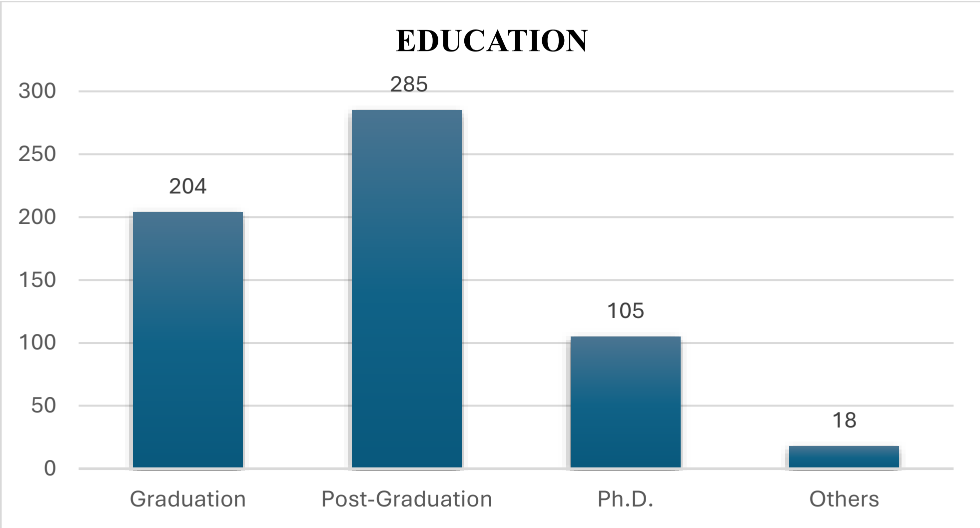


Source: Compiled from primary data

4.4.3 EDUCATION

Education plays a crucial role in entrepreneurship, as evidenced by the high percentage of founders holding postgraduate degrees as depicted in Figure 4.3. Nearly half of the founders (46.6%) have a postgraduate degree, which suggests that higher education is often associated with better business sense, technical expertise, and market insights. 33.3% of founders have graduation-level education, meaning a substantial number of entrepreneurs enter the startup ecosystem with just a bachelor's degree. While 17.2% hold a PhD, this may indicate that startups are focusing on research-intensive or deep-tech areas, such as biotechnology, artificial intelligence, or advanced engineering. Finally, 2.9% of founders fall into the 'Others' category, which may include diploma holders, self-taught entrepreneurs, or those with unconventional education backgrounds. This data suggests that while higher education can be an advantage in entrepreneurship, it is not necessarily a strict requirement for success.

Figure 4.3: Education level of Startup Founders

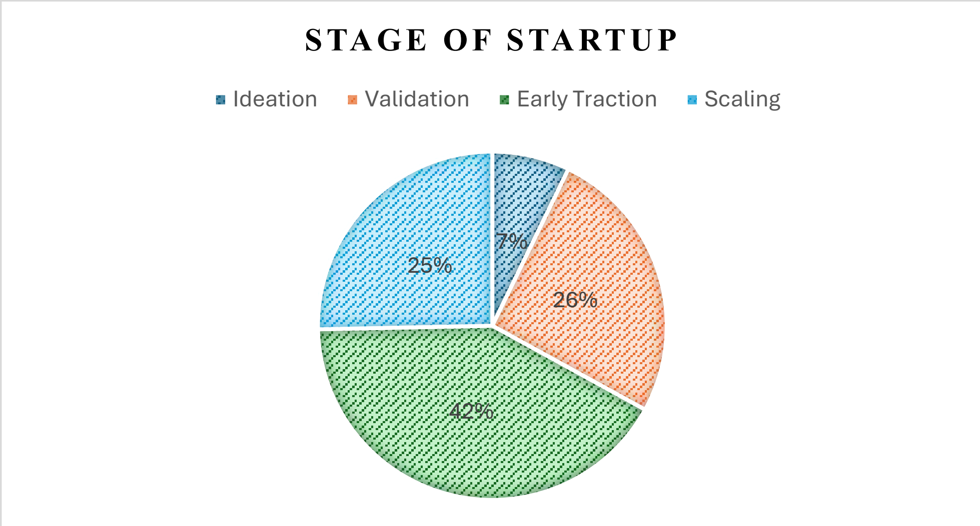


Source: Compiled from primary data

4.4.4 STAGE

The majority of startups were in the Early Traction (41.7%) and Validation (25.8%) stages. This suggests that many startups are actively testing their ideas, securing customers, and refining their business models. The Ideation stage (7.2%) has the least number of startups, implying that a smaller proportion of respondents are in the very initial phase of brainstorming and concept validation. The Validation stage (25.8%) indicates that many startups are in the process of proving the feasibility of their product or service. The Scaling stage (25.3%) represents startups that have already gained traction and are focusing on expanding their market presence. As depicted in Figure 4.4, this distribution suggests that the startup ecosystem is fairly mature, with a substantial portion of companies advancing beyond the initial stages.

Figure 4.4: Stage of Startup



Source: Compiled from primary data

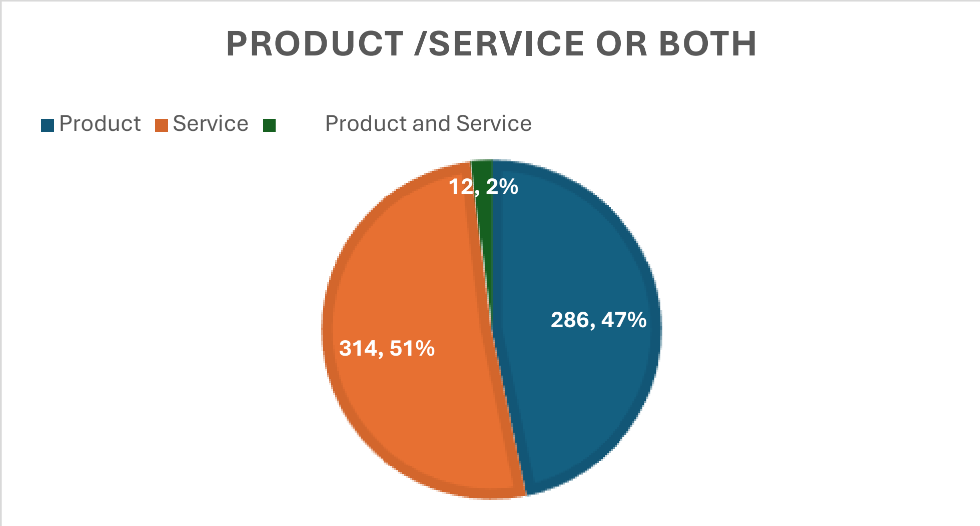
4.4.5 PRODUCT/SERVICE OR BOTH

The Figure 4.5 indicates that service-based startups (51.3%) slightly outnumber product-based startups (46.7%), reflecting a growing inclination towards service-oriented businesses, such as IT services, consulting, and digital platforms. Service startups are easier to scale and often require lower initial investment compared to product-based businesses, which involve manufacturing, logistics, and inventory management. Product-based startups (46.7%) suggest a strong presence in hardware, manufacturing, and consumer goods sectors. Only 2% of startups offer both products and services, likely because handling both requires significant operational capabilities and resources. This trend aligns with the broader global shift toward service-based economies and the rise of digital and subscription-based business models.

4.4.6 DURATION OF INCUBATION

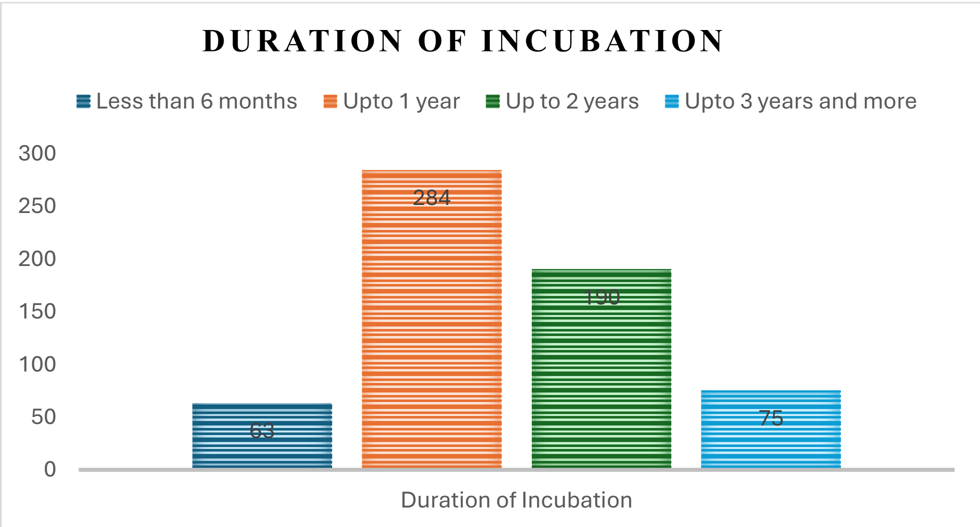
As seen in Figure 4.6, the majority of startups in the sample (77.4%) had been incubated for a period between 1 and 2 years, suggesting that this duration is generally necessary for establishing a stable foundation. A smaller proportion (10.3%) had joined the incubation program within the last six months, indicating their early-stage status. Startups with longer incubation periods (12.3%) may require extended support due to the complexity of their business models, industry-specific demands, or the cost-effectiveness of remaining within the incubator, particularly in terms of subsidised rentals and shared resources.

Figure 4.5: Product/Service or both offered



Source: Compiled from primary data

Figure 4.6: Duration of Incubation

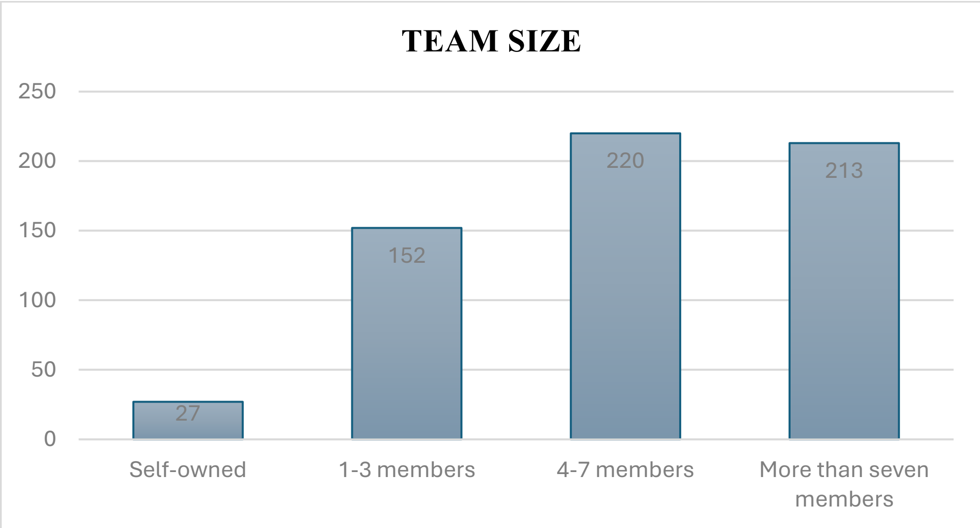


Source: Compiled from primary data

4.4.7 TEAM SIZE

Figure 4.7 shows that team sizes are fairly distributed between small and large teams. The majority of startups (70.7%) operate with four or more members, highlighting the need for a diverse team to manage various aspects of the business. 24.8% of startups have very small teams (1-3 members), often indicating early-stage startups that are bootstrapped or founder-driven. Only 4.4% are solo founders, suggesting that entrepreneurship is essentially a team-driven endeavour.

Figure 4.7: Size of Startup Team

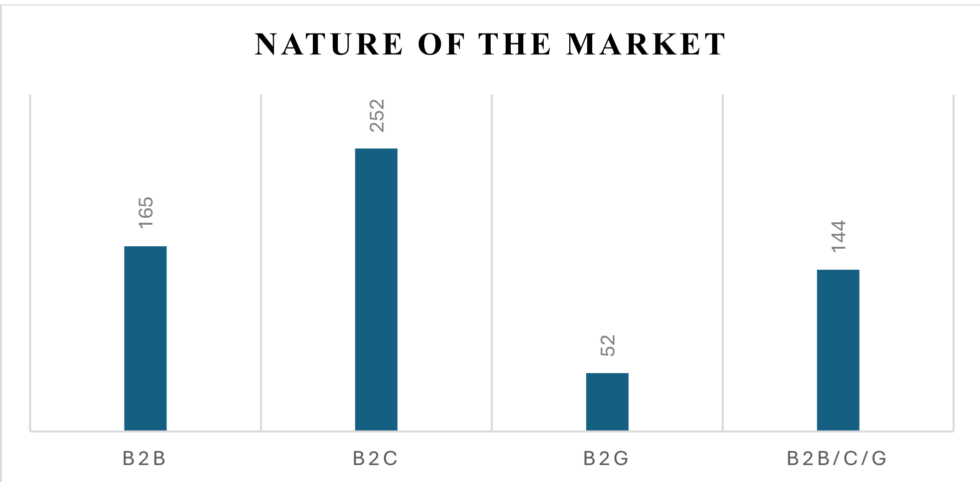


Source: Compiled from primary data

4.4.8 NATURE OF MARKET

The results depicted in Figure 4.8 shows that B2C startups dominate (41.18%), indicating a large number of startups that directly sell to consumers, such as e-commerce, Fintech, and EdTech. The B2B startups (27%) are significant, showing a strong presence of businesses targeting enterprises. While B2G (8.49%) startups are fewer, indicating that working with government agencies is less common, this may be due to regulatory challenges and procurement complexities. 23.53% of startups operate in multiple segments (B2B, B2C, or B2G), showing flexibility in their business models.

Figure 4.8: Nature of the Market

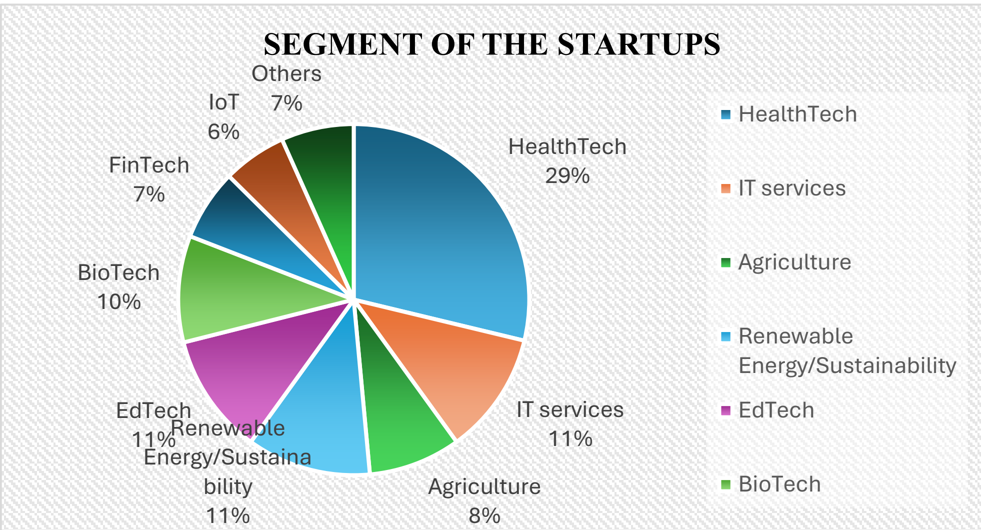


Source: Compiled from primary data

4.4.9 SEGMENT OF THE STARTUPS

Figure 4.9 shows that the sample is dominated by HealthTech (28.76%), reflecting strong investor interest in digital health solutions, medical devices, and telemedicine, particularly following the pandemic. Renewable Energy & Sustainability (11.44%) is gaining momentum, driven by global climate goals and government incentives. While IT Services (11.27%) and EdTech (11.11%) maintain a strong presence, they are fuelled by increasing digital transformation and remote learning demands. The BioTech segment (9.80%) is a research-intensive sector, focusing on pharmaceutical advancements and biomedical engineering, which often requires more extended incubation periods. FinTech (6.54%), though promising, faces regulatory challenges and competition from established players. IoT (5.88%) is emerging in smart devices and industrial automation, while niche sectors (6.70%) such as gaming, fashion tech, and legal tech continue to evolve. Overall, HealthTech leads, Sustainability is on the rise, IT and EdTech remain stable, and Deep-tech sectors require more incubation support.

Figure 4.9: Segment of the Startups



Source: Compiled from primary data

4.5 ASSESSMENT OF SMARTPLS 4 PATH MODEL RESULTS

The SmartPLS4 is the newest addition released to the general public in 2022, designed to run Structural Equation Modelling (*Wikipedia*, 2025). Marketing researchers have extensively applied SmartPLS 3, which features an easy-to-use interface and advanced capabilities, including HTMT, model fit indices, multigroup analysis, and PLSpredict, to examine complex associations between latent variables. It also enabled complementary approaches such as importance-performance map analysis and confirmatory tetrad analysis. Building on this, SmartPLS 4 features a revamped interface, enhanced processing speed, and expanded model assessment tools, including cross-validation predictive ability testing, endogeneity assessment, and necessary condition analysis (Cheah et al., 2024).

In this study, the path model assessment was conducted using SmartPLS 4, after following a thorough process of data checking and screening as described in the preceding section. The initial stage involved data cleaning, which addressed missing values, outliers, and data quality concerns, particularly those arising from respondent misconduct, to ensure a valid and reliable dataset for analysis. In SmartPLS 4, data analysis involves two fundamental steps: the measurement model and the structural model (Hair et al., 2022; Ramayah et al., 2016; Ringle et al., 2024; Chua, 2023).

After thorough checking and screening of the data, our study follows a structured two-step approach, consisting of the Measurement Model Assessment and the Structural Model Assessment, as recommended by Hair et al. (2014) and Henseler et al.(2009). The first step, *Measurement Model Assessment*, evaluates the reliability and validity of the constructs used in the model. This process begins with assessing factor loadings, where the loading values of each indicator on its respective latent construct are examined to ensure adequate representation, typically greater than 0. 7(J. F. Hair et al., 2013). Next, the reliability of the constructs is tested using Cronbach's Alpha and Composite Reliability (CR) to confirm internal consistency among the items(J. F. Hair et al., 2012). The model then undergoes validation through the assessment of convergent validity, measured by the Average Variance Extracted (AVE), where values above 0.5 indicate sufficient convergence of the construct with its indicators. To ensure the distinctiveness of constructs, discriminant validity is evaluated using the Heterotrait-Monotrait (HTMT) Ratio, which is the preferred method (Henseler et al., 2015), the Fornell-Larcker Criterion, and cross-loadings. Once these conditions are met, the study reports the measurement model as valid and reliable. The assessment of measurement models depends on whether the model is reflective or formative, as each category entails unique evaluation criteria. It is essential to first understand the conceptual differentiation between the two before assessing their validity. Chin (1998) distinguishes between reflective and formative models within the framework of Partial Least Squares Structural Equation Modelling (PLS-SEM) as follows:

- **Reflective Model (Mode A):** In this type of model, all indicators are designed to measure the same underlying construct. Any change at the conceptual level is expected to be similarly reflected in each indicator, implying high intercorrelation and interchangeability among them (Jarvis et al., 2003). This means the direction of causality flows from the latent variable to its indicators, and graphically, the arrows point from the construct to the observed items.
- **Formative Model (Mode B):** In this model, indicators are not necessarily correlated and do not measure the same aspect of the construct. Instead, each indicator contributes a unique component that collectively defines the construct (J. F. Hair et al., 2014; Jarvis et al., 2003). In this model, the causal direction goes from the indicators to the latent construct, and arrows are drawn from the indicators to the latent variable.

The decision to specify a construct as reflective or formative is based on prior theoretical justification (Cenfetelli & Bassellier, 2009). In accordance with the literature reviewed in earlier chapters, the constructs of Frequency of Usage, Perception of Importance, Perception of Effectiveness, Degree of Incubator's Intervention and Assistance and Startup performance are modelled reflectively. Conversely, the higher-order construct *Startup Characteristics* is modelled formatively. Therefore, *Startup Characteristics* is treated as a second-order reflective-formative construct.

The validation of reflective measurement models involves assessing internal consistency, convergent validity, and discriminant validity. In contrast, the evaluation of formative measurement models focuses on assessing convergent validity, indicator collinearity, and the significance and relevance of the outer weights. Table 4.4 summarises the criteria and recommended thresholds for evaluating reflective and formative measurement models, as outlined by (J. F. Hair et al., 2017). Each criterion listed in the table is subsequently discussed in detail in the following sections.

Table 4.4 Measurement Assessment Criteria

Reflective Measurement Model		**Formative Measurement Model**	
Criteria	Rule of Thumb	Criteria	Rule of Thumb
Internal Consistency	Cronbach's alpha (CA) > 0.70 Composite reliability (CR) > 0.70	Convergent validity	Correlation between formative construct and an alternative reflective construct ≥ 0.70

Convergent validity	Indicator's outer loading > 0.70 Average variance extracted (AVE) > 0.50	Collinearity of indicators	Variance Inflation Factor (VIF) for each indicator < 5
Discriminant validity	1. Heterotrait-monotrait (HTMT) ratio ≤ 0.85 2. Fornell-Larcker Criterion – The square root of the AVE for each construct should be greater than the correlation between that construct and any other construct. 3. Cross-Loading- an indicator should load higher on its associated construct than on any other	Significance and relevance	Retain indicator if: 1. The indicator's weight is significant, or 2. The weight is not significant, but the corresponding item loading is significant

Source : Compiled by author based on (J. F. Hair et al., 2017)

4.5.1 SECOND ORDER CONSTRUCT SPECIFICATION

Before performing the measurement model evaluation, it is crucial to pay particular attention when the structural model incorporates a higher-order construct. As previously stated, Startup Characteristics is defined as a second-order construct that has no directly measured indicators. PLS-SEM requires observable indicators to assess the scores of latent constructs (J. M. Becker et al., 2012). To resolve this issue, two principal strategies have been suggested for delineating higher-order constructs: the repeated indicators approach and the two-stage approach (Ringle et al., 2024). In the repeated indicators method, all indicators from the corresponding lower-order constructs are allocated to the higher-order construct (J. M. Becker et al., 2012). The two-stage methodology initiates by assessing the scores of the lower-order constructs in a model that excludes the higher-order construct during the initial stage. During this phase, the lower-order constructs are directly associated with all other constructs that are theoretically related to the higher-order construct (Sarstedt et al., 2019). Subsequently, in the second phase, the scores acquired for the lower-order constructs are recorded and utilised as indicators for the higher-order construct (J. M. Becker et al., 2012). A simulation research by Becker et al. (2012) presented that the two-stage technique produces less biased path coefficient estimates in structural model relationships involving higher-order constructs. Consequently, researchers advocate for the use of the two-stage method, where the principal aim is to mitigate parameter bias in structural model estimations (Sarstedt et al., 2019). This study aims to investigate whether Startup Characteristics, a higher-order construct, influences usage and the perceptions of importance and effectiveness, which in turn affect the startup performance of incubatees. A two-stage approach is deemed suitable to reduce potential estimation bias in the structural relationships.

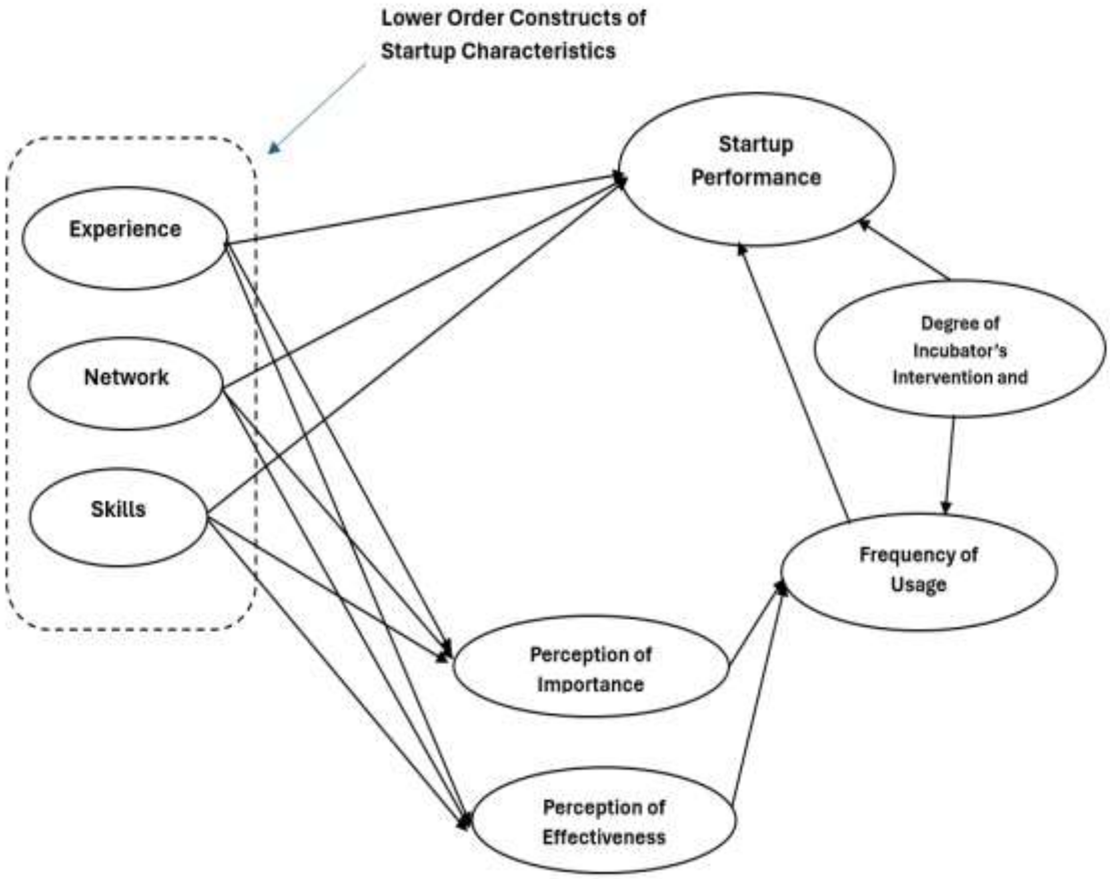
The second step, *Structural Model Assessment*, tests the hypothesised relationships among latent constructs. The process begins with evaluating collinearity using Variance Inflation Factors (VIFs) to ensure that predictor variables do not exhibit multicollinearity (J. F. Hair et al., 2013). Following this, the study assesses the significance and strength of relationships using bootstrapping, a non-parametric resampling technique that estimates the precision of the path coefficients (J. F. Hair et al., 2012). This includes examining bootstrapped path coefficients, T-statistics, and p-values. A T-value greater than 1.96 (two-tailed) and a p-value less than 0.05 indicate statistically significant relationships and support for the alternate hypotheses. Additionally, the model's explanatory power is evaluated using the coefficient of determination (R^2), with higher values indicating a better model fit.

Additionally, the f^2 effect size is calculated to determine the impact of each exogenous construct on the endogenous variables, where values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively (Cohen, 1988; J. F. Hair et al., 2012). Finally, the study examines predictive relevance using the PLS-Predict technique (Shmueli et al., 2016), which determines the model’s capability to predict new observations. These comprehensive steps ensure that the research model developed using SmartPLS 4 is robust, reliable, and has strong predictive validity.

4.5.2 REFLECTIVE MEASUREMENT MODEL EVALUATION

In the measurement model, the primary focus is to ensure that the constructs are both reliable and valid (Ramayah et al., 2016). This is achieved by evaluating key criteria, including indicator reliability, internal consistency, convergent validity, and discriminant validity, as recommended by several scholars (J. F. Hair et al., 2012, 2013; Henseler & Chin, 2010). Following the criteria presented in Table 4.4, the upcoming subsections will evaluate the reflective constructs depicted in Figure 4.10 by examining their indicator reliability, internal consistency, convergent validity, and discriminant validity.

Figure 4.10 Stage-One Research Model



Source: Compiled by author

4.5.2.1 INDICATOR RELIABILITY

Outer loading refers to the regression coefficient linking an indicator (or measurement variable) to its corresponding latent variable (or construct) within a model. It reflects the strength of the relationship between the observed variables (indicators) and the unobserved constructs (latent variables) they are intended to measure. Outer loading plays a crucial role in evaluating indicator quality, as it indicates how well each indicator represents its associated latent variable. A standard guideline is that the latent variable should account for at least 50% of the variance in each indicator. This suggests that the shared variance between the construct and its indicator exceeds the measurement error (Subhaktiyasa, 2024). For this reason, an outer loading value should typically exceed 0.708, since squaring this value (0.708^2) yields 0.50. In practice, a loading of 0.70 is generally considered acceptable, as it is sufficiently close to the recommended threshold (J. F. Hair et al., 2019). Manifest variables with outer loadings of 0.7

or higher are considered highly satisfactory, indicating a strong association with the underlying latent construct (Henseler et al., 2009; Oliver et al., 2010). While loading values of 0.5 or above are generally deemed acceptable, manifest variables with loadings below 0.5 are typically considered weak and should be removed from the model to ensure measurement reliability and validity (Hair, J.; Chin, 1998).

The analysis of outer loading values for the constructs in the study is shown in Table 4.5. reveals that the majority of the indicators demonstrate strong reliability and effectively represent their respective latent variables. All items under the constructs *Experience*, *Skills*, *Network*, *Frequency of Usage*, *Perception of Importance*, *Perception of Effectiveness*, and *Startup Performance* exhibit outer loadings above 0.70, indicating high indicator reliability. The items under *Degree of Incubator's Intervention and Assistance (DIIA)* also show acceptable loadings, ranging from 0.666 to 0.742. Although DIIA7 has a slightly lower loading of 0.666, it still meets the minimum threshold (Hair J et al., 2010; Chin, 1998) for acceptance in exploratory research and may be retained based on its theoretical significance. Overall, the measurement model demonstrates satisfactory indicator reliability, supporting the appropriateness of the items used to measure each construct.

4.5.2.2 INTERNAL CONSISTENCY RELIABILITY

Composite reliability is regarded as a more reliable approach to evaluating internal consistency. It is one of the most frequently employed reliability estimators, along with Cronbach's alpha. In accordance with the methodologies of Hair Jr et al. (2014) and Peterson & Kim (2013), this study has employed both composite reliability and Cronbach's alpha to assess the internal consistency of the adopted measures.

Henseler et al. (2009) recommended that Cronbach's alpha should be greater than 0.70. Similarly, Hair et al. 2011), based on the criteria established by Nunnally & Bernstein (1994), stated that composite reliability should also exceed the 0.70 threshold. Table 4.6 presents the composite reliability and Cronbach's alpha values for all variables. The composite reliability scores for the latent constructs ranged from 0.861 to 0.942, all surpassing the minimum threshold of 0.70. Similarly, Cronbach's alpha values ranged from 0.801 to 0.929. These results indicate that the latent variables in this study demonstrate strong reliability and produce satisfactory outcomes.

Table 4.5: Outer Loadings

Construct	Items	Loading value
Startup Characteristics [SC] (HOC)		
Experience [EXP]	**EXP1**	0.790
	EXP2	0.790
	EXP3	0.808
	EXP4	0.842
Skills [SKL]	**SKL1**	0.820
	SKL2	0.818
	SKL3	0.790
	SKL4	0.758
	SKL5	0.782
Network [NET]	**NET1**	0.799
	NET2	0.762
	NET3	0.798
	NET4	0.787
	NET5	0.818
	NET6	0.751
	NET7	0.785
Degree of Incubator’s Intervention and Assistance [DIIA]	**DIIA1**	0.725
	DIIA2	0.690
	DIIA3	0.742
	DIIA4	0.731
	DIIA5	0.712
	DIIA6	0.728
	DIIA7	0.666
Frequency of Usage [FU]	**FU1**	0.789
	FU2	0.794
	FU3	0.790
	FU4	0.771
	FU5	0.757
Perception of Importance [PoI]	**PoI1**	0.705
	PoI2	0.767
	PoI3	0.769
	PoI4	0.744
	PoI5	0.733
Perception of Effectiveness [PoE]	**PoE1**	0.819
	PoE2	0.779
	PoE3	0.772
	PoE4	0.732
	PoE5	0.777
Startup Performance [SP]	**SP1**	0.822
	SP2	0.839
	SP3	0.838
	SP4	0.837
	SP5	0.846
	SP6	0.840
	SP7	0.835

Source: Compiled from primary data

Table 4.6: Cronbach's Alpha and Composite Reliability Values

Latent Construct	Cronbach's Alpha (CA)	Composite Reliability (CR)
Startup Characteristics [SC] (HOC)		
Experience [EXP]	0.824	0.883
Skills [SKL]	0.899	0.895
Network [NET]	0.854	0.920
Degree of Incubator's Intervention and Assistance [DIIA]	0.840	0.879
Frequency of Usage [FU]	0.840	0.886
Perception of Importance [PoI]	0.801	0.861
Perception of Effectiveness [PoE]	0.836	0.884
Startup Performance [SP]	0.929	0.942

Source: Compiled from primary data

4.5.2.3 CONVERGENT VALIDITY

Convergent validity assesses the degree to which different dimensions of the same construct are closely related, indicating whether multiple indicators measuring the same concept converge or share a high degree of variance (Subhaktiyasa, 2024). A standard metric for assessing convergent validity at the construct level is the Average Variance Extracted (AVE), which is calculated by dividing the sum of the squared factor loadings by the number of indicators. A construct's convergent validity is indicated by an AVE value of 0.50 or higher, which suggests that it explains over half of the variance in its indicators (J. F. Hair et al., 2019). In contrast, an AVE below 0.50 indicates that the variance explained is primarily due to error. In general, the construct's capacity to represent the variance of its indicators is enhanced by higher AVE values. In this study, as shown in Table 4.7, the AVE values ranged from 0.510 to 0.700. This indicates that the constructs explained a sufficient portion of the variance in their indicators, confirming the reliability and validity of the survey items in the measurement model.

4.5.2.4 DISCRIMINANT VALIDITY

Discriminant validity assesses the degree to which constructs are distinct from one another, ensuring that indicators intended to measure one construct do not overlap significantly with those of other constructs (Duarte & Raposo, 2010).

Table 4.7: Average Variance Extracted of the constructs

Latent Construct	Average Variance Extracted (AVE)
Startup Characteristics [SC] (HOC)	
Experience [EXP]	0.654
Skills [SKL]	0.632
Network [NET]	0.622
Degree of Incubator's Intervention and Assistance [DIIA]	0.510
Frequency of Usage [FU]	0.609
Perception of Importance [PoI]	0.553
Perception of Effectiveness [PoE]	0.603
Startup Performance [SP]	0.700

Source: Compiled from primary data

It helps confirm that each construct captures a unique aspect of the model (J. F. Hair et al., 2017). Common methods include Cross-Loading, Fornell-Larcker, and the Heterotrait-Monotrait Ratio (HTMT). **Cross-loading** involves comparing an indicator's loading on its own latent variable to its loadings on other constructs. For good discriminant validity, an indicator should load higher on its associated construct than on any other, indicating that it better represents its own construct than others (J. F. Hair et al., 2016). The **Fornell & Larcker (1981) Criterion** compares the square root of the Average Variance Extracted (AVE) for a construct with its correlations with other constructs. Discriminant validity is established when the square root of the AVE of a construct is greater than its highest correlation with any other construct. **HTMT** (Heterotrait-Monotrait Ratio) assesses discriminant validity by examining the ratio of correlations across constructs (heterotrait) to those within the same construct (monotrait). A value below 0.90 suggests that the constructs are sufficiently distinct, whereas a value of 0.85 or less is required if the constructs are significantly dissimilar (Henseler et al., 2015). This method is considered more accurate and reliable than the others. Among these approaches, Henseler et al. (2015) strongly recommend the use of HTMT, as it provides more consistent and empirically robust results in assessing inter-construct validity in measurement models. All three methods—HTMT, Cross-Loading, and Fornell-Larcker Criterion—were utilised in this study to evaluate discriminant validity comprehensively.

The HTMT ratio technique was applied, and the results are shown in Table 4.8. All the square roots of HTMT ranged between 0.053 and 0.626. This indicates that each construct shares more variance with its own indicators than with those of other constructs. This confirms that discriminant validity has been established.

Table 4.8 Discriminant Validity Analysis using Heterotrait-Monotrait Ratio (HTMT)

	EXP	NET	SKL	DIIA	FU	PoI	PoE	SP
EXP								
NET	0.328							
SKL	0.366	0.352						
DIIA	0.102	0.081	0.067					
FU	0.122	0.122	0.096	0.344				
PoI	0.088	0.114	0.134	0.425	0.368			
PoE	0.131	0.053	0.072	0.339	0.342	0.327		
SP	0.115	0.124	0.181	0.480	0.626	0.566	0.578	

Source: Compiled from primary data

Table 4.9 Fornell-Larcker Discriminant Validity Analysis

	EXP	NET	SKL	DIIA	FU	PoI	PoE	SP
EXP	**0.809**							
NET	0.284	**0.789**						
SKL	0.309	0.311	**0.795**					
DIIA	-0.058	0.035	0.02	**0.714**				
FU	0.101	0.106	0.078	0.293	**0.780**			
PoI	0.051	0.100	0.105	0.349	0.313	**0.744**		
PoE	0.111	0.005	0.057	0.288	0.293	0.266	**0.777**	
SP	0.100	0.113	0.161	0.426	0.556	0.493	0.513	**0.837**

Source: Compiled from primary data

Next, the Fornell & Larcker (1981) criterion was applied and the results are shown in Table 4.9. As shown in Table 4.13, the correlation values ranged from 0.714 to 0.837, each being higher with its respective construct than with any other latent construct. This indicates that each reflective latent construct demonstrated stronger associations with its own indicators, confirming that discriminant validity was achieved across all constructs in the model.

Table 4.10 Discriminant Validity Assessment using Indicator and Cross Loadings

	DIIA	EXP	FU	NET	PoE	PoI	SKL	SP
DIIA1	**0.725**	-0.018	0.223	0.014	0.227	0.262	0.079	0.303
DIIA2	**0.69**	0.024	0.159	0.012	0.191	0.202	0.015	0.296
DIIA3	**0.742**	0.011	0.22	0.1	0.248	0.277	0.054	0.351

DIIA4	**0.731**	-0.073	0.211	0.044	0.237	0.303	-0.027	0.332
DIIA5	**0.712**	-0.037	0.226	0.037	0.169	0.242	0.039	0.271
DIIA6	**0.728**	-0.083	0.239	-0.066	0.186	0.235	-0.038	0.306
DIIA7	**0.666**	-0.122	0.177	0.031	0.172	0.207	-0.029	0.261
EXP1	-0.086	**0.802**	0.075	0.231	0.104	0.058	0.242	0.043
EXP2	-0.042	**0.813**	0.105	0.259	0.042	0.02	0.251	0.092
EXP3	-0.072	**0.818**	0.073	0.233	0.106	0.029	0.271	0.069
EXP4	0.017	**0.802**	0.072	0.191	0.111	0.06	0.235	0.122
FU1	0.224	0.059	**0.789**	0.054	0.302	0.252	0.068	0.471
FU2	0.269	0.082	**0.794**	0.078	0.215	0.293	0.071	0.459
FU3	0.205	0.131	**0.79**	0.133	0.225	0.24	0.062	0.426
FU4	0.254	0.017	**0.772**	0.081	0.204	0.233	0.057	0.422
FU5	0.183	0.111	**0.756**	0.067	0.186	0.194	0.044	0.384
NET1	0.024	0.24	0.104	**0.779**	0.01	0.097	0.258	0.113
NET2	0.004	0.216	0.057	**0.788**	0.023	0.031	0.257	0.091
NET3	0.026	0.239	0.112	**0.794**	0.019	0.067	0.225	0.1
NET4	0.053	0.239	0.072	**0.785**	0.027	0.101	0.304	0.102
NET5	0.081	0.23	0.091	**0.792**	-0.003	0.125	0.219	0.125
NET6	0.018	0.189	0.056	**0.791**	-0.024	0.06	0.23	0.022
NET7	-0.012	0.213	0.091	**0.794**	-0.029	0.071	0.219	0.071
PoE1	0.253	0.127	0.275	0.03	**0.819**	0.236	0.076	0.453
PoE2	0.212	0.104	0.219	0.05	**0.782**	0.208	0.048	0.403
PoE3	0.236	0.075	0.217	-0.042	**0.768**	0.172	0.016	0.371
PoE4	0.2	0.039	0.206	0.004	**0.74**	0.224	0.005	0.36
PoE5	0.213	0.072	0.208	-0.038	**0.774**	0.186	0.063	0.394
PoI1	0.269	0.061	0.156	0.067	0.21	**0.704**	0.105	0.321
PoI2	0.264	0.059	0.277	0.105	0.157	**0.769**	0.072	0.374
PoI3	0.248	0.034	0.26	0.095	0.218	**0.768**	0.098	0.402
PoI4	0.25	0.067	0.225	0.05	0.222	**0.742**	0.122	0.372
PoI5	0.277	-0.043	0.216	0.041	0.196	**0.734**	-0.017	0.352
SKL1	0.033	0.221	0.117	0.237	0.031	0.084	**0.793**	0.154
SKL2	0.004	0.245	0.092	0.23	0.062	0.086	**0.814**	0.114
SKL3	0.013	0.3	0.041	0.286	0.043	0.101	**0.795**	0.138
SKL4	0.015	0.236	0.007	0.255	0.034	0.071	**0.787**	0.113
SKL5	0.014	0.222	0.057	0.222	0.055	0.072	**0.784**	0.121
SP1	0.371	0.1	0.469	0.101	0.421	0.438	0.132	**0.822**
SP2	0.34	0.06	0.475	0.102	0.455	0.405	0.122	**0.839**
SP3	0.35	0.097	0.468	0.083	0.441	0.368	0.182	**0.838**
SP4	0.38	0.073	0.446	0.088	0.412	0.456	0.12	**0.837**
SP5	0.369	0.073	0.474	0.117	0.421	0.423	0.141	**0.846**
SP6	0.346	0.082	0.47	0.084	0.426	0.402	0.106	**0.84**
SP7	0.341	0.1	0.455	0.088	0.431	0.393	0.141	**0.835**

Source: Compiled from primary data

To assess whether a construct accurately measures what it is intended to measure, a cross-loading analysis is performed. This evaluates the variance explained by each latent variable. As per Hair et al. (2011), a cross-loading value of 0.5 or higher is considered acceptable. Table 4.10 presents the comparison between each indicator's loading on its own construct and its loadings on other constructs. The results show that all indicators loaded more strongly on their respective constructs than on others, indicating adequate discriminant validity for proceeding with further analysis.

Figure 4.11 presents the overall picture of the measurement model as generated by the SmartPLS 4 software. This figure visually represents the relationships between latent constructs and their corresponding observed indicators, illustrating how each item contributes to measuring its respective construct.

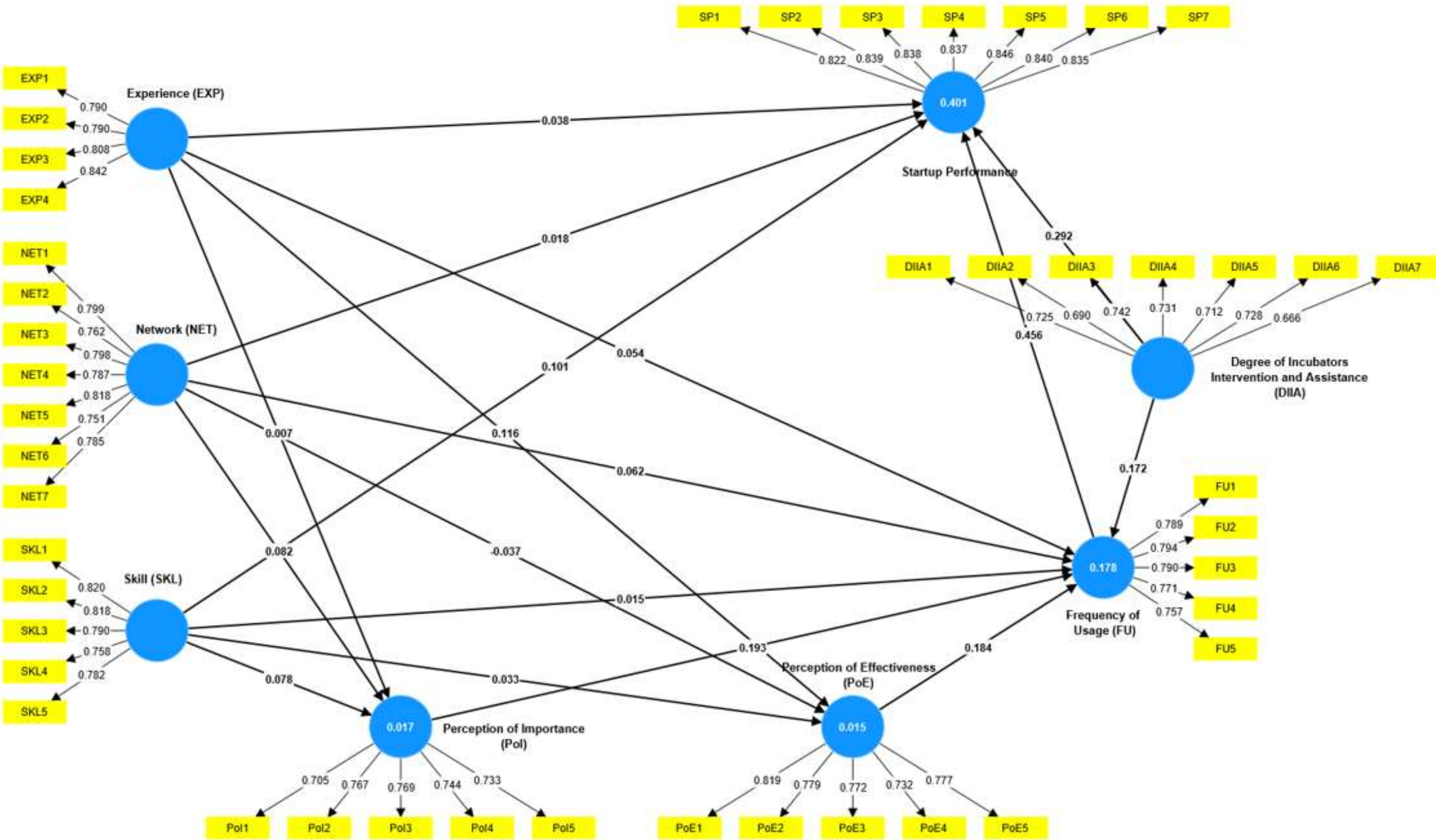
4.5.3 FORMATIVE MEASUREMENT MODEL ASSESSMENT

Based on the criteria presented in Table 4.4, the following subsections will evaluate the convergent validity of the second-order formative construct, as well as the collinearity and significance of its indicators. As previously mentioned, the formative indicators—Experience, Network, and Skills—reflect the construct scores obtained during Stage One of the analysis.

4.5.3.1 CONVERGENT VALIDITY OF THE SECOND-ORDER CONSTRUCT

Convergent validity of formative constructs is examined using redundancy analysis (Chin, 1998; J. F. Hair et al., 2014). This technique assesses the correlation between a formative construct and a reflective construct that captures the same concept using different indicators. A strong correlation suggests that the formative indicators collectively provide a reliable representation of the underlying concept (Cheah et al., 2018). In this study, the correlation is measured through the path coefficient (β) between the formative and reflective constructs of Startup Characteristics, as illustrated in Figure 4.12, the Redundancy Analysis Model. The PLS-SEM algorithm yielded a path coefficient of 0.813, surpassing the commonly accepted threshold of 0.7. Therefore, the formative construct of Startup Characteristics demonstrates adequate convergent validity.

Figure 4.11: Measurement Model

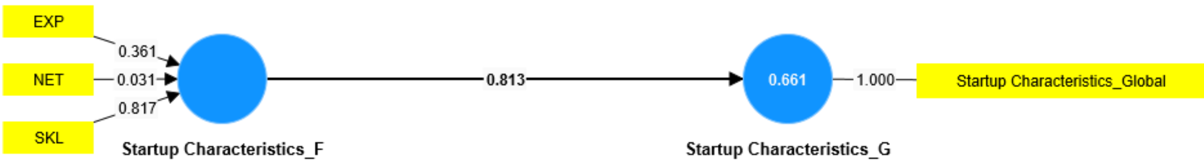


Source: Smart PLS 4 output

Table 4.11 Global Indicators

Global Indicator Name	Global Indicator Description
Startup Characteristics_Global	The average level of company experience, startup team skills, and the strength of your network circle prior to joining the business incubator

Figure 4.12 Redundancy Analysis Model



Source: SmartPLS 4 Output

4.5.3.2 COLLINERAITY ANALYSIS OF THE SECOND ORDER CONSTRUCT INDICATORS

Collinearity refers to a strong correlation between two or more formative indicators(J. F. Hair et al., 2017). As previously discussed, formative indicators are not expected to be highly correlated, as this could distort the results by inflating standard errors or misestimating indicator weights(J. F. Hair et al., 2017). To assess collinearity, the variance inflation factor (VIF) is calculated. VIF indicates the inverse of the variance in a formative indicator that is not explained by the other indicators within the same construct. A VIF value of 5 or more (equivalent to an unexplained variance of 0.20 or less) suggests potential collinearity concerns(J. F. Hair et al., 2012).

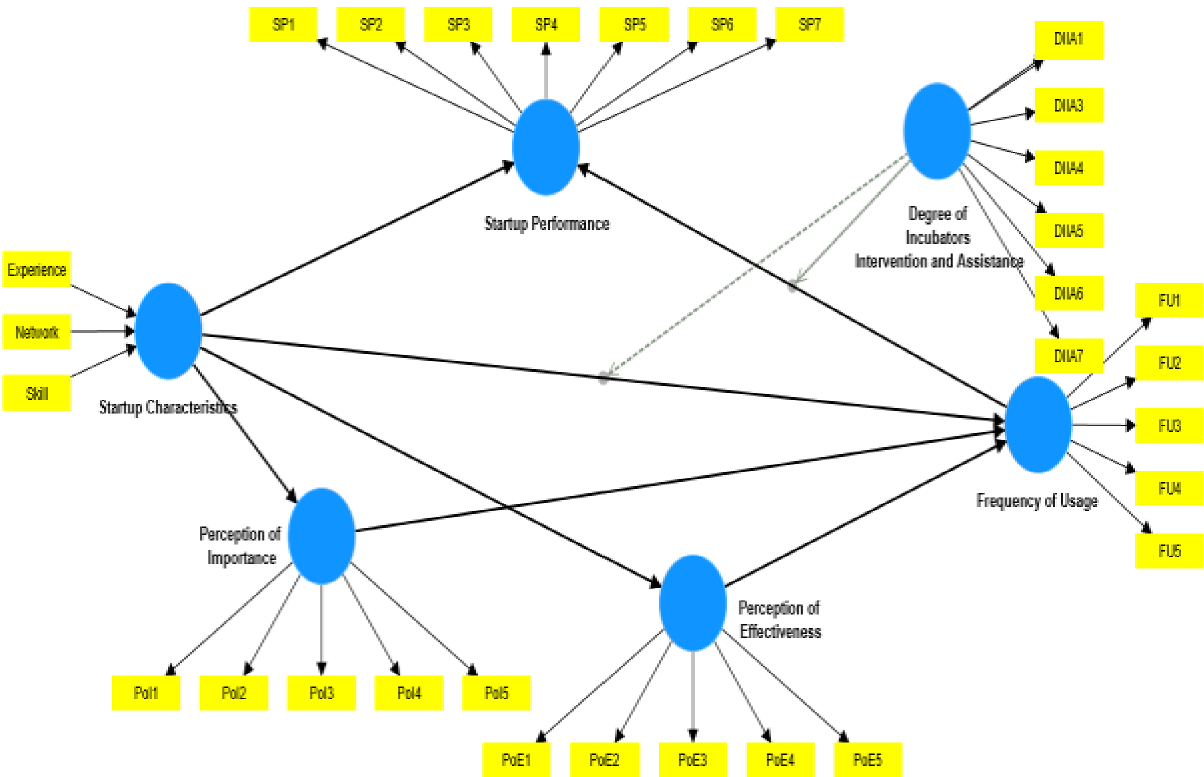
In this study, VIF values were derived by executing the PLS-SEM algorithm for the final stage-two model illustrated in Figure 4.13. As shown in Table 4.12, all VIF values are well below the critical threshold of 5, indicating that collinearity is not an issue for the formative indicators.

Table 4.12 Collinearity Assessment for Formative Indicators

Formative Indicators	VIF
EXP	1.152
NET	1.154
SKL	1.171

Source: Compiled from primary data

Figure 4.13 Stage -Two Final Research Model



Source: SmartPLS 4 Output

4.5.3.3 SIGNIFICANCE OF THE SECOND ORDER INDICATORS OUTER WEIGHTS

The final step in evaluating the formative measurement model involves examining the significance of the outer weights of the formative indicators. These outer weights reflect the relative importance of each indicator in shaping the formative construct(J. F. Hair et al., 2017). To determine whether the outer weights are significantly different from zero, a bootstrapping procedure was applied to the research model illustrated in Figure 4.13. The results indicated that the path coefficient for Skills (SKL → SC) was significant (outer weight = 0.568, t-value

= 2.206, p = 0.027), leading to the acceptance of Hypothesis H1a(iii). However, the paths from Experience (EXP → SC) and Network (NET → SC) were not statistically significant (p-values of 0.196 and 0.123, respectively), resulting in the non-acceptance of Hypotheses H1a(i) and H1a(ii).

However, when an indicator's outer weight is not significant but its outer loading is high (typically above 0.50), it is considered to be absolutely important, although not relatively important (Ramayah et al., 2016). As shown in Table 4.14, all outer loadings exceed 0.50 and are statistically significant. According to Cenfetelli & Bassellier (2009) and J. F. Hair et al. (2017), decisions to exclude indicators should be guided by their absolute contribution—defined as the unique information each indicator provides to the construct, independent of other indicators. This captures the magnitude and significance of the outer loading. Therefore, in light of their high and significant outer loadings, the indicators, despite having non-significant outer weights, remain meaningful and are retained within the model.

Table 4.13 Significance of Formative Indicators' Outer Weights

Hypothesis	Indicator Path	Indicator Outer Weight	t-value	p-value	Result
H1a(i)	**EXP -> SC**	0.365	1.293	0.196	Not Accepted
H1a(ii)	**NET -> SC**	0.425	1.542	0.123	Not Accepted
H1a(iii)	**SKL -> SC**	0.568	2.206	0.027	Accepted

Source: Compiled from primary data

Table 4.14 Significance of Formative Indicators' Outer Loadings

Hypothesis	Indicator Path	Indicator Outer Loading	t-value	p-value	Result
H1a(i)	**EXP -> SC**	0.658	3.164	0.002	Accepted
H1a(ii)	**NET -> SC**	0.703	3.364	0.001	Accepted
H1a(iii)	**SKL -> SC**	0.810	4.506	0.000	Accepted

Source: Compiled from primary data

4.5.4 ASSESSMENT OF STRUCTURAL MODEL

After evaluating the reliability and validity of the measurement models, the next phase in the PLS-SEM analysis involves assessing the structural model, which focuses on the relationships between the constructs within the model. The procedures for evaluating the structural model are summarised in Table 4.15, along with the recommended assessment criteria as outlined by (J. F. Hair et al. (2021).

Table 4.15 Structural Model Assessment Criteria

Criteria	Guidelines
Collinearity of Constructs	No Collinearity if the variance inflation factor (VIF) < 5
Path Coefficient Significance	Bootstrapping with 5000 subsamples Significance level: p-value < 0.05 (t-value > 1.65) Test type: one-tailed
Model Fit	A Standardised Root Mean Square Residual (SRMR) value less than 0.08, A Normed Fit Index (NFI) value greater than 0.90.
Coefficient of Determination (R^2)	Substantial: R^2 = 0.75 Moderate: R^2 = 0.50 Weak: R^2 = 0.25
Effect Size (f^2)	Small: f^2 = 0.75 Medium: f^2 = 0.50 Large: f^2 = 0.25
Predictive Relevance (Q^2)	Q^2 > 0: The model has predictive relevance, and the values of the endogenous constructs are well reconstructed.

Source : Compiled by author based on (J. F. Hair et al. (2021)

4.5.4.1 COLLINEARITY OF CONSTRUCTS

Construct collinearity is evaluated to confirm that the path coefficient estimates are not biased due to high correlations among the predictor constructs. Specifically, the Variance Inflation

Factor (VIF), referred to as the inner VIF in this context, is calculated for each predictor construct and compared against the recommended upper limit of 5(J. F. Hair et al., 2017).

Table 4.16 presents the VIF values for all combinations of endogenous constructs (listed in the columns) and their corresponding exogenous or predictor constructs (listed in the rows). The analysis focuses on assessing potential collinearity issues among the following sets of predictor constructs:

(a) Startup Characteristics as a predictor of Perception of Importance, Perception of Effectiveness, Frequency of Usage, and Startup Performance,

(b) Perception of Importance as a predictor of Frequency of Usage,

(c) Perception of Effectiveness as a predictor of Frequency of Usage, and

(d) Frequency of Usage as a Predictor of Startup Performance.

Table 4.16 Collinearity Statistics (VIF values in the structural Model)

	VIF
FU -> SP	1.232
PoE -> FU	1.138
PoI -> FU	1.195
SC -> FU	1.057
SC -> PoE	1.000
SC -> PoI	1.000
SC -> SP	1.019

Source: Compiled from primary data

The results shown in Table 4.15 reveal that all VIF values fall well below the recommended threshold of 5. Therefore, collinearity does not pose a significant concern among the predictor constructs within the structural model.

4.5.4.2 PATH COEFFICIENT SIGNIFICANCE

Path coefficients represent the estimated strengths of the hypothesized relationships between the constructs in the model, with values ranging from -1 to +1. These coefficients indicate the extent to which a one-unit change in an independent variable affects the dependent variable, assuming all other variables and relationships remain unchanged (J. F. Hair et al., 2017). A higher absolute value, whether positive or negative, signifies a stronger relationship. To determine whether these path coefficients are statistically significant—that is, meaningfully different from zero, a bootstrapping procedure is employed. The results of this bootstrapping analysis for each dataset are presented in Table 4.17.

The results indicate that hypotheses H1b(SC -> FU), H2a(SC -> PoI), H3a(PoI -> FU), H3b(PoE -> FU), H6(FU -> SP), and H7(SC -> SP) were fully supported, as indicated by their statistically significant p-values (p-value < 0.05).

Table 4.17 Structural Model Hypotheses Testing Results

Hypotheses	Path	Coefficient	t-value	p-value	Result
H1b	SC -> FU	0.14	2.838	0.005	Accepted
H2a	SC -> PoI	0.126	2.51	0.012	Accepted
H2b	SC -> PoE	0.077	1.338	0.181	Not Accepted
H3a	PoI -> FU	0.191	3.667	0.000	Accepted
H3b	PoE -> FU	0.181	3.04	0.002	Accepted
H6	FU -> SP	0.498	12.003	0.000	Accepted
H7	SC -> SP	0.191	4.351	0.000	Accepted

Source: Compiled from primary data

This confirms the positive and significant impact of Startup Characteristics on Frequency of Usage, Startup Characteristics on Perception of Importance, Perception of Importance on Frequency of Usage, Perception of Effectiveness on Frequency of Usage, Frequency of Usage on Startup Performance, and Startup Characteristics on Startup Performance. On the other hand, hypothesis H2b (SC -> PoE) was not supported, confirming that there is no significant positive impact of Startup Characteristics on Perception of Effectiveness and is therefore rejected by the data.

4.5.4.2 (i) MEDIATING EFFECTS

To gain a broader understanding of the impact of Startup Characteristics on Frequency of Usage, the path coefficients of the indirect relationships were assessed. Referring to the research model shown in Figure 4.13, the indirect or mediating effects include H4a(SC -> PoI -> FU) and H4b(SC -> PoE -> FU) as depicted in Table 4.17. The mediation analysis reveals that Perception of Importance (PoI) serves as a weak but statistically acceptable mediator in the relationship between Startup Characteristics (SC) and Frequency of Usage (FU), as indicated by hypothesis H4a. Although the p-value (0.053) slightly exceeds the conventional threshold of 0.05, the result is considered marginally significant and thus accepted. This suggests that PoI partially mediates the relationship between SC and FU, as both the direct effect (SC -> FU) and the indirect effect (SC -> PoI -> FU) are significant (Nitzl et al., 2016).

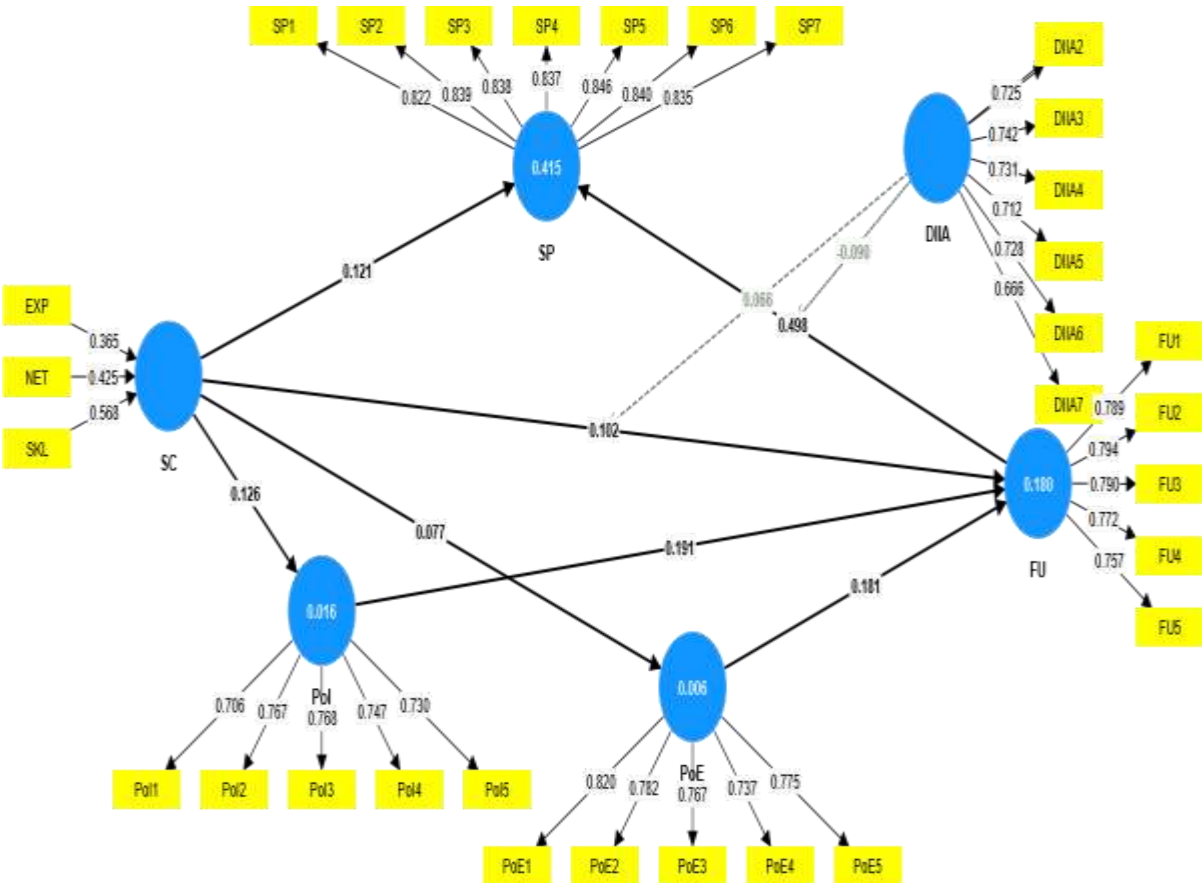
In contrast, hypothesis H8, which tests the mediating role of Perception of Effectiveness (PoE) between SC and FU, was not supported. With a high p-value of 0.26 and a low t-value, the result indicates that PoE does not significantly mediate the relationship between SC and FU. Therefore, while PoI demonstrates a modest mediating effect, PoE does not contribute significantly as a mediator in this context.

Table 4.18: Mediating/Indirect Effects of Startup Characteristics on Frequency of Usage

Hypotheses	Path	Coefficient	t-value	p-value	Result
H4a	SC -> PoI -> FU	0.024	1.938	0.053	Accepted
H4b	SC -> PoE -> FU	0.014	1.126	0.26	Not Accepted

Source: Compiled from primary data

Figure 4.14: Bootstrapping Results of the Model



Source: SmartPLS 4 Output

4.5.4.2(ii) MODERATING RELATIONSHIPS

The moderating effects of Degree of Incubator's Intervention and Assistance (DIIA) on two key relationships—(i) between Startup Characteristics (SC) and Frequency of Usage (FU), and (ii) between FU and Startup Performance (SP)—are analysed as presented in Table 4.18 and illustrated in Figure 4.14. The interaction term DIIA exhibits a positive effect on FU (coefficient = 0.066), while the direct effect of SC on FU is 0.102. These results indicate that at an average level of DIIA, the relationship between SC and FU stands at 0.102. However, when DIIA increases by one standard deviation, the relationship strengthens to 0.168 (0.102 + 0.066), suggesting that a higher degree of incubator support enhances the positive impact of SC on FU.

In contrast, the moderating effect of DIIA on the relationship between FU and SP is negative, with the interaction term showing a coefficient of -0.090. The simple direct effect of FU on SP is 0.498, meaning that at an average level of DIIA, this is the strength of the relationship. When DIIA increases by one standard deviation, the relationship weakens to 0.408 (0.498 - 0.090), indicating that higher levels of incubator intervention may dampen the impact of FU on SP. Conversely, at lower levels of DIIA, the relationship strengthens to 0.588 (0.498 + 0.090), suggesting that in less-intervention contexts, FU has a more pronounced effect on SP. These findings highlight the nuanced role of DIIA as a moderator, enhancing certain relationships while diminishing others depending on its intensity.

Table 4.19: Moderating Effects

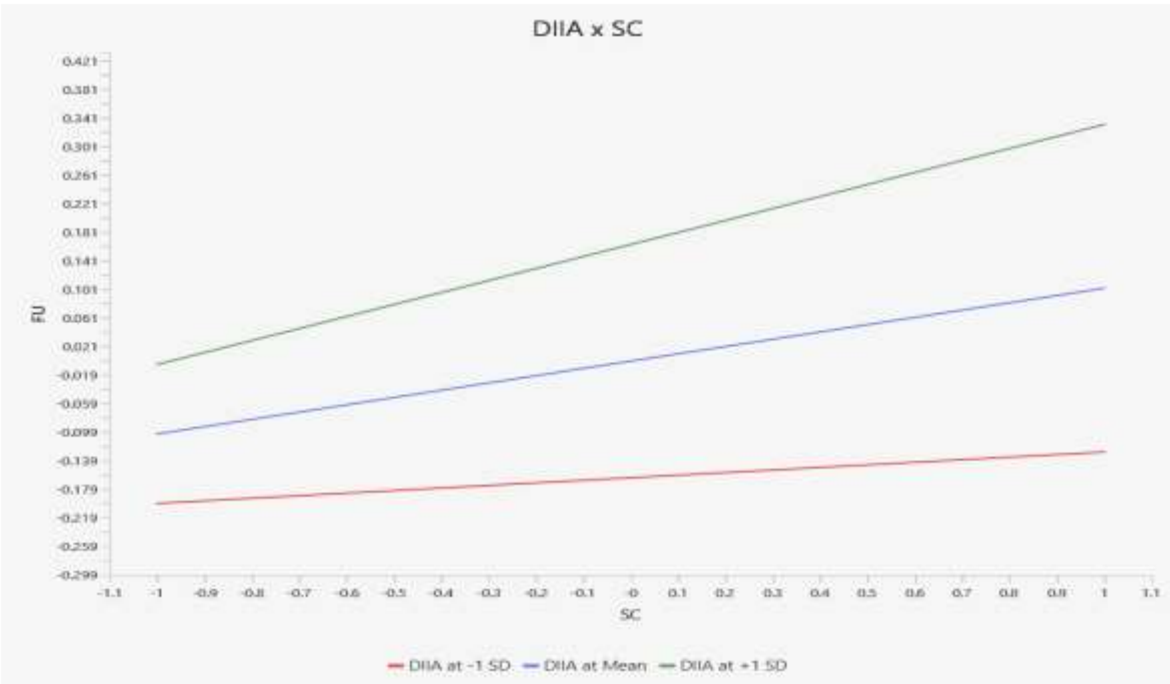
Hypotheses	Path	Coefficient	t-value	p-value	Result
H5a	DIIA x SC -> FU	0.066	1.02	0.308	Not Accepted
H5b	DIIA x FU -> SP	-0.09	3.784	0.000	Accepted

Source: Compiled from primary data

To better understand the results of the moderator analysis, a simple interaction plot has been used to visually represent the two-way interaction effect(J. Hair et al., 2023). Figure 4.15 illustrates the relationship between Startup Characteristics (SC) on the x-axis and Frequency of Usage (FU) on the y-axis, under varying levels of the moderator variable, Degree of Incubator's Intervention and Assistance (DIIA). The three lines in the plot represent different levels of DIIA: the blue line shows the relationship at an average level of DIIA. In contrast, the green line and red line correspond to high (mean + 1 SD) and low (mean - 1 SD) levels of

DIIA, respectively. The plot reveals that all three lines have a positive slope, indicating that as SC increases, FU also increases, regardless of the level of DIIA. However, the strength of this relationship varies with the intensity of incubator support. At low levels of DIIA (red line), the relationship is weak and nearly flat, suggesting minimal influence of SC on FU. At an average level of DIIA (blue line), the relationship is moderately positive. In contrast, at high levels of DIIA (green line), the slope is steepest, indicating a strong and significant positive relationship between SC and FU. These visual insights confirm that DIIA positively moderates the relationship between Startup Characteristics and Frequency of Usage. In essence, when the degree of incubator interventions and assistance is more actively and extensively provided, the positive impact of favourable startup characteristics on the usage of incubation services is considerably amplified. Therefore, incubator support plays a critical role in enhancing engagement, especially for startups with strong foundational characteristics.

Figure 4.15 Simple Slope Plot (DIIA x SC)



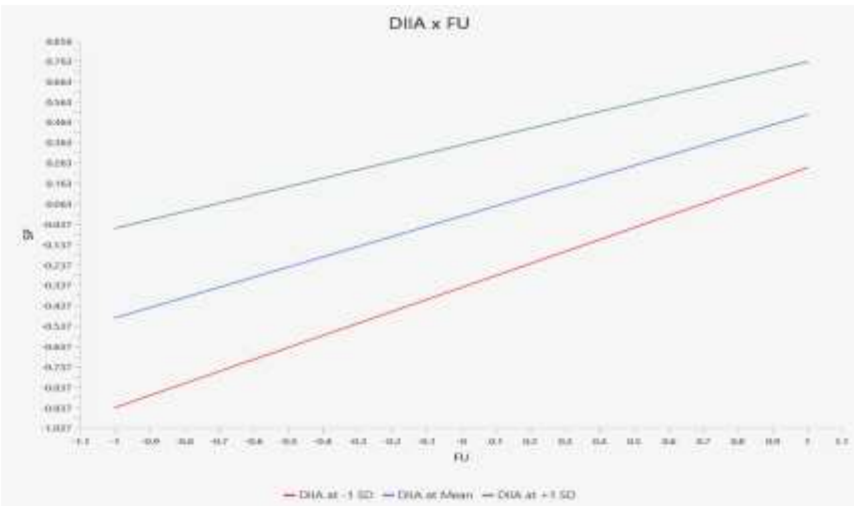
Source: SmartPLS 4 Output

Figure 4.16 presents a visual representation of the moderating effect of Degree of Incubator Intervention and Assistance (DIIA) on the relationship between Frequency of Usage (FU) and Startup Performance (SP). The three lines in the plot capture this interaction across different levels of the moderator variable. The blue line reflects the relationship at the average level of

DIIA, while the green and red lines correspond to high (mean + 1 SD) and low (mean - 1 SD) levels of DIIA, respectively. The plot shows that all three lines have a positive slope, indicating that as FU increases, SP also increases, regardless of the level of DIIA. However, the steepness of these lines—which reflects the strength of the relationship—varies notably with the degree of incubator intervention. At low levels of DIIA (red line), the slope is steepest, suggesting that FU has the strongest positive impact on SP when incubator support is limited. At the average level of DIIA (blue line), the slope is moderate, indicating a typical positive effect. Conversely, at high levels of DIIA (green line), the slope is flattest, implying a weaker relationship between FU and SP.This pattern suggests that while incubator services are essential, excessive intervention may reduce the marginal benefit of frequent service usage on startup performance. In other words, excessive assistance may inadvertently limit the positive influence of proactive engagement (FU) on outcomes (SP), possibly by reducing startup autonomy or fostering dependency.

While this figure focuses on the FU → SP pathway, it reinforces the broader findings from the moderator analysis. Specifically, it highlights that DIIA moderates relationships in nuanced ways: strengthening the link between SC and FU (as seen in earlier analysis) but dampening the impact of FU on SP when support becomes excessive. This emphasises the need for a balanced approach to incubation—providing sufficient support to encourage engagement, without undermining the startup's independent growth trajectory.

Figure 4.16 Simple Slope Plot (DIIA x FU)



Source: SmartPLS 4 Output

4.5.4.3 MODEL FIT

In the context of Partial Least Squares Structural Equation Modelling (PLS-SEM), approximate model fit is assessed using indices such as the Standardised Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI)(Ringle et al., 2024). SRMR is an absolute measure of fit that quantifies the difference between the observed correlation matrix and the model-implied correlation matrix. In PLS-SEM, a value of SRMR less than 0.08 is commonly considered indicative of a good model fit(Henseler & Sarstedt, 2013). A low SRMR value, such as 0.043 (Table 4.20) in the saturated model, indicates that the discrepancies between the predicted and observed relationships are minimal, thereby reinforcing the model's appropriateness. NFI**,** or the Normed Fit Index, is a comparative fit index that assesses how much better the proposed model fits the data compared to a null (independence) model, in which all variables are assumed to be uncorrelated (Bentler & Bonett, 1980). Values of NFI greater than 0.90 are generally seen as indicative of a good fit. The NFI value of 0.901 (Table 4.19) for the saturated model thus reflects a satisfactory improvement over the null model, suggesting that the model captures meaningful relationships in the data. When both SRMR and NFI fall within the acceptable thresholds (SRMR < 0.08, NFI > 0.90), the model is considered to exhibit an acceptable level of approximate fit.

Table 4.20: Model Fit indices

	Saturated model
SRMR	0.043
NFI	0.901

Source: Compiled from primary data

4.5.4.4 COEFFICIENT OF DETERMINATION (R^2)

The next criterion for assessing the structural model is the coefficient of determination *(R^2)* for endogenous constructs, which indicates the model's predictive power(Everitt & Skrondal, 2010). The coefficient of determination (R^2) reflects the combined influence of all related exogenous constructs on an endogenous construct, indicating the model's in-sample predictive power(Rigdon, 2012; Sarstedt et al., 2014). R^2 values range from 0 to 1, with higher values signifying greater predictive accuracy. However, acceptable R^2 thresholds vary depending on model complexity and research context, making it challenging to define a universal standard. In marketing research, R^2 values of 0.75, 0.50, and 0.25 are typically interpreted as substantial, moderate, and weak, respectively (J. F. Hair et al., 2011; Henseler et al., 2009), and these benchmarks are often used as general guidelines. Since more complex models may introduce bias by artificially inflating R^2 values, the adjusted coefficient of determination (R^2 adj) has been introduced as an additional assessment metric. This adjusted measure takes into account model complexity and provides a more precise assessment of the model's explanatory power.

Table 4.21: R^2 and R^2_{adj}

Endogenous Constructs	R-square	R-square adjusted
Frequency of Usage	0.181	0.174
Startup performance	0.411	0.408

Source: Compiled from primary data

In Table 4.21, for Frequency of Usage, the R^2 is 0.181 and the adjusted R^2 is 0.174, suggesting that approximately 18.1% of its variance is explained by the model, which is considered weak predictive accuracy. For Startup Performance, the R^2 is 0.411 and the adjusted R^2 is 0.408, indicating that about 41.1% of its variance is explained, reflecting a moderate level of predictive power. The adjusted R^2 values, which account for model complexity, show only a slight reduction compared to the unadjusted values, suggesting that the number of predictors does not artificially inflate the model's explanatory power. These results demonstrate that while the model explains a modest proportion of the variance in Frequency of Usage, it provides a more meaningful explanation for Startup Performance.

4.5.4.5 EFFECT SIZES (f^2)

In addition to examining R^2 values, changes in R^2 can be assessed using the effect size (f^2), an evaluation criterion introduced by Cohen (1988) and further discussed by Ellis (2012). The f^2 effect size measures the magnitude of the impact that each independent construct has on a dependent construct, helping to determine the substantive contribution of individual predictors within the structural model. According to Cohen (1988), the commonly used benchmarks for interpreting f^2 effect sizes are 0.35 (large effect), 0.15 (medium effect), and 0.02 (small effect). An f^2 value below 0.02 indicates that the exogenous construct has no meaningful impact on the dependent variable. As seen in Table 4.22, the path from Frequency of Usage (FU) to Startup Performance (SP) demonstrates the strongest influence, with an effect size of 0.344, which is just below the threshold for a significant effect and indicates a substantial impact.

Table 4.22: Effect Sizes (*f²*)

	SC	FU	PoI	PoE	DIIA	SP
SC		0.012	0.016	0.006		0.025
FU						0.344
PoI		0.037				
PoE		0.035				
DIIA		0.027				0.160

Source: Compiled from primary data

The path from Degree of Incubators Intervention and Assistance (DIIA) to Startup Performance shows a moderate effect ($f^2 = 0.16$), while its implications for Frequency of Usage are small ($f^2 = 0.027$). The constructs Perception of Effectiveness (PoE) and Perception of Importance (PoI) both have small effects on Frequency of Usage, with effect sizes of 0.035 and 0.037, respectively.

In contrast, the paths originating from Startup Characteristics (SC) mostly show negligible effects, with f^2 values below the 0.02 threshold: SC → FU (0.012), SC → PoE (0.006), and SC → PoI (0.016), suggesting that SC does not have a meaningful direct impact on these constructs. However, SC → SP shows a small effect ($f^2 = 0.025$), indicating a minor but notable influence on startup performance. Overall, these results help to identify which exogenous constructs have substantive impacts within the structural model and emphasise the critical role of Frequency of Usage in driving startup performance.

4.5.4.6 PREDICTIVE RELEVANCE (Q^2)

Another important criterion for evaluating the structural model is its predictive relevance, which reflects the model's out-of-sample predictive power. To assess the predictive relevance of the model, a Q^2 predict analysis was conducted using the PLS Predict feature available in SmartPLS 4 (J. F. Hair et al., 2022; Shmueli et al., 2016). This procedure involves selecting the endogenous constructs of interest, after which the software employs a blindfolding technique to estimate predictive accuracy. SmartPLS generates Q^2 values at both the indicator and construct levels, offering insights into the model's capability to predict observed values. A Q^2 value greater than zero indicates that the model exhibits predictive relevance for the respective construct.

Furthermore, SmartPLS provides a comparative analysis by calculating Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for the PLS model and contrasts these with the results from a naïve benchmark model, typically based on linear regression. This comparison facilitates an evaluation of the relative predictive performance, highlighting the practical utility of the model beyond its explanatory power. In Table 4.23, the Q^2 predict value, which shows how well the model can make predictions, is higher for SP (0.19) than for FU (0.074). This means that SP has better overall predictive ability. SP also has a lower RMSE (0.905 vs. 0.97), indicating smaller prediction errors. However, when looking at MAE, which measures the average size of the errors, FU performs slightly better (0.662 vs. 0.669). In summary, SP is stronger in terms of predictive power and lower overall error, while FU has a slight edge in average prediction accuracy.

Table 4.23: Q^2 Values for Endogenous Constructs

	Q^2 predict	RMSE	MAE
FU	0.074	0.97	0.662
SP	0.19	0.905	0.669

Source: Compiled from primary data

4.6 TESTING FOR MEASUREMENT MODEL INVARIANCE

Before conducting Multi-Group Analysis (MGA), it is essential to establish measurement invariance to determine the appropriate type of MGA that can be applied. In SmartPLS, the Measurement Invariance of Composite Models (MICOM) procedure—proposed by Henseler et al. (2016) was specifically designed to replace earlier methods used in covariance-based SEM, which are not suitable for SmartPLS.

4.6.1 MICOM ANALYSIS

The MICOM procedure involves three key steps: establishing configural invariance, assessing compositional invariance, and testing for equality of means and variances. If only the first two steps are satisfied, then partial measurement invariance is confirmed, allowing for comparison of model results across groups. If all three conditions are met, full measurement invariance is achieved, permitting both between-group and pooled-group comparisons.

Configural Invariance – This is the foundational level and the simplest to achieve. It requires that the measurement models in all groups use the *same indicators*, follow an *identical data treatment process* (e.g., dealing with missing values, transformations), and apply the *same algorithmic settings* during model estimation. In simpler terms, both the model structure and the preprocessing must be uniform across the groups being compared. In the context of our study, this condition has already been satisfied since the dataset for both groups was prepared and processed identically, ensuring consistency at the configural level.

Compositional Invariance – Following the confirmation of configural invariance as outlined in the first step of the MICOM procedure, the next step involved evaluating compositional invariance. This was conducted using a permutation test with at least 1,000 permutations. The objective of this assessment was not to reject the null hypothesis at the 5% significance level, which posits that the correlation (c) between the composite scores of Group 1 and Group 2 equals one (Henseler et al. 2016). As shown in Table 4.24, the comparison of the observed correlation values (c) with the 5% quantile revealed that the quantile was consistently lower than the correlation value for each composite, indicating that compositional invariance was established.

Additionally, this conclusion was supported by the permutation p-values, all of which were greater than 0.5. This further supports the failure to reject the null hypothesis at the 5% significance level. The establishment of compositional invariance confirms partial measurement invariance, thereby justifying the use of multigroup analysis (MGA) to compare the path coefficients across groups.

Table 4.24 MICOM 2nd STEP RESULTS

Composite	Correlation (c)	Correlation Permutation Mean	5%	Permutation p-Values	Compositional Invariance Established
DIIA	0.997	0.996	0.991	0.429	YES
FU	0.998	0.999	0.997	0.084	YES
PoE	0.987	0.99	0.976	0.107	YES
PoI	0.977	0.99	0.976	0.057	YES
SC	0.931	0.667	0.174	0.844	YES
SP	1	1	1	0.915	YES

Source: Compiled from primary data

Equality of Composite Means and Variances – The final step involves comparing the *average scores (means)* and the *spread of scores (variances)* of each construct across groups (Henseler et al. 2016). Again, permutation tests are employed to determine if these differences are statistically significant. This step ensures that not only are constructs formed similarly, but their distributions are also statistically indistinguishable between groups.

The implications of the results from these tests are critical:

- If only the first two steps (configural and compositional invariance) are confirmed, then partial measurement invariance is established. This means the structural model results can be compared *between groups*, but conclusions must be made cautiously, as potential differences in means and variances may still influence interpretations.
- If all three steps are satisfied, then full measurement invariance is confirmed. In this case, you can confidently compare both *group-specific results* and *pooled model outcomes*, as the constructs are measured equivalently in every respect.

Table 4.25 MICOM 3rd (a) STEP RESULTS

Composite	Differences of the Composite Mean Value (=0) (Male-Female)	95% Confidence Interval	p-Values	Equal mean values?
DIIA	-0.036	[-0.154; 0.139]	0.354	YES
FU	0.027	[-0.157; 0.147]	0.396	YES
PoE	0.027	[-0.152; 0.157]	0.393	YES
PoI	0.073	[-0.156; 0.142]	0.211	YES
SC	-0.087	[-0.147; 0.152]	0.171	YES
SP	0.009	[-0.155; 0.146]	0.441	YES

Source: Compiled from primary data

Having established compositional invariance in the previous step, the study proceeded to the final stage of the MICOM procedure, which involves testing the equality of composite mean values and variances across the two groups. As presented in Table 4.25, the results revealed that all 95% confidence intervals included the original differences in mean values. This outcome indicates that there are no statistically significant differences in the latent variable means between the groups. Furthermore, these findings were reinforced by the associated permutation p-values, all of which exceeded the conventional significance level of 0.05.

Table 4.26 MICOM 3rd (b) STEP RESULTS

Composite	Logarithms of the Composite's Variance (=0) (Male-Female)	95% Confidence Interval	p-Values	Equal Variance?
DIIA	0.013	[-0.373; 0.455]	0.285	YES
FU	0.013	[-0.279; 0.356]	0.162	YES
PoE	0.016	[-0.302; 0.364]	0.505	YES
PoI	0.006	[-0.337; 0.369]	0.348	YES
SC	0.01	[-0.286; 0.324]	0.185	YES
SP	0.006	[-0.194; 0.238]	0.457	YES

Source: Compiled from primary data

In terms of composite variances presented in Table 4.26, the analysis demonstrated that the 95% confidence intervals also contained the logarithmic differences in variances, further indicating no significant group differences in variability. Consistently, the p-values for variance equality were also greater than 0.05. Collectively, these results confirm the establishment of full measurement invariance, thereby justifying the comparison of structural model relationships across the two groups using multi-group analysis (MGA).

4.7 MULTI-GROUP ANALYSIS (GENDER MODERATION)

The MICOM procedure confirmed both compositional invariance and the equality of means and variances, thereby establishing full measurement invariance. This indicates that the constructs are measured consistently across the male and female groups, enabling a reliable comparison of structural path coefficients through Multi-Group Analysis (MGA).

To assess the moderating role of gender, MGA was conducted using SmartPLS 4, incorporating bias-corrected bootstrapping with 5,000 subsamples (Mishra et al., 2018). According to J. F. Hair et al. (2017), moderation is considered statistically significant at the 5% level of error when the p-value is either below 0.05 or above 0.95. The MGA was applied across all hypothesised paths to test the proposed moderation effects and to explore any additional potential moderating influences within the structural model.

To gain a more comprehensive understanding of group differences, the study employed three analytical approaches—PLS-MGA, the Parametric Test, and the Welch–Satterthwaite t-test. The results of these analyses are presented in Table 4.27 and further elaborated in the subsequent discussion.

The results of the Multi-Group Analysis (MGA) shown in Table 4.27, performed to test the moderating role of gender on the hypothesised relationships (H8a–H8g), were conducted using three different statistical approaches—PLS-MGA, Parametric Test, and Welch–Satterthwaite Test—indicating that most path differences between male and female groups were statistically non-significant.

Except for one hypothesis, the analysis revealed no statistically significant differences in path coefficients between male and female groups. Specifically, hypotheses H8a (Frequency of Usage → Startup Performance), H8b (Perception of Effectiveness → Frequency of Usage), H8c (Perception of Importance → Frequency of Usage), H8e (Startup Characteristics → Perception of Effectiveness), H8f (Startup Characteristics → Perception of Importance), and H8g (Startup Characteristics → Startup Performance) all yielded p-values greater than 0.05 across all three methods, indicating non-significant moderation by gender. However, hypothesis H8d (Startup Characteristics → Frequency of Usage) demonstrated a statistically significant difference, with a consistent path coefficient difference of -1.959 and p-values of 0.005 (PLS-MGA), 0.001 (Parametric Test), and 0.004 (Welch–Satterthwaite Test).

This consistent significance indicates that gender significantly moderates the relationship between startup characteristics and the frequency of usage of incubator services, with the negative difference suggesting that the relationship is stronger for females compared to males.

4.8 IMPORTANCE – PERFORMANCE MAP ANALYSIS (IPMA) AND NECESSITY CONDITION ANALYSIS (NCA); COMBINED IPMA (cIPMA)

Our study has incorporated a novel approach introduced by Hauff et al. (2024) that extends the application of Importance-Performance Map Analysis (IPMA) in Partial Least Squares Structural Equation Modelling (PLS-SEM) by incorporating findings from a Necessary Condition Analysis (NCA).

Table 4.27 Multi-Group Analysis for testing the Moderation Effects of Gender using Bootstrap-MGA, Parametric Test and Welch-Satterthwaite Test

Hypothesis	Relationship	Bootstrap-MGA		Parametric Test		Welch-Satterthwaite Test		Result
		Difference in path coefficients (Male-Female)	p-Value for difference (Male Vs Female)	Difference in path coefficients (Male-Female)	p-Value for difference (Male Vs Female)	Difference in path coefficients (Male-Female)	p-Value for difference (Male Vs Female)	
H8a:	Startup Characteristics -> Frequency of Usage	-1.959	0.005	-1.959	0.001	-1.959	0.004	**Sig**
H8b:	Perception of_ Effectiveness -> Frequency of Usage	0.078	0.54	0.078	0.576	0.078	0.544	**N-Sig**
H8c:	Startup Characteristics -> Perception of_ Effectiveness	-0.049	0.82	-0.049	0.884	-0.049	0.915	**N-Sig**
H8d:	Perception of_ Effectiveness -> Frequency of Usage	0.078	0.54	0.078	0.576	0.078	0.544	**N-Sig**
H8e:	Perception of_ Importance -> Frequency of Usage	-0.083	0.529	-0.083	0.535	-0.083	0.53	**N-Sig**
H8f:	Frequency of Usage -> Startup Performance	0.283	0.198	0.283	0.182	0.283	0.219	**N-Sig**
H8g:	Startup Characteristics -> Startup Performance	0.013	0.911	0.013	0.948	0.013	0.941	**N-Sig**

Source: Compiled from primary data

Comparing the importance and performance of attributes to achieve a specific outcome is a well-established management practice (Martilla & James, 1977). This relationship is typically illustrated using a two-dimensional grid with four quadrants based on high and low levels of importance and performance. This visualisation is known by various names, including the importance-performance grid (Martilla & James, 1977) or, more generally, importance-performance map analysis(Ringle & Sarstedt, 2016). Necessary Condition Analysis (NCA) identifies critical factors or constraints that must be met to achieve a desired outcome. These necessary conditions are essential in management, as the outcome cannot occur without them (Dul et al., 2020; Hauff et al., 2021; Richter & Hauff, 2022). Notably, even constructs with weak or insignificant effects in PLS-SEM may still be necessary and overlooking them can result in incomplete or misleading recommendations.

Step 1: Specifying the research objective and theoretical background

▼

Step 2: Checking and preparing the data

▼

Step 3: Running the PLS-SEM analysis

▼

Step 4: Evaluating the reliability and validity of the measurement models

▼

Step 5: Running the IPMA and transferring the latent variable scores

▼

Step 6: Running the NCA

▼

Step 7: Evaluate the structural model

▼

Step 8: Interpret the findings

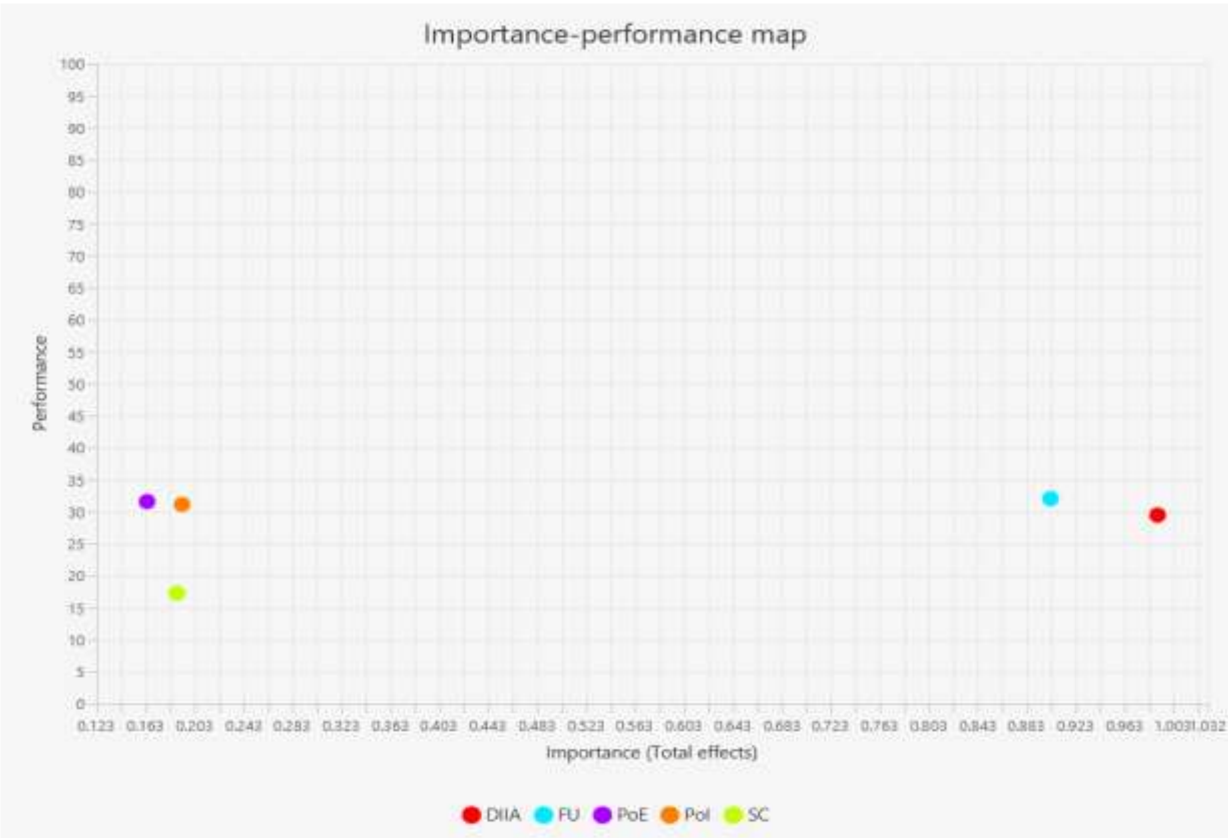
Figure 4.17 Process for conducting cIPMA

The integration of NCA and PLS-SEM (Richter et al., 2020) offers a novel approach to assessing causality by combining necessity (NCA) and sufficiency (PLS-SEM), earning recognition as a significant methodological contribution(Bergh et al., 2022). Recent studies (e.g., Bolívar et al., 2022; Richter et al., 2021; Sukhov et al., 2022; Tiwari et al., 2024) have adopted this approach. Hauff et al. (2024) have proposed that incorporating NCA into IPMA enhances its value by revealing which antecedents are not only essential but also necessary, thus offering a more comprehensive understanding for both researchers and practitioners. Figure 4.17 outlines an eight-step procedure for conducting the Combined Importance-Performance Map Analysis (cIPMA), as suggested by Hauff et al. (2024). We will begin the cIPMA from Step 5, as the first four steps and Step 7 have already been completed in the preceding sections.

Step 5: Running the IPMA and transferring the latent variable scores

In this step, the Importance-Performance Map Analysis (IPMA) is used to assess and compare the total effects from the structural model (reflecting the importance of each construct) with the average latent variable scores (indicating performance). This method helps pinpoint areas where performance improvements can be made. In this study, the importance and performance of five predictor variables are analysed in relation to their influence on startup performance. As shown in Figure 4.18, the results highlight critical areas for strategic improvement, offering a clear direction for enhancing startup performance by addressing identified performance gaps.

Figure 4.18 Importance-Performance Map



Source: SmartPLS 4 Output

Figure 4.18 presents the Importance-Performance Map (IPMA), where the x-axis represents the total effects (importance) and the y-axis indicates the average latent variable scores (performance) of each construct in influencing Startup Performance. The analysis reveals that Degree of Incubator Intervention & Assistance (DIIA) and Frequency of Usage (FU) exhibit high importance but only moderate performance, suggesting that these constructs are critical drivers of Startup Performance and should be prioritised for improvement efforts. In contrast, Perception of Effectiveness (PoE) and Perception of Importance (PoI) demonstrate moderate performance but relatively low importance, indicating that while they are functioning adequately, they have a lesser impact on overall Startup Performance. Startup Characteristics (SC) falls into the low-importance, low-performance quadrant, suggesting it currently contributes minimally to Startup Performance and may not require immediate strategic focus. Overall, the map offers a clear, data-driven guide for targeting improvements, particularly by enhancing the performance of the highly important constructs, DIIA and FU. The latent variable scores of the key constructs were stored for subsequent analysis.

Step 6: Running the NCA

The latent scores obtained in Step 5 were utilised to perform the Necessary Condition Analysis (NCA), following the procedure outlined by Sarstedt et al. (2024). Figures 4.19 a–e display the NCA ceiling line charts for the five predictor variables examined in relation to the outcome variable, Startup Performance. Each chart illustrates the minimum level of a predictor (x-axis) required to achieve a specific level of satisfaction (y-axis), as represented by the ceiling line. Data points falling below this line indicate instances where the absence of inadequacy of a predictor limits the outcome. These visualisations provide an initial basis for identifying necessary conditions. Notably, the empty upper-left areas of the charts imply that all five predictors are essential for achieving satisfaction. At the same time, differences in the size of these gaps suggest varying degrees of necessity among the predictors.

Following this, the necessary conditions were examined for potential bottlenecks, and their significance was tested using 10,000 permutation samples. This analysis aimed to determine both the magnitude and statistical significance of the effects. As summarized in Table 4.28, all five predictor variables in the study were found to be significant necessary conditions for achieving higher levels of overall satisfaction ($p < .01$). The observed effect sizes ranged from 0.033 to 0.072, which, based on Dul's (2016) classification, correspond to small ($0 < d < 0.1$) to medium-sized effects (0.1 ≤ d < 0.3). The bottleneck analysis further clarifies the role of each predictor variable as a necessary condition for achieving varying levels of startup performance. As shown in the table, the percentage values in the first column represent different thresholds of startup performance, with corresponding minimum levels of each predictor required to reach those thresholds. 'NN' (Not Necessary) indicates that the predictor is not needed at lower performance levels, whereas specific values reflect the minimum necessary levels at higher performance thresholds.

At 20% performance, only Perception of Effectiveness, Perception of Importance, and Startup Characteristics are found to be necessary. From 30% onwards, the Degree of Incubator Intervention and assistance, as well as the frequency of Usage, also become essential. At the highest satisfaction level (100%), all predictors require substantially higher values, with Degree of Incubator Intervention and Assistance and Frequency of Usage showing particularly high thresholds (82.393 and 92.847, respectively), reinforcing their critical importance.

The effect sizes (d) of the predictors range from 0.033 to 0.072, indicating small effects according to Dul's (2016) guidelines (small: 0 < d < 0.1). Despite the small magnitude, all predictors are statistically significant (p < .001), confirming their necessity in achieving high levels of startup performance. These findings provide valuable insights for incubator management, emphasising the importance of meeting certain minimum thresholds across all key support areas to ensure startup success.

Table 4.28, the bottleneck table, also allows for the estimation of the proportion of cases that fail to reach the specified target level of performance. To conduct this analysis, researchers must define the desired outcome level in advance, guided by theoretical frameworks or practical managerial objectives(Sarstedt et al., 2024). In the context of this study, an 80% performance level has been established as the target benchmark.

Step 8: Interpreting the results

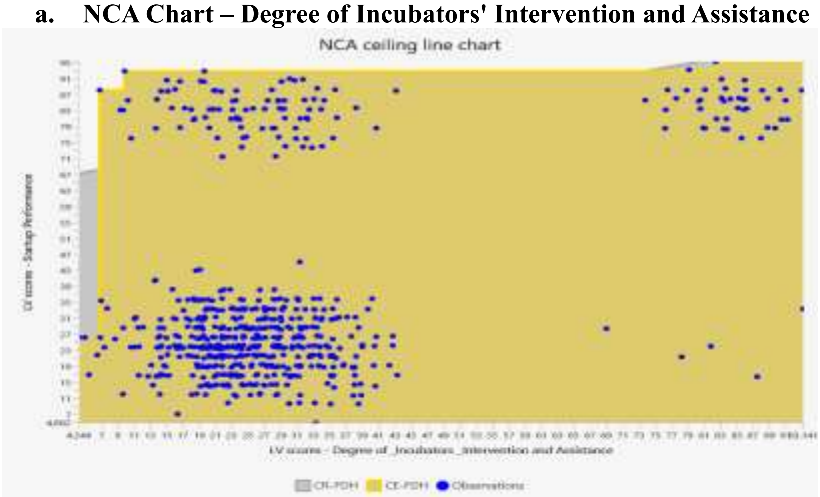
In this final step, the findings from the PLS-SEM algorithm, IPMA, and NCA are brought together for an integrated interpretation. Guided by the framework proposed by Hauff et al. (2024), an extended IPMA chart is constructed. In this visualisation, the X-axis indicates the importance of each predictor variable (based on total effects), while the Y-axis represents their performance (average latent scores). The size of each bubble corresponds to the proportion of cases that do not meet the required level of satisfaction. As established in Step 6, the desired performance threshold for this study is set at 80%. This extended IPMA provides a holistic view, enabling the identification of high-impact areas with performance gaps and substantial bottlenecks, thus guiding targeted interventions for improvement.

Table 4.28 Bottleneck Table – CE-FDH values

	Degree of Incubators' Intervention and Assistance	Frequency of Usage	Perception of Effectiveness	Perception of Importance	Startup Characteristics
0.00%	NN	NN	NN	NN	NN
10.00%	NN	NN	NN	NN	NN
20.00%	NN	NN	6.107	5.227	6.024
30.00%	6.775	NN	6.35	5.227	6.024
40.00%	6.775	6.643	6.35	6.025	6.024
50.00%	6.775	6.643	7.088	6.025	6.024
60.00%	6.775	6.643	7.088	6.025	6.024
70.00%	6.775	6.643	7.088	6.025	6.024
80.00%	6.775	6.643	7.088	6.025	6.838
90.00%	6.775	6.643	9.443	6.025	6.838
100.00%	82.393	92.847	31.315	27.308	12.326
Effect Size (d)	0.046	0.072	0.044	0.044	0.033
Significance*(p)*	.000***	.000***	.000***	.000***	.000***

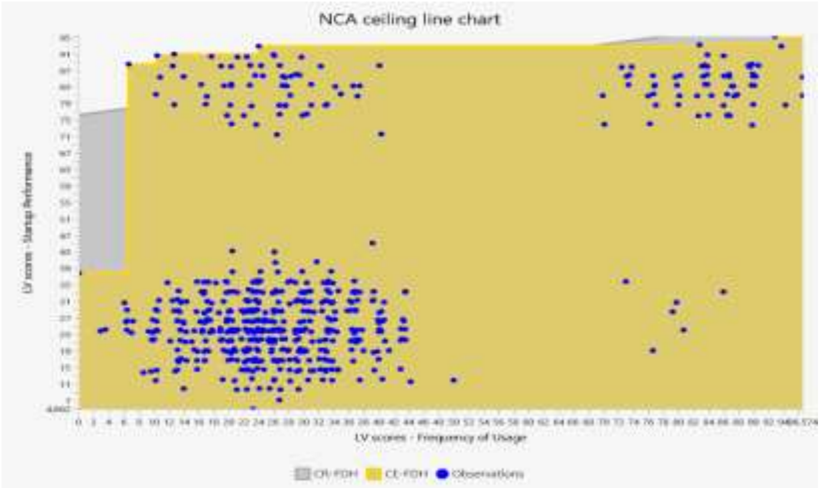
Source: Compiled from primary data

a. NCA Chart – Degree of Incubators' Intervention and Assistance



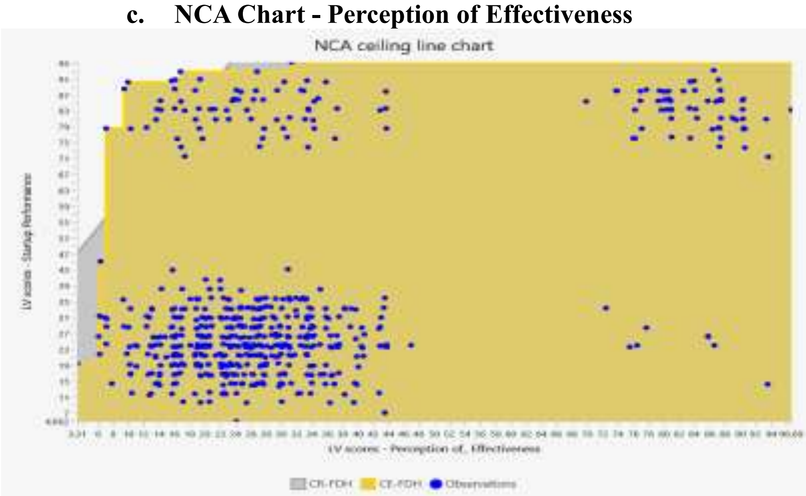
Source: SmartPLS 4 Output

b. NCA Chart – Frequency of Usage



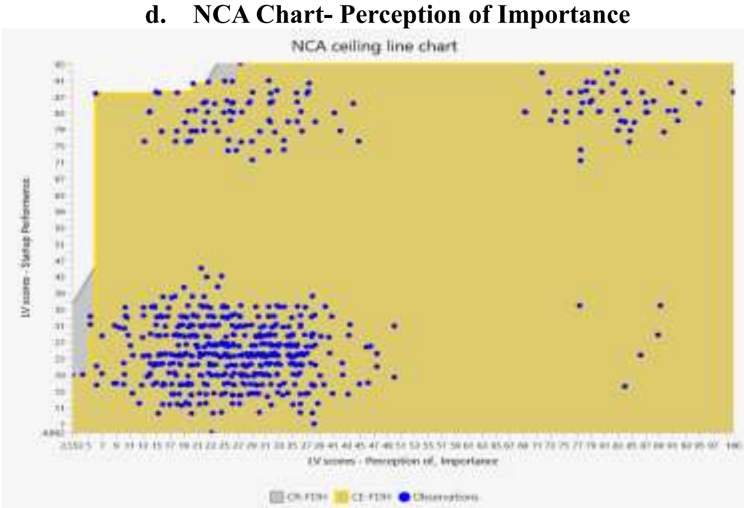
Source: SmartPLS 4 Output

c. NCA Chart - Perception of Effectiveness



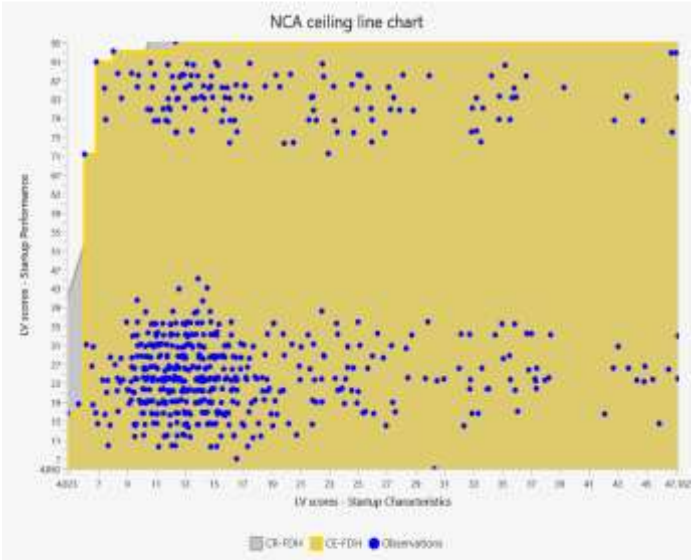
Source: SmartPLS 4 Output

d. NCA Chart- Perception of Importance



Source: SmartPLS 4 Output

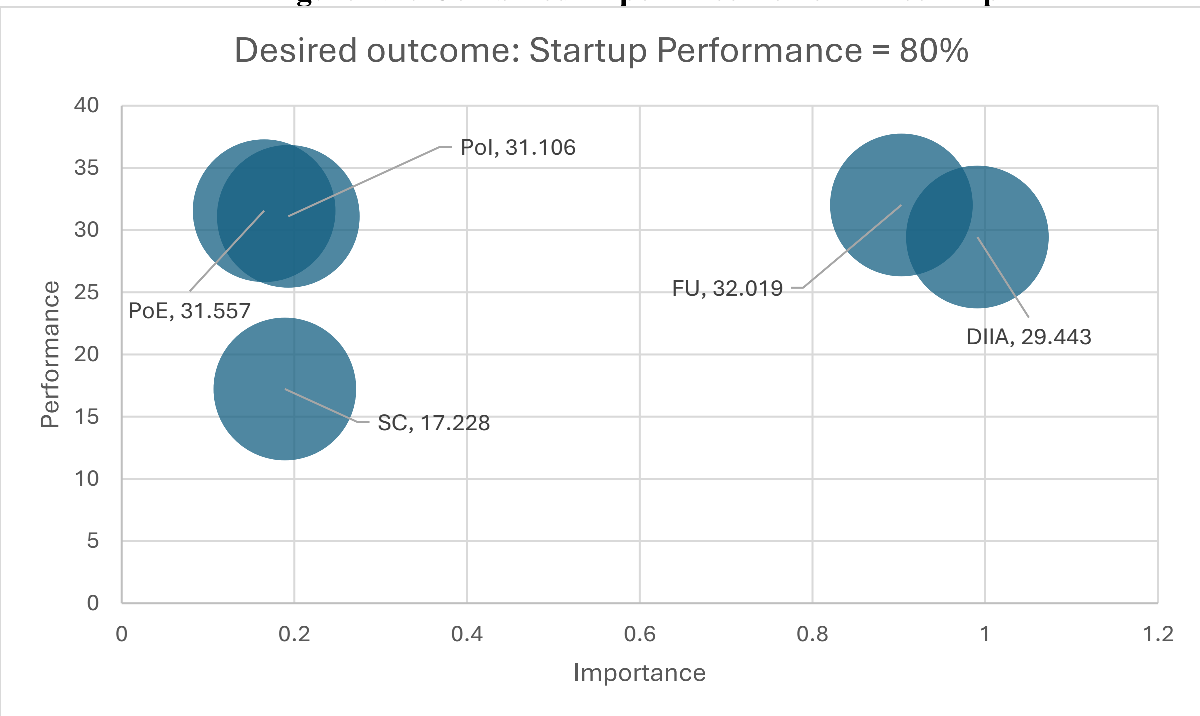
e. NCA Chart- Startup Characteristics



Source: SmartPLS 4 Output

Figure 4.19 (a) NCA Charts – Degree of Incubators' Intervention and Assistance; (b) NCA Chart – Frequency of Usage; (c) NCA Chart - Perception of Effectiveness; (d) NCA Chart- Perception of Importance; (e) NCA Chart- Startup Characteristics

Figure 4.20 Combined Importance-Performance Map



Source: SmartPLS 4 Output

The integration of findings from Table 4.28 (Bottleneck Analysis) and Figure 4.20 (Combined Importance-Performance Map) provides a comprehensive understanding of the necessary and sufficient conditions required to achieve the target startup performance level of 80%. Figure 4.20 plots the importance (total effects) of each predictor variable on the X-axis and their performance (average latent scores) on the Y-axis, with bubble sizes representing the percentage of cases that fail to meet the 80% satisfaction threshold. The analysis reveals that Degree of Incubator Intervention and Assistance (DIIA) and Frequency of Usage (FU) are positioned in the upper-right quadrant, indicating high importance and moderate performance. However, the large bubble sizes associated with these variables suggest that a considerable number of startups fall short of the required thresholds, confirming them as critical bottlenecks. This is supported by Table 4.26, which shows that DIIA and FU have the highest minimum requirements at 100% performance, along with significant necessity effects. Perception of Effectiveness (PoE) and Perception of Importance (PoI), though lower in importance, exhibit moderate performance and similarly large bubble sizes, indicating that these are necessary but less influential constructs. Startup Characteristics (SC), while lowest in both importance and performance, also appears as a bottleneck for a subset of startups, emphasising the need to strengthen foundational capacities. All five predictors are statistically significant necessary conditions ($p < .001$), with effect sizes ranging from 0.033 to 0.072, which fall within the small effect range, as per Dul (2016). These results suggest that achieving high levels of startup performance requires not only improving performance on high-importance constructs, such as DIIA and FU, but also ensuring that necessary thresholds are met across all key predictors.

4.9 SUMMARY

Chapter 4 presents a detailed interpretation of the empirical data collected from 612 incubated startups located in Goa, Karnataka, and Maharashtra. The analysis begins with the demographic profiling of the respondents, which revealed several key trends ***(Refer Table 4.3 , Page no.100).*** A majority of the respondents were male (73.7%), and most belonged to the age group of 31–40 years (47.4%), suggesting that startup leadership is largely male-dominated and concentrated among early- to mid-career professionals. The respondents were highly educated, with 46.6% holding postgraduate degrees. In terms of the startup characteristics, the majority of ventures were in the Early Traction stage (41.7%), service-oriented (51.3%), and had been incubated for up to one year (46.4%). Most teams had 4–7 members (35.9%), operated in the B2C market (41.18%), and were largely concentrated in the HealthTech sector (28.76%).

The next stage involved assessing the measurement model using SmartPLS 4. Reliability and validity tests confirmed that all constructs met the required thresholds. Indicator loadings exceeded 0.7 ***(Refer Table 4.5 , Page no.113)***, Cronbach's Alpha and Composite Reliability values were above 0.7 ***(Refer Table 4.6 , Page no.115)***, Average Variance Extracted (AVE) values were above 0.5 ***(Refer Table 4.7 , Page no.116)***, and discriminant validity was established using the HTMT criterion, Fornell-Larcker criterion and using indicator and cross loadings ***(Refer Table 4.8, 4.9 and 4.10 on Pages no.117 and 118)***. With the reflective measurement model validated, further reflective measurement model assessment was done. Convergent validity of the second-order construct, *Startup Characteristics*, was confirmed through redundancy analysis, with the PLS-SEM algorithm yielding a path coefficient of 0.813, exceeding the recommended threshold of 0.70 ***(Refer Figure 4.12 , Page no.122)***. Additionally, collinearity analysis was performed to assess the formative indicators, where Variance Inflation Factor (VIF) values were obtained using the PLS-SEM algorithm ***(Refer Table 4.12 , Page no.123)***. The results indicated that collinearity was not a concern, affirming the robustness of the measurement model. The significance of the second-order construct's formative indicators was assessed through bootstrapping. Results revealed that *Skills* (SKL → SC) had a significant contribution (outer weight = 0.568, $t = 2.206$, $p = 0.027$), while *Experience* and *Network* were not statistically significant ***(Refer Table 4.13 , Page no.124)***. However, since all outer loadings exceeded 0.50 (Ramayah et al., 2016), these indicators were retained, confirming their absolute importance in forming the *Startup Characteristics* construct ***(Refer Table 4.14 , Page no.124)***. Further, the structural model was analyzed to test the hypothesized relationships among the key constructs ***(Refer Table 4.17 , Page no.127)***. The results supported hypotheses H1b, H2a, H3a, H3b, H6, and H7 ($p < 0.05$), confirming significant positive effects of *Startup Characteristics* on *Frequency of Usage*, *Perception of Importance*, and *Startup Performance*, as well as the influence of *Perception of Importance* and *Perception of Effectiveness* on *Frequency of Usage*, and *Frequency of Usage* on *Startup Performance*. However, H2b (*SC → PoE*) was not supported, indicating that *Startup Characteristics* did not significantly influence *Perception of Effectiveness*.

Mediation analysis further revealed that perception of importance significantly mediated the relationship between startup characteristics and frequency of usage of incubation services, whereas perception of effectiveness did not ***(Refer Table 4.18 , Page no.128)***. This implies that the way startups value the importance of services plays a stronger role in determining service usage than their perception of how effective those services are. The moderation analysis examined the role of the Degree of Incubator's Intervention and Assistance (DIIA) in influencing two key relationships ***(Refer Table 4.19 , Page no.129)***. While DIIA did not significantly moderate the relationship between startup characteristics and service usage, it significantly moderated the relationship between frequency of usage and startup performance. Interestingly, the negative coefficient suggests that excessive incubator intervention might slightly reduce the positive effect of service usage on performance, possibly due to over-reliance or reduced autonomy.

The Multi-Group Analysis (MGA) results ***(Refer Table 4.27 , Page no.140)*** examined gender-based moderation (H8a–H8g) using PLS-MGA, Parametric, and Welch–Satterthwaite tests. Findings indicated that most path differences between male and female groups were statistically non-significant ($p > 0.05$), except for H8d (*Startup Characteristics → Frequency of Usage*), which showed a significant difference across all three methods ($p < 0.01$), confirming partial moderation by gender.

Importance-Performance Map Analysis (IPMA) identified startup characteristics and frequency of usage as high-impact constructs with strong performance, highlighting their strategic importance in driving startup success ***(Refer Figure 4.18 , Page no.143)***. Lastly, Necessary Condition Analysis (NCA) confirmed that both startup characteristics and frequency of usage were essential conditions for achieving high performance—suggesting that without these, success is unlikely even if other factors are favorable ***(Refer Figure 4.20 , Page no.148)***.

In summary, Chapter 4 offers strong empirical support for the proposed conceptual model and demonstrates how various factors within the business incubation process interact to influence startup performance. These findings serve as a crucial foundation for the conclusions, practical implications, and recommendations presented in the final chapter.

CHAPTER 5

SUMMARY, FINDINGS, CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This chapter summarises the key findings of the study and integrates them into a set of objective-wise conclusions. The chapter also presents the theoretical and practical implications of the findings, outlines the study's limitations, and suggests directions for future research to strengthen the understanding of Technology Business Incubators (TBIs) and their impact on startup performance.

5.1 INTRODUCTION

This chapter presents a comprehensive overview of the study by summarising its objectives, methodology, and main results. It summarises the significant empirical findings derived from the analysis and discusses their implications in relation to the existing body of literature. Based on these insights, the chapter outlines the primary conclusions drawn from the research and reflects on their theoretical, practical, and policy-related contributions. Additionally, it identifies limitations encountered during the study and proposes directions for future research that can build upon the current findings to deepen understanding and expand knowledge within the domain.

5.2 SUMMARY

The study has developed a relational model that examines the linkages between startup characteristics and the support services provided by business incubators. This includes an assessment of usage patterns of these services, as well as the perceptions of incubated startups regarding the importance and effectiveness of such interventions. The model further integrates the degree of intervention and assistance offered by incubators and evaluates their influence on overall startup performance. Grounded in the theoretical framework of new venture performance and aligned with the research of Gartner (1985), Cooper (1993), and Afriana (2018), the model incorporates the business incubation process as a critical component to understand its intermediary role in enhancing startup outcomes. By incorporating the incubation process into the model, the study aims to understand how incubators act not only as service providers but also as active contributors to startup success through customised support. This approach enables a complete evaluation of how effective the incubation process is in helping startups grow. The data collected from incubated startups reflects their actual experiences, including how they utilised the services and the opinions they formed during their time in the incubation program. These insights help explain how startups engage with incubators and how they perceive the support they receive as influencing their performance and growth. In the literature review, the initial model (Figure 2.2) served as a framework for identifying key factors that impact business incubation programs and the performance of startups. These identified factors were then included in the questionnaire and used as measurement indicators for constructing and evaluating the final model. With these objectives in focus, the present study was undertaken to assess the impact of Technology Business Incubators (TBIs) on the performance of startups. To achieve this, a representative sample of startup founders was selected from key entrepreneurial hubs across three Indian states - Goa (North and South Goa), Karnataka (Bangalore and Hubli), and Maharashtra (Mumbai). These regions were chosen due to their active startup ecosystems and the presence of well-established incubation programs.

To guide the empirical analysis, a set of clearly defined research objectives was formulated. These objectives served as the basis for developing corresponding hypotheses that were empirically tested using data collected from incubated startups. The findings of this research not only aim to offer evidence-based insights into the effectiveness of TBIs but also to provide practical recommendations for improving incubation strategies and fostering startup success across diverse regional contexts.

For the **first objective**, the analysis confirmed that Startup Characteristics have a significant positive influence on the Frequency of Usage of incubator support services ($\beta = 0.14, p = 0.005$). Startups led by experienced, skilled, and well-networked entrepreneurs were more inclined to use incubator facilities regularly and effectively, demonstrating that human and social capital play a decisive role in shaping engagement behavior. With regard to the **second objective**, Startup Characteristics were found to significantly influence the Perception of Importance of incubator services ($\beta = 0.126, p = 0.012$), though their effect on the Perception of Effectiveness was not significant ($\beta = 0.077, p = 0.181$). This suggests that while experienced entrepreneurs recognize the relevance and necessity of incubation support, they may critically assess its effectiveness, reflecting their selective evaluation of service quality. Under the **third objective**, both Perception of Importance ($\beta = 0.191, p < 0.001$) and Perception of Effectiveness ($\beta = 0.181, p = 0.002$) were found to significantly affect the Frequency of Usage of incubator services. These results validate the view that cognitive evaluations, how entrepreneurs perceive the value and quality of incubator support and that strongly determines their behavioral engagement. The **fourth objective** explored the mediating role of these perceptions and revealed partial mediation through Perception of Importance ($\beta = 0.024, p = 0.053$), but no significant mediation through Perception of Effectiveness ($\beta = 0.014, p = 0.26$). This highlights that recognizing the importance of services, rather than judging their efficiency, primarily drives startups' active utilization of incubation offerings.

The **fifth objective** focused on the moderating role of the Degree of Incubator's Intervention and Assistance (DIIA). The results showed that DIIA did not significantly moderate the relationship between Startup Characteristics and Frequency of Usage ($\beta = 0.066, p = 0.308$), suggesting that engagement is primarily determined by the startups' internal attributes. However, DIIA significantly strengthened the relationship between Frequency of Usage and Startup Performance ($\beta = -0.09, p < 0.001$), indicating that higher levels of tailored mentoring, networking, and resource support amplify the performance benefits derived from frequent incubator engagement.

The **sixth objective** examined the direct influence of Frequency of Usage on Startup Performance and found a strong, positive relationship ($\beta = 0.498, p < 0.001$). This confirms that startups that engage more frequently with incubator services achieve superior performance in terms of growth, innovation, and market expansion, highlighting the practical significance of active participation.

The **seventh objective** demonstrated that Startup Characteristics have a direct and significant impact on Startup Performance ($\beta = 0.191, p < 0.001$), independent of mediation or moderation effects. This finding reinforces the centrality of intrinsic entrepreneurial capabilities such as prior experience, technical expertise, and managerial competence in determining venture success.

Finally, the **eighth objective** assessed the moderating role of Gender across the structural relationships. The Multi-Group Analysis revealed that gender significantly moderated only the relationship between Startup Characteristics and Frequency of Usage ($t = -1.959, p = 0.004$), indicating that gender differences influence how entrepreneurial traits translate into engagement behavior. The remaining relationships were not significant, suggesting that male and female founders perceive and utilize incubation support in broadly similar ways.

Taken together, the findings confirm that startup performance within TBIs is the outcome of a complex interaction between entrepreneurial inputs, cognitive mediators, and institutional mechanisms. Startup Characteristics and Perceptions jointly drive engagement behavior, while the Degree of Incubator's Intervention magnifies the effect of usage on performance. Gender-based differences, though limited, reveal subtle variations in how entrepreneurs engage with incubation services.

5.3 FINDINGS & CONCLUSIONS

The findings of this study are presented in two parts: the first part focuses on the demographic profile of the respondents. In contrast, the second part outlines the findings corresponding to each research objective.

5.3.1 FINDINGS FROM THE DEMOGRAPHIC PROFILE

The study examined various demographic characteristics of the respondents, including age, gender, educational background, stage of the startup, type of offering (product, service, or both), duration of incubation, team size, nature of the target market, and market segment ***(refer to Chapter 4, Table 4.3, Page No.100)***. These factors provide essential context for understanding the profile of the incubated startups. A summary of the key demographic trends observed in the study is presented in Table 5.1.

Table 5.1 Demographic Trends- Dominant Characteristics

Demographic characteristics	Category	No. of respondents with %
Gender	Male	451 (73.7)
Age	31 to 40 years	290 (47.4)
Education	Post-Graduation	285 (46.6)
Stage	Early Traction	255(41.7)
Product/Service or both	Service	314 (51.3)
Duration of Incubation	Up to 1 year	284 (46.4)
Team-size	4-7 members	220 (35.9)
Nature of the Market	B2C	252 (41.18)
Segment of the startup	HealthTech	176 (28.76)

Source: Compiled from primary data

The demographic profile of the respondents, as presented in Table 5.1 above, reveals several significant trends that help contextualise the overall analysis of startup performance. A considerable majority of the respondents were male (73.7%), indicating that entrepreneurship within the studied incubation centres remains largely male-dominated. In terms of age distribution, the largest group of founders (47.4%) fell within the 31–40 years category, reflecting the participation of early- to mid-career professionals who likely possess a mix of industry experience and entrepreneurial drive.

Regarding educational qualifications, nearly half of the respondents (46.6%) had completed post-graduate studies, suggesting a relatively high level of academic preparedness among incubated entrepreneurs. This is indicative of a knowledge-driven startup ecosystem, where formal education may play a key role in business planning and execution.

The majority of startups were found to be in the Early Traction stage (41.7%), indicating that most had moved beyond the ideation phase and were beginning to establish their market presence. Service-oriented startups comprised the most significant portion (51.3%), highlighting the prominence of the service sector, which may be attributed to its lower capital requirements and faster deployment compared to product-based ventures.

When analysing the duration of incubation, most startups (46.4%) had been engaged with the incubators for up to one year. This highlights the early phase of their journey within the incubation environment, where structured support and interventions are most crucial.

Team sizes were generally small, with 35.9% of startups comprising 4 to 7 members, a typical feature of early-stage ventures striving for agility and efficient resource management.

A substantial proportion of startups (41.18%) operated in the Business-to-Consumer (B2C) market, indicating a strong focus on direct consumer engagement and customer-driven value creation.

Among industry sectors, HealthTech emerged as the most represented segment (28.76%), reflecting the growing importance of technology-enabled healthcare solutions in response to evolving public health needs and digital transformation trends.

5.3.2 OBJECTIVE-WISE FINDINGS OF THE STUDY

This section presents the study's significant findings, organised according to the eight research objectives. Drawing on the statistical analysis presented in the previous chapter, the results highlight how startup characteristics, perceptions of incubator support, usage patterns, the degree of incubator intervention, and gender collectively influence startup performance within Technology Business Incubators (TBIs).

As outlined in Chapter 1, the primary objectives of this study are as follows:

RO1: To examine the influence of startup characteristics on the frequency of usage of support services offered by Technology Business Incubators (TBIs).

RO2: To assess the impact of startup characteristics on startups' perception of the importance and effectiveness of incubator support services.

RO3: To analyse how startups’ perceptions of the importance and effectiveness of incubator services influence their frequency of usage.

RO4: To examine the mediating role of Perception of Importance (PoI) and Perception of Effectiveness (PoE) in the relationship between Startup Characteristics (SC) and Frequency of Usage (FU) of incubator services.

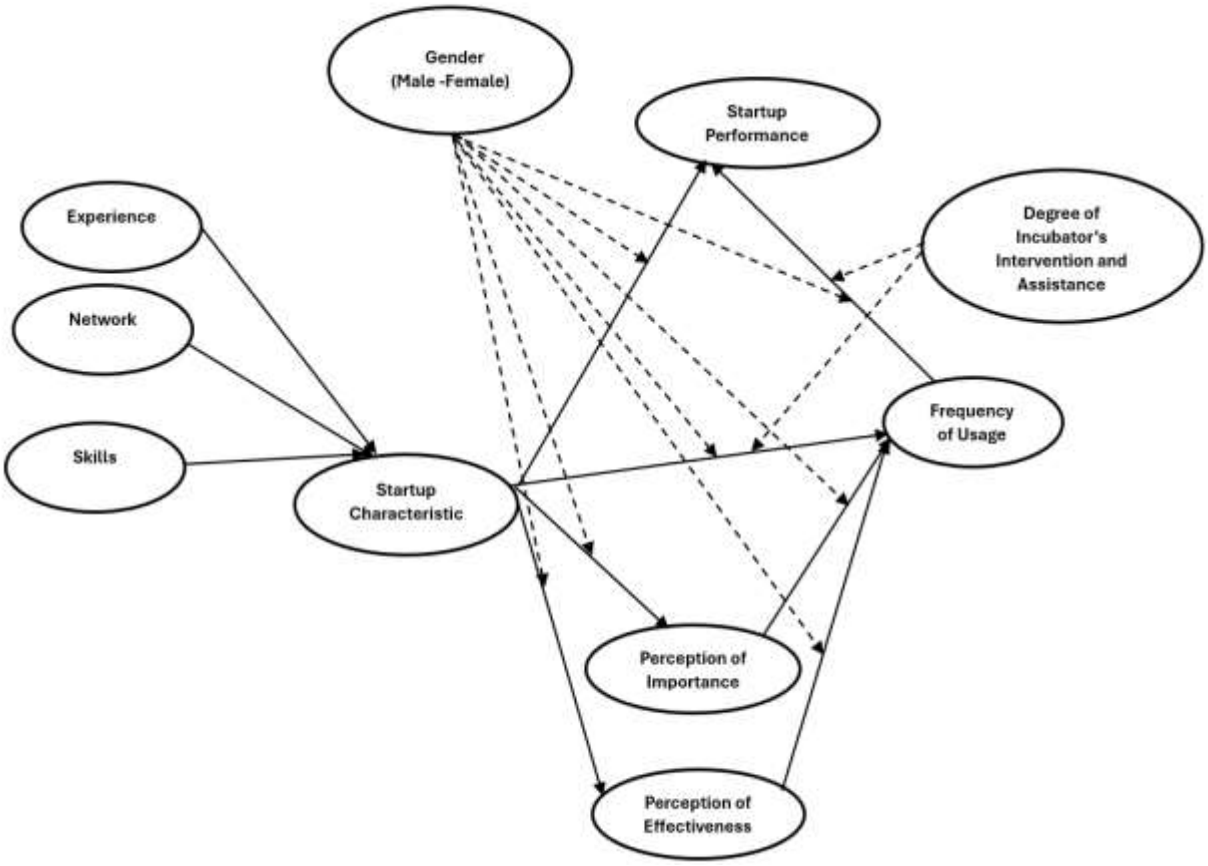
RO5: To investigate whether the Degree of Incubator’s Intervention and Assistance moderates (a) the relationship between frequency of usage and startup performance, and (b) the relationship between startup characteristics and frequency of usage.

RO6: To evaluate the extent to which the frequency of usage of incubator support services affects startup performance.

RO7: To determine whether startup characteristics have a direct effect on startup performance, independent of any mediating constructs.

RO8: To explore the moderating role of gender in the relationships among startup characteristics, perceptions of incubator support, frequency of usage, and startup performance.

Fig 5.1 Final tested Model



Source: Compiled by author

Findings from Objective 1: Influence of Startup Characteristics on Frequency of Usage of Incubator Support Services

The key findings are as follows:

- Hypothesis H1b proposed a positive relationship between Startup Characteristics (SC) and Frequency of Usage (FU) of incubator support services ***(refer to Chapter 4, Table 4.17, Page No.125)***. The structural model confirmed this relationship as statistically significant ($\beta = 0.14$, $t = 2.838$, $p = 0.005$), thereby supporting H1b**.**
- The results indicate that startups with stronger characteristics—such as prior entrepreneurial experience, technological capability, and network strength—are more likely to use incubator services frequently and systematically.

- Founders who possess prior exposure to entrepreneurship or small-business management exhibit greater confidence, strategic clarity, and self-reliance, enabling them to make better use of incubation resources and programs.
- These findings reinforce the notion that human and social capital are central determinants of engagement within incubation environments.
- They are consistent with previous studies, which found that entrepreneurs' experience, education, and network relationships significantly shape the extent of incubator participation and benefit realisation (A. C. Cooper, 1993; Pena, 2004; Monsson & Jørgensen, 2016; Hughes et al., 2007; Scillitoe & Chakrabarti, 2010).

Findings from Objective 2: Influence of Startup Characteristics on Perceptions of the Importance and Effectiveness of Incubator Support Services

- Hypotheses H2a and H2b examined whether Startup Characteristics (SC) significantly influence startups' Perception of Importance (PoI) and Perception of Effectiveness (PoE) of incubator services, respectively ***(refer to Chapter 4, Table 4.17, Page 125)***.
- The structural model revealed that H2a was supported, showing a significant positive relationship between SC and PoI ($\beta = 0.126$, $t = 2.51$, $p = 0.012$). This suggests that startups with stronger entrepreneurial backgrounds, managerial experience, and domain expertise are more likely to view incubator services as essential for their business development. Such entrepreneurs tend to recognise the strategic value of incubation offerings and display higher appreciation for their relevance to venture growth.
- In contrast, H2b was not supported ($\beta = 0.077$, $t = 1.338$, $p = 0.181$), suggesting that startup characteristics do not significantly shape founders' perceptions of the effectiveness of these services. Although experienced entrepreneurs value incubation programs, they may not necessarily view them as more effective—possibly because their prior exposure to entrepreneurship makes them more critical or selective in judging program outcomes.
- These results support prior research emphasising that cognitive and experiential heterogeneity among entrepreneurs influences how they interpret and evaluate incubation support (Bergek & Norrman, 2008; Hackett & Dilts, 2004; Colombo & Grilli, 2005). They also align with Bøllingtoft & Ulhøi (2005b), who argued that incubation programs should be customised to accommodate varying levels of entrepreneurial capability and prior experience.

Findings from Objective 3: Influence of Perceptions of Importance and Effectiveness on Frequency of Usage of Incubator Support Services

- Hypotheses H3a and H3b tested the effect of startups' Perception of Importance (PoI) and Perception of Effectiveness (PoE) on the Frequency of Usage (FU) of incubator services. The structural model supported both hypotheses ***(refer to Chapter 4, Table 4.17, Page No. 125)***.
- The path from PoI → FU was significant ($\beta = 0.191$, $t = 3.667$, $p = 0.000$), confirming H3a, while the relationship PoE → FU was also significant ($\beta = 0.181$, $t = 3.04$, $p = 0.002$), supporting H3b. These findings demonstrate that startups that perceive incubator services as important and effective tend to utilise them more frequently and consistently.
- This outcome supports the Theory of Planned Behaviour (Ajzen, 1991) and the Theory of Reasoned Action (Fishbein & Ajzen, 1975), both of which posit that positive attitudes toward an offering lead to stronger behavioural engagement. Empirically, similar results were observed by Abduh et al. (2007) and Phan et al. (2005), who found that startups perceiving services as useful and effective are more likely to participate actively in incubation activities.
- In essence, the findings highlight that cognitive evaluations—how essential and effective entrepreneurs believe incubation services to be—serve as crucial behavioural drivers of engagement. When founders perceive high value in these services, they demonstrate more substantial commitment, higher utilisation frequency, and greater participation in the incubation process.

Findings from Objective 4: Mediation of Perceptions between Startup Characteristics and Frequency of Usage of Incubator Support Services

- This objective examined whether the perceptions of incubator services, specifically the Perception of Importance (PoI) and Perception of Effectiveness (PoE), mediate the relationship between Startup Characteristics (SC) and Frequency of Usage (FU).
- The results revealed that H4a, representing the indirect path SC → PoI → FU, was supported, with the mediation effect found to be significant at the 5% level ($\beta = 0.024$, $t = 1.938$, $p = 0.053$) ***(refer to Chapter 4, Table 4.18, Page No. 126)***.

- This suggests that startups with stronger entrepreneurial characteristics, such as prior experience, managerial skills, and network strength, are more likely to perceive incubator services as necessary. Consequently, this enhanced perception increases their level of engagement and usage. The mediation is partial, as the direct path between SC and FU also remained significant.
- Conversely, H4b, representing the indirect path SC → PoE → FU, was not supported (β = 0.014, t = 1.126, p = 0.26*), suggesting that perceiving services as effective does not significantly mediate the relationship between startup characteristics and their usage behaviour.
- In other words, while entrepreneurs' backgrounds and experiences lead them to value incubator services as necessary, their view of service effectiveness does not necessarily influence how often they engage with these services.
- These findings underscore the crucial role of cognitive appraisal—particularly perceived *importance*—in linking entrepreneurial characteristics with behavioural outcomes. Similar mediation effects have been documented in previous studies emphasising the role of psychological and perceptual mechanisms in entrepreneurial decision-making (Baron & Baron, 2008; van Weele et al., 2017; Albort-Morant & Ribeiro-Soriano, 2016)
- Overall, the results highlight that it is the entrepreneurs' recognition of *why* services matter, rather than their perception of *how well* they are delivered, that primarily drives engagement with incubation programs.

Findings from Objective 5: Moderating Role of Degree of Incubator's Intervention and Assistance (DIIA)

- This objective examined whether the Degree of Incubator's Intervention and Assistance (DIIA) moderates two key relationships in the model: (1) between Startup Characteristics (SC) and Frequency of Usage (FU), and (2) between Frequency of Usage (FU) and Startup Performance (SP) ***(refer to Chapter 4, Table 4.19, Page No. 127)***.
- The structural model results revealed contrasting outcomes for the two hypotheses.
- For H5a, representing the moderating effect of DIIA on the SC → FU path, the relationship was not supported (β = 0.066, t = 1.02, p = 0.308). This indicates that the level of incubator intervention and support does not significantly alter the influence of startup characteristics

on their frequency of using incubator services. In essence, startups' intrinsic traits—such as experience, skill, and network strength—independently determine how actively they engage with incubator offerings, regardless of the intensity of institutional assistance provided.

- However, H5b, which proposed that DIIA moderates the relationship between Frequency of Usage (FU) and Startup Performance (SP), was supported (*β* = –0.09, *t* = 3.784, *p* < 0.001*). This finding confirms that the effect of usage on performance varies significantly with the level of incubator intervention.
- Startups that frequently utilise incubator services and simultaneously receive higher levels of tailored mentoring, networking, and resource support experience greater improvements in performance outcomes.
- These results suggest that while the degree of incubator assistance does not influence *how often* startups use services, it does affect *the degree of benefit that usage provid*es for performance. High levels of incubator engagement strengthen the positive effects of usage by enhancing learning, capability development, and access to critical networks.
- This pattern is consistent with previous studies by Hackett & Dilts (2008), who found that high-intensity incubation programs generate superior venture outcomes, and by Vanderstraeten & Matthyssens (2012), who argued that incubator intervention amplifies rather than substitutes for entrepreneurs' inherent capabilities.

Findings from Objective 6: Influence of Frequency of Usage on Startup Performance

- Hypothesis H6 proposed a positive relationship between the Frequency of Usage (FU) of incubator support services and Startup Performance (SP). The structural model results strongly supported H6, indicating a statistically significant and robust relationship (*β* = 0.498, *t* = 12.003, *p* < 0.001*) ***(refer to Chapter 4, Table 4.17, Page No. 125)***.
- This finding demonstrates that startups that utilise incubator facilities more consistently and actively—such as through mentoring programs, training sessions, networking opportunities, and shared infrastructure—tend to exhibit higher levels of performance.
- Frequent engagement enables startups to access specialised knowledge, technical assistance, and collaborative networks, which in turn enhance growth, innovation, and survival prospects.

- The result aligns with the resource-based and knowledge-based perspectives, suggesting that regular utilisation of incubator resources strengthens a startup's intangible assets and dynamic capabilities.
- It also reinforces the view that the benefits of incubation are realised not merely through the availability of services but through their sustained and strategic use.
- Similar empirical evidence has been reported by Schwartz & Hornych (2010), A. Amezcua (2010), and Bruneel et al. (2012), who found that consistent participation in incubation programs significantly improves venture performance by facilitating experiential learning, capability development, and market exposure.
- In summary, the findings confirm that frequency of usage acts as a crucial behavioural mediator connecting incubator support to tangible entrepreneurial outcomes. The higher the degree of engagement, the greater the positive impact on startup performance.

Findings from Objective 7: Direct Effect of Startup Characteristics on Startup Performance

- Hypothesis H7 examined whether Startup Characteristics (SC) have a direct and significant influence on Startup Performance (SP), independent of any mediating or moderating constructs.
- The structural model results supported H7, revealing a statistically significant positive relationship between SC and SP ($\beta = 0.191$, $t = 4.351$, $p < 0.001$*) ***(refer to Chapter 4, Table 4.17, Page No. 117)***.
- This finding confirms that startups possessing stronger internal characteristics—such as prior entrepreneurial experience, managerial capability, technical expertise, and social capital—tend to achieve better performance outcomes. These characteristics contribute directly to the venture's ability to innovate, adapt, and sustain growth, even beyond the formal support mechanisms of incubation programs.
- The result aligns with the Resource-Based View (RBV) and Human Capital Theory, both of which emphasise that the quality of founders' experience and knowledge constitutes a critical strategic resource influencing business success. It also supports earlier empirical findings by Davidsson & Honig (2003), Unger et al. (2011), and Colombo & Grilli (2010), who reported that human and social capital significantly predict entrepreneurial performance and growth.

- Overall, this relationship highlights that while incubator services can enhance startup outcomes, the intrinsic attributes of the founding team remain a core determinant of long-term success.
- Entrepreneurs who enter incubation programs with strong skills, experience, and networks are better equipped to leverage available resources, translate opportunities into results, and sustain superior performance in competitive markets.

Findings from Objective 8: Gender as a Moderator

- This objective examined whether gender moderates the key relationships among startup characteristics, perceptions of incubator support, frequency of usage, and startup performance.
- The analysis was conducted using Multi-Group Analysis (MGA) in SmartPLS, comparing structural paths between male- and female-led startups to determine the presence of significant differences in the hypothesised relationships.
- The results revealed that among the seven hypothesised moderation effects (H8a–H8g), only one, H8a, was statistically significant ***(refer to Chapter 4, Table 4.27, Page No. 129)***.
- Specifically, H8a, which assessed the moderation of gender in the relationship between Startup Characteristics (SC) and Frequency of Usage (FU), was significant ($t = -1.959$, $p = 0.004$).
- This suggests that gender differences meaningfully affect how startup characteristics influence the usage of incubator services.
- The negative sign suggests that the relationship between SC and FU is stronger among one gender group (likely male founders, depending on the directionality of the test) and weaker for the other.
- In practical terms, this implies that gender moderates the behavioural translation of entrepreneurial characteristics into engagement with incubation services.
- In contrast, the remaining paths—H8b (PoE → FU), H8c (SC → PoE), H8d (PoE → FU, duplicate test for robustness), H8e (PoI → FU), H8f (FU → SP), and H8g (SC → SP)—were not significant ($p > 0.05$). This indicates that, except for the SC–FU relationship, the influence of gender on the structural relationships among perception, usage, and performance was statistically insignificant.

- Overall, these results suggest that gender-based differences exist primarily in how startup characteristics translate into behavioural engagement. At the same time, other relationships within the model—particularly those linking perceptions, usage, and performance—remain largely consistent across male and female entrepreneurs.
- These findings partially align with prior research highlighting gender-based variations in entrepreneurial engagement and cognitive processing (Díaz-garcía & Jiménez-moreno, 2010; Jennings & Brush, 2013).
- While some studies argue that women may place greater emphasis on relational and experiential learning aspects of incubation, the present study finds that gender differences are not universal across all dimensions.
- The results underscore the need for gender-sensitive incubation strategies, where programs consider the distinct motivational and experiential patterns that influence entrepreneurs' engagement and utilisation behaviours.

Across all eight objectives, the findings confirm that startup performance within TBIs emerges from the complex interplay of entrepreneurial inputs (Startup Characteristics)**,** cognitive mediators (Perceptions of Importance and Effectiveness)**,** and institutional mechanisms (Usage and Intervention)**.** While startup characteristics and perceptions drive engagement, incubator intervention amplifies its impact on performance. Gender differences, though limited, highlight nuanced behavioural variations that warrant policy attention.

5.4. CONCLUSION OF THE STUDY

This section presents the study's conclusions, aligned with each of the eight research objectives. The empirical results provide clear evidence that a single determinant does not shape startup performance; rather, it is the outcome of interconnected relationships among entrepreneurial inputs, cognitive mediators, and institutional mechanisms. Specifically:

Objective 1: The findings confirm that Startup Characteristics, such as prior experience, managerial skills, and professional networks, serve as foundational inputs that significantly influence the frequency of engagement with incubator support services. Startups led by experienced founders with stronger social and cognitive resources are more inclined to utilise incubator facilities regularly, underscoring the role of entrepreneurial capital in driving participation.

Objective 2: The analysis revealed that Startup Characteristics influence founders' perception of the importance of incubator services, while the effect on perceived effectiveness was comparatively weaker. This suggests that while internal competencies determine awareness of service relevance, satisfaction with effectiveness is more closely tied to the incubator's delivery and support mechanisms.

Objective 3: Results demonstrate that Perceptions of Importance and Effectiveness significantly influence the Frequency of Usage. Startups that attach higher importance and believe in the effectiveness of incubator support are more likely to engage actively, confirming that cognitive evaluation drives behavioural engagement.

Objective 4: The study found that Perception of Importance acts as a significant mediating mechanism, strengthening the link between startup characteristics and service utilisation. However, the Perception of Effectiveness did not mediate this relationship, indicating that perceived relevance, rather than perceived quality, motivates consistent usage.

Objective 5: Moderation analysis revealed that DIIA significantly enhances the positive effect of Frequency of Usage on Startup Performance**,** confirming the complementary value of institutional support. However, the moderating effect of DIIA on the link between Startup Characteristics and Frequency of Usage was not significant, implying that incubator intervention cannot replace the influence of strong entrepreneurial capabilities.

Objective 6: A positive and significant relationship was found between Frequency of Usage and Startup Performance, affirming that sustained engagement with mentoring, networking, and funding opportunities leads to improved growth and innovation outcomes.

Objective 7: The results confirm that Startup Characteristics have a direct and independent effect on Startup Performance, supporting the Resource-Based View (RBV) that internal competencies and founder capabilities are enduring sources of competitive advantage, even beyond the mediation of perceptions or behaviours.

Objective 8: A multi-group analysis showed that Gender moderates selective pathways, notably the relationship between Startup Characteristics and Frequency of Usage. While male and female founders exhibit nuanced behavioural differences, the overall model structure remains consistent across genders.

Overall, the study validates the Input–Mediator–Outcome (IMO) framework, demonstrating that entrepreneurial success within incubation ecosystems results from the dynamic interaction between startup inputs, cognitive and behavioural processes, and institutional facilitation.

5.5 THEORETICAL IMPLICATIONS

This study contributes to theory in several significant ways:

1. **Extension of the IMO Framework to Entrepreneurship Research**: By integrating the Input–Mediator–Outcome framework into the context of business incubation, this research provides a holistic theoretical lens for understanding how entrepreneurial inputs (experience, skills, networks) translate into performance outcomes through mediating perceptions and engagement behaviour. It emphasises the processual nature of incubation and bridges organisational behaviour and entrepreneurship literature.
2. **Empirical Validation of Cognitive Mediation in Entrepreneurial Contexts:** The finding that *perception of importance* mediates the relationship between startup characteristics and engagement behaviour advances Entrepreneurial Cognition Theory. It shows that how founders *think* about incubation support—its relevance, necessity, and strategic importance—has a measurable effect on how they *act* within the incubation system.
3. **Integration of Resource-Based and Institutional Perspectives:** The study strengthens the Resource-Based View (RBV) and Human Capital Theory by empirically demonstrating that intrinsic entrepreneurial capabilities remain vital even within institutionalised incubation frameworks. At the same time, it complements these theories by incorporating the moderating influence of institutional support (DIIA), thereby linking firm-level and system-level perspectives.
4. **Gender as a Boundary Condition in Incubation Research:** By identifying gender-specific moderation effects, the study adds a nuanced dimension to incubation theory. It highlights that while structural mechanisms operate similarly across genders, the cognitive translation of entrepreneurial attributes into engagement varies, extending insights from

the Gender and Entrepreneurship literature (Díaz-garcía & Jiménez-moreno, 2010; Jennings & Brush, 2013).

5.6 MANAGERIAL AND POLICY IMPLICATIONS

From a practical perspective, the findings have several implications for incubator managers, policymakers, and entrepreneurs:

1. **Customisation of Incubator Services:** Since startup characteristics significantly influence perceptions and usage, incubators should adopt differentiated support models tailored to their specific needs. Tailoring mentoring, training, and networking activities based on startups' experience levels and sectoral backgrounds can improve perceived relevance and utilisation.
2. **Enhancing Perceived Importance through Communication and Orientation:** Since perceived importance strongly mediates engagement, incubators should prioritise clearly communicating the strategic value of their services during the onboarding stage. Regular orientation sessions and the dissemination of success stories can help startups recognise the importance of these services.
3. **Intensifying Degree of Intervention and Assistance:** The moderation effect of DIIA suggests that active, high-touch intervention yields better performance outcomes. Incubators should maintain a proactive mentoring system, with dedicated relationship managers ensuring consistent founder engagement, collecting feedback, and providing follow-up assistance.
4. **Strengthening Learning and Knowledge Networks:** As frequent usage correlates strongly with performance, TBIs should facilitate knowledge exchange platforms, collaborative events, and peer-to-peer learning networks that encourage continuous interaction and capability enhancement.
5. **Gender-Sensitive Incubation Policies:** The study found that gender moderates the influence of startup characteristics on engagement. Policymakers should therefore ensure inclusive incubation environments by offering gender-focused mentoring, networking opportunities, and flexible program designs that cater to diverse entrepreneurial needs.
6. **Capacity Building for Early-Stage Entrepreneurs:** Since founders with limited experience may underutilise incubation resources, targeted capacity-building workshops

on financial literacy, business modelling, and networking can enhance their readiness to benefit from incubation services.

7. **Policy Support for Continuous Engagement Metrics:** The government and funding agencies should encourage incubators to track engagement frequency as a performance metric, given its proven relationship with startup success. Incentivising incubators to achieve higher engagement rates could enhance the effectiveness of national incubation programs.

5.7 SUGGESTIONS FOR FUTURE RESEARCH

While this study makes several contributions, it also opens new avenues for scholarly inquiry:

- **Use Long-Term Studies**

This study used cross-sectional data, capturing startup performance at a single point in time. Future research could use a longitudinal design to track startups over a longer duration. This would provide a clearer picture of how incubator support influences startup growth at different stages—from ideation to scaling and beyond.

- **Study Specific Sectors Individually**

Startups from different industries have unique needs. Future research could focus on specific sectors, such as health tech, edtech, agritech, or fintech, to explore how incubation programs can be customised for different domains. This would help in designing sector-specific support services.

- **Add New Influencing Factors to the Model**

While this study focused on key variables such as service usage, perception, and degree of intervention, future studies can include additional factors, including founder education, digital literacy, prior entrepreneurial experience, and access to external funding. These factors may influence how startups benefit from incubator support.

- **Compare Incubation Across Regions or Countries**

Future research could compare TBIs across different states or countries to explore how regional economic conditions, policy environments, and cultural factors influence the effectiveness of incubation. Such comparisons can help identify best practices and challenges across geographies.

- **Explore Post-Incubation Outcomes**

The current study focused on startups that are still in the incubation phase. Future research could examine what happens after startups exit the incubator. Do they continue to grow? Do they receive further support? This would help understand the long-term impact of incubation programs.

- **Evaluate Incubator Management and Strategy**

Another area for future research is the internal functioning of incubators themselves. How do leadership, strategy, resource allocation, and governance affect the services they provide? Studying incubator management could uncover key factors that contribute to startup success.

- **Use Qualitative Methods for Deeper Insights**

While this study used quantitative methods, future research could adopt qualitative approaches such as interviews, focus groups, or case studies. These methods would provide rich, detailed insights into the experiences of startup founders and incubator managers.

- **Study the Entire Startup Ecosystem**

Incubators do not work in isolation. Future studies could explore the roles of other ecosystem players, such as co-working spaces, investors, universities, government agencies, and accelerators. Understanding this broader network can help identify how different actors contribute to startup development.

- **Focus on Gender and Inclusion**

This study touched on gender as a moderator. Future research can explore in more detail how women-led startups or those from rural and marginalised areas experience incubation. This can help design more inclusive and equitable incubation programs.

- **Include Non-Financial Measures of Performance**

Startup performance is often measured by revenue or growth. However, future research could include other success indicators, such as innovation capacity, social impact, sustainability, or customer satisfaction, to provide a more holistic evaluation of startup outcomes.

5.8 LIMITATIONS OF THE STUDY

While this study provides valuable theoretical and empirical insights into the dynamics of Technology Business Incubators (TBIs) and startup performance, several limitations should be acknowledged. These limitations do not undermine the findings but instead define the scope within which the results should be interpreted and provide direction for future research.

1. **Cross-sectional Design:** The study adopted a cross-sectional research design, capturing data from incubated startups at a single point in time. As a result, causal inferences regarding the long-term effects of startup characteristics, perceptions, and usage behaviour on performance are limited. Longitudinal studies could provide deeper insight into how these relationships evolve across different stages of incubation and post-incubation growth.
2. **Self-reported Data and Perceptual Measures:** Most constructs—such as perception of importance, perception of effectiveness, and frequency of usage—were measured using self-reported survey data. Although standard procedures were applied to minimise common method bias, self-reported data may be influenced by subjective interpretation or social desirability bias. Triangulation with secondary performance indicators (e.g., revenue growth, investment raised) could improve the robustness of future findings.
3. **Use of a Structured Questionnaire-**While structured questionnaires allow for systematic data collection, they may limit the depth of insights compared to qualitative methods. Respondents may also interpret fixed response options differently, which can affect consistency.
4. **Non-random Sampling-** The use of purposive or convenience sampling for reaching incubated startups—primarily due to the difficulty in accessing founders—could limit the representativeness of the sample, introducing sampling bias.
5. **Geographical and Institutional Scope:** The research focused primarily on TBIs located in selected Indian states (Goa, Maharashtra, and Karnataka). While this regional focus ensures contextual relevance, it may limit the generalizability of findings to other regions or countries where incubation ecosystems operate under different policies, economic, or cultural environments. Replicating the study across diverse geographies could validate the broader applicability of the results.

6. **Limited Moderators and Mediators:** The study included specific mediating and moderating constructs—Perceptions (PoI, PoE), Degree of Incubator Intervention (DIIA), and Gender. However, other potential variables such as entrepreneurial orientation, innovation capability, financial literacy, and risk tolerance were not examined. Including such constructs in future models may offer a more comprehensive understanding of incubation outcomes.
7. **Measurement of Startup Performance:** Startup performance in this study was assessed through subjective indicators (self-assessed growth, innovation, and market expansion). While these are consistent with established entrepreneurship research, objective performance metrics such as profitability, sales turnover, or funding raised were not included. Future research could combine both subjective and objective measures to provide a multidimensional evaluation of startup success.
8. **Variation in Incubator Models and Support Mechanisms:** TBIs differ in their management structures, sectoral specialisation, and service offerings. The present study treated TBIs as a relatively homogeneous group to maintain model parsimony. However, variations between public, private, and university-based incubators could influence how startups perceive and utilise support services. Future comparative studies could investigate these contextual nuances.
9. **Gender Distribution and Representativeness:** Although gender was examined as a moderating variable, the sample contained a relatively smaller number of female-led startups compared to male-led ventures. This uneven distribution may have constrained the detection of subtler gender effects. A more balanced sample in future studies would allow for stronger conclusions regarding gender differences in incubation outcomes.
10. **Use of PLS-SEM Analytical Approach:** The study employed Partial Least Squares Structural Equation Modelling (PLS-SEM), which is suitable for exploratory and prediction-oriented research. However, it focuses more on variance explanation than on model fit optimisation. Future research could validate these findings using Covariance-Based SEM (CB-SEM) or hybrid analytical approaches to strengthen model generalizability.
11. **Contextual Limitation to Technology-based Startups:** The sample primarily consisted of technology-oriented startups operating within TBIs. While this focus aligns with the study's objectives, non-technology or social ventures might exhibit different behavioural

patterns regarding perception, engagement, and performance. Comparative studies across diverse sectors could yield more generalised insights.

12. **Potential Influence of External Environmental Factors:** Macroeconomic variables, policy changes, and ecosystem maturity were not explicitly modelled in the analysis. These external factors may indirectly affect the relationships examined, particularly startup performance and incubator effectiveness. Including ecosystem-level variables in future frameworks could help contextualise incubation outcomes more accurately.

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ANNEXURE A: RESEARCH PAPER PRESENTATIONS

Research Paper Presentations

1. Presented a paper titled "Role of Government and Incubators in Fostering Entrepreneurship by Assisting in Startups Sustenance in India: A Review" at the 12^{th} Asian Society for Innovation and Policy (ASIP) Conference- 2022, organised by Indian Institute of Science (IISc) and M.S Ramaiah University of Applied Sciences (MSRUAS), Bangalore during 24-26 November 2022.

2. Presented a paper titled "Technology Business Incubators as Catalysts: Linking Support Service Usage to Startup Performance" at the One-Day International Conference on "Digital Innovations in Business and Service Sectors", organised by Departments of Commerce and Computing Sciences of Patrician College of Arts and Science in collaboration with Don Bosco Arts and Science College, Chennai in Online mode on 13^{th} September 2024.

3. Presented a paper titled "Influence of Incubated Startup's Behaviour on their Performance: An Empirical Study in India" at the International Conference in Emerging Trends in Research, Innovation & Entrepreneurship – A way forward jointly in association with Entrecon Global- World's First Global Startup Ecosystem on 24^{th} & 25^{th} September 2024.

ANNEXURE B: RESEARCH PAPER PUBLICATION

Noronha, C. L., & Pillai, S. K. V. B. (2025). Fostering startups through the vehicle of entrepreneurial support organisations like technology business incubators (TBIs): a systematic literature review. *Journal of Global Entrepreneurship Research*, *15*(4), https://doi.org/10.1007/s40497-024-00419-y

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ANNEXURE C- RESEARCH QUESTIONNAIRE

Respected Sir/Madam,

I am Ms. Concy Liberata Noronha, Ph.D. Research Scholar, Goa Business School, Goa University, Goa. I am conducting a survey to understand how support services received from business incubator has impacted your startup growth and success. Please spare your valuable time to fill in this questionnaire. Your responses will be kept highly confidential, and the findings of this research will be reported collectively.

Concy Noronha, Research Scholar , Goa University

Part I: Startup's Information - Please give your response by stating wherever required or by a ticking (✓) the most appropriate option below

Name (Optional)								
Start up's name								
Product/ Service the startup delivers								
Role / Position in the startup								
Nature of Market	B2B	B2C	B2G	B2B/C/G				
Segment of your startup	Robotics	IT services	IoT	Travel and Tourism	Renewable Energy	Enterprise software	Bio Tech	Other (Please state)
Stage of your startup	Ideation or pre-seed stage or bootstrapped	Validation i.e your prototype needs validation	Early Traction i.e your products are already launched	Scaling	Other (Please state)			
Gender	Male	Female						
Age	Less than 20 years	21 to 30 years	31 to 40 years	41 to 50 years	51 years and above			
Education	Graduation	Post-Graduation	Ph.D.	Others				
Location (Address) E-mail:								

Duration of incubation	Less than 6 months	Upto 1 year	Upto 2 years	Upto 3 years and more
Team size	Self-owned	1-3 members	4-7 members	More than 7 members

Part II: Startup Characteristics

1. Startup experience – Please tell us the average level of company experience before joining business incubator.

(*1- Totally Inexperienced, 2- Inexperienced, 3- Slightly inexperienced, 4- Neutral, 5- Moderately experienced, 6- Very experienced, 7- Extremely experienced)*

	1	2	3	4	5	6	7
Working experience in top managerial level							
Working experience in the same industry							
Experience in startup or entrepreneurial activities							
Technical experience or subject matter expert							

2. Startup team skill- Please rate your startup team skill before joining business incubation.

(1- Totally Incompetent, 2- Incompetent, 3- Slightly Incompetent, 4- Neutral, 5- Moderately competent, 6- Very competent, 7- Extremely competent)

	1	2	3	4	5	6	7
Marketing, Sales, and Business Development							
Finance and Accounting							
Administration and Human Resource (HR)							
Engineering, Technology, and R&D							
Operational, Production, and Manufacturing							

3.Startup team network access – Please tell us how your network circle was before joining the business incubator.

(Please state your answers 1- Not at all, 2- Very few, 3- A few, 4- Neither a few nor many, 5- Many, 6- Quite a bit, 7- A great deal)

	1	2	3	4	5	6	7
Well-developed informal alliances/partners such as friends, families, and acquaintances							
Business partnerships with external institutions or governments							
Technical project collaborations							
Joining trade or business associations							
Contacts with potential or targeted customers							

Contacts with potential or established suppliers							
Contacts with capital or funding sources							

4. Please indicate the average level of company experience, startup team skills, and the strength of your network circle prior to joining the business incubator

(Please state your answers 1- Very poor, 2- Poor, 3- Fair, 4- Good, 5-Very Good, 6- Excellent, 7- Outstanding)

1	2	3	4	5	6	7

Part III: Intervention and assistance offered by TBI (Incubation Manager and the team)-Please tell us how Incubation manager and team intervenes in providing support related to incubation.

(Please state your answers 1- Never, 2- Rarely, 3- Occasionally, 4- Neutral, 5-Sometimes, 6- Frequently, 7- Always)

	1	2	3	4	5	6	7
The incubation manager and/or team provides personalized support and guidance to our startup							
The incubation manager and/or team facilitates access to resources (e.g., funding, equipment)							
Networking opportunities (e.g., events, introductions to investors) are offered by Incubator							
The TBI offers professional development opportunities (e.g., workshops, training) relevant to our team.							
TBI provides guidance on financial planning and management.							
TBI facilitate opportunities for market access and customer acquisition.							
TBI offer support in intellectual property (IP) management and legal issues.							

Part IV: Business Incubation Process

Please inform us of your experience when participating in business incubation programs, services and facilities.

Frequency of usage	**Perceived Importance**	**Perceived Effectiveness**
1. Never 2. Rarely 3. Occasionally 4. Sometimes 5. Frequently 6. Usually 7. Every time	1. Not at all important 2. Low Importance 3. Slightly important 4. Neutral 5. Moderately important 6. Very important 7. Extremely important	1. Totally ineffective 2. Ineffective 3. Slightly ineffective 4. Neutral 5. Moderately effective 6. Very Effective 7. Extremely Effective

Frequency of Usage							
	1	2	3	4	5	6	7
Physical Capital – Utilization of workspace and infrastructure provided by the incubator for our daily operations							
Financial Capital- Utilization of financial capital facilitated in the form of leveraging government loans and grants, accessing equity financing, securing debt financing such as bank loans, obtaining seed financing in exchange for equity.							
Knowledge- Utilization of knowledge capital support in the form of business planning and development, marketing and sales assistance, R & D support, management and legal assistance.							
Social Capital- Utilization of incubator's assistance in connecting with outside businesses, strategic partners, other incubatees for peer networking, educational institutions and potential customers.							
Legitimacy-Utilization of incubator's address to enhance our visibility and credibility in the market.							

Perception of Importance							
	1	2	3	4	5	6	7
Physical Capital – Our perception of importance towards…. Office and working space, shared office services and equipment such as conference rooms, meeting rooms, cafeteria, and printer, as well as technology specific infrastructure							
Financial Capital- Our perception of importance towards…. Government loans and grants facilitated by the incubator, access to equity financing, debt financing including bank loans							
Knowledge- Our perception of importance towards…. Business planning and developmental support, marketing and sales assistance, management and legal assistance.							
Social Capital- Our perception of importance towards…. Incubator's assistance in connecting with outside businesses , strategic partners, business support service providers, other incubatees for networking, other educational institutions, and potential customers.							
Legitimacy- Our perception of importance towards…. Use of incubator's address to enhance our visibility and credibility							

Perception of Effectiveness							
	1	2	3	4	5	6	7
Physical Capital – Our perception of effectiveness towards…. Office and working space, shared office services and equipment such as conference rooms, meeting rooms, cafeteria, and printer, as well as technology specific infrastructure							
Financial Capital- Our perception of effectiveness towards…. Government loans and grants facilitated by the incubator, access to equity financing, debt financing including bank loans							
Knowledge- Our perception of effectiveness towards…. Business planning and developmental support, marketing and sales assistance, management and legal assistance.							
Social Capital- Our perception of effectiveness towards…. Incubator's assistance in connecting with outside businesses , strategic partners, business support service providers, other incubatees for networking, other educational institutions, and potential customers.							
Legitimacy- Our perception of effectiveness towards…. Use of incubator's address to enhance our visibility and credibility							

Part V: Startup Performance

The following are the indicators to measure startup performance. To what extent your incubator was supportive to you in achieving them. Give your level of agreement using a seven-point scale.

[1 - Completely false / 2- Moderately false/ 3 - Somewhat false / 4 - Neither true nor false / 5 - Somewhat true / 6- moderately true /7- Completely true]

		1	**2**	**3**	**4**	**5**	**6**	**7**
1	**Financial Performance-** Our startup has achieved significant revenue growth, improved profit margins, and successfully acquired external funding, helping us reach financial breakeven and sustain profitability.							
2	**Operational Performance**: Through the incubator's support, our startup has made substantial progress in product development, market penetration, and operational efficiency, leading to increased productivity and cost management.							
3	**Human Capital and Team Development**: The incubator has enabled us to grow our team size, enhance employee skills and professional development, and maintain high employee retention and satisfaction rates.							
4	**Networking and Market Position**: With the incubator's assistance, we have established strong strategic partnerships, engaged effectively with industry peers, and							

	enhanced our brand reputation, competitiveness, and customer satisfaction.							
5	**Innovation and Sustainability**: Our startup has launched innovative products/services, scaled operations into new markets, and demonstrated long-term viability, contributing to both environmental sustainability and social impact.							
6	**Prototype development-** Our incubator has been instrumental in helping us successfully develop a functional and effective prototype.							
7	**Graduation-** With the incubator's support, we are confident that our company will not only survive but also record consistent growth for at least three years after graduating from the business incubation program.							

ANNEXURE D: DATA NORMALITY

Table 1: Missing Value

	N	Mean	Std. Deviation	Missing
				Count
EXP1	611	2.96	1.612	1
EXP2	611	2.88	1.553	1
EXP3	612	2.99	1.520	0
EXP4	611	3.00	1.611	1
SKL1	612	2.97	1.610	0
SKL2	611	2.88	1.645	1
SKL3	611	3.01	1.594	1
SKL4	611	2.97	1.607	1
SKL5	612	2.93	1.652	0
NET1	612	3.05	1.599	0
NET2	612	3.04	1.646	0
NET3	611	2.96	1.693	1
NET4	612	3.07	1.646	0
NET5	611	2.94	1.704	1
NET6	612	3.03	1.671	0
NET7	612	3.01	1.598	0
DIIA1	612	2.78	1.452	0
DIIA2	612	2.78	1.431	0
DIIA3	612	2.73	1.434	0
DIIA4	612	2.82	1.446	0
DIIA5	612	2.81	1.407	0
DIIA6	611	2.67	1.494	1
DIIA7	612	2.78	1.450	0
FU1	612	2.95	1.576	0
FU2	611	2.91	1.581	1
FU3	612	2.88	1.537	0
FU4	612	2.94	1.576	0
FU5	612	2.92	1.568	0
PoI1	612	2.93	1.467	0
PoI2	612	2.84	1.458	0
PoI3	611	2.87	1.461	1
PoI4	612	2.88	1.467	0
PoI5	611	2.82	1.472	1
PoE1	611	2.93	1.612	1
PoE2	612	2.86	1.570	0
PoE3	612	2.86	1.528	0
PoE4	611	2.89	1.529	1
PoE5	612	2.92	1.531	0
SP1	611	3.18	1.785	1

SP2	612	3.15	1.821	0
SP3	612	3.26	1.788	0
SP4	611	3.26	1.750	1
SP5	612	3.16	1.828	0
SP6	612	3.24	1.756	0
SP7	612	3.18	1.820	0
Total				**16**

Source : Compiled from primary data

Table 2: Normality test

Normality Test- Skewness and Kurtosis				
Item	Skewness		Kurtosis	
	Statistic	Std. Error	Statistic	Std. Error
EXP1	0.766	0.099	0.101	0.197
EXP2	0.711	0.099	-0.065	0.197
EXP3	0.606	0.099	-0.024	0.197
EXP4	0.692	0.099	-0.013	0.197
SKL1	0.698	0.099	-0.039	0.197
SKL2	0.773	0.099	0.016	0.197
SKL3	0.623	0.099	-0.038	0.197
SKL4	0.676	0.099	-0.055	0.197
SKL5	0.705	0.099	-0.147	0.197
NET1	0.640	0.099	-0.075	0.197
NET2	0.705	0.099	-0.050	0.197
NET3	0.773	0.099	-0.066	0.197
NET4	0.604	0.099	-0.166	0.197
NET5	0.770	0.099	-0.110	0.197
NET6	0.678	0.099	-0.134	0.197
NET7	0.625	0.099	-0.228	0.197
DIIA1	0.797	0.099	0.558	0.197
DIIA2	0.667	0.099	0.405	0.197
DIIA3	0.807	0.099	0.499	0.197
DIIA4	0.674	0.099	0.311	0.197
DIIA5	0.681	0.099	0.396	0.197
DIIA6	0.878	0.099	0.552	0.197
DIIA7	0.631	0.099	0.153	0.197
FU1	0.703	0.099	0.112	0.197
FU2	0.760	0.099	0.178	0.197
FU3	0.692	0.099	0.052	0.197
FU4	0.732	0.099	0.133	0.197
FU5	0.670	0.099	-0.031	0.197
PoI1	0.608	0.099	0.258	0.197
PoI2	0.686	0.099	0.300	0.197

PoI3	0.588	0.099	0.103	0.197
PoI4	0.743	0.099	0.411	0.197
PoI5	0.769	0.099	0.420	0.197
PoE1	0.861	0.099	0.405	0.197
PoE2	0.753	0.099	0.118	0.197
PoE3	0.622	0.099	-0.109	0.197
PoE4	0.701	0.099	0.153	0.197
PoE5	0.711	0.099	0.239	0.197
SP1	0.573	0.099	-0.538	0.197
SP2	0.626	0.099	-0.584	0.197
SP3	0.598	0.099	-0.536	0.197
SP4	0.502	0.099	-0.592	0.197
SP5	0.621	0.099	-0.550	0.197
SP6	0.576	0.099	-0.511	0.197
SP7	0.567	0.099	-0.608	0.197

Source : Compiled from primary data

Table 3: Common Method Variance

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.846	23.789	23.789	12.846	23.789	23.789
2	6.922	12.818	36.607	6.922	12.818	36.607
3	3.753	6.950	43.557	3.753	6.950	43.557
4	3.219	5.960	49.517	3.219	5.960	49.517
5	2.892	5.356	54.873	2.892	5.356	54.873
6	2.619	4.849	59.722	2.619	4.849	59.722
7	2.550	4.723	64.445	2.550	4.723	64.445
8	1.715	3.175	67.621	1.715	3.175	67.621
9	.783	1.450	69.070			
10	.741	1.372	70.443			
11	.699	1.294	71.737			
12	.671	1.243	72.980			
13	.638	1.181	74.161			
14	.612	1.133	75.294			
15	.611	1.132	76.426			
16	.594	1.100	77.526			
17	.577	1.069	78.595			
18	.564	1.045	79.640			
19	.560	1.037	80.677			

20	.547	1.012	81.690			
21	.528	.977	82.666			
22	.516	.955	83.622			
23	.512	.949	84.570			
24	.493	.912	85.482			
25	.480	.888	86.371			
26	.475	.879	87.250			
27	.452	.837	88.087			
28	.444	.822	88.910			
29	.439	.813	89.723			
30	.437	.809	90.532			
31	.427	.792	91.324			
32	.410	.759	92.082			
33	.399	.740	92.822			
34	.391	.724	93.546			
35	.375	.695	94.241			
36	.371	.688	94.928			
37	.349	.647	95.575			
38	.340	.630	96.205			
39	.324	.601	96.806			
40	.319	.591	97.397			
41	.305	.565	97.962			
42	.287	.531	98.492			
43	.282	.522	99.014			
44	.270	.500	99.515			
45	.262	.485	100.000			
Extraction Method: Principal Component Analysis.						

Source : Compiled from primary data

ANNEXURE E: Insights from Literature studies (Compiled by the Author) **The dynamic relationship between inputs, mediators, and outcomes as identified from the referenced studies, curated to provide comprehensive insights into the subject matter.**						
Sr. No	**Study and Country**	**Sample**	**Inputs**	**Mediators**	**Outcomes**	**Key findings**
1	(Wang et al., 2020), China	The panel representing 31 Chinese provinces	Psychological capital of entrepreneurs, internal synergy	Service capacity, Finance capacity, Incubation capacity of business incubators, regional communication infrastructure	Regional innovation performance	Knowledge transfer opportunities provided by incubators that enable better innovation activities are preferred over assets and financial support.
2	(Bøllingtoft, 2012), NA	4 participants focus-group interview, seven in-depth interview	Networking and cooperation activities of the entrepreneur	The incubator facilitated physical proximity, entry/screening criteria	Embedding companies in the entrepreneurial network	The networking activities are characterized by no financial transactions between the companies (business support and support services), and the cooperation activities are marked by financial transactions between the companies (horizontal and vertical cooperation).
3	(Del Sarto et al., 2020), Italy	38 accelerated startups	Firm size, Industry sector, Technological nature of a startup and Export activity	Mentorship, office space, and networking	Firm survival	The technological nature of a startup's export activity on firm survival through “learning by exporting” is positively related to firm survival.
4	(Gao et al., 2021),China	5 Chinese high-tech business incubators	NA	Clients-interface, market-interface, and knowledge recombination practices of business incubators	Internationalization of startups	This role of incubators as knowledge intermediaries is achieved through several networking and learning mechanisms, including clustering and coaching of international clients, upstream and downstream networking in international markets, and client-market matchmaking internally.

5	(Lukeš et al., 2019),Italy	2544 innovative startups	*Firm-related variables*: Startups' initial capital, age, industry, independence/ownership structure, and number of peers in the incubator. *Firm's incubator characteristics*-certified incubator, private or mixed incubator ownership, *Characteristics of firms' environment*- regional GDP, city size	N/A	Sales revenue and Job creation	There is a significant negative effect of incubator tenancy on sales revenues and no significant effect of incubation on job creation. Findings also suggest that the initially negative effect of incubation on sales revenues turns into a positive effect in the long term.
6	(Harper-Anderson & Lewis, 2018), USA		N/A	Shared administration and office equipment, general legal services, networking within the incubator, marketing services, in-house investment fund, intellectual property, protection, manufacturing process assistance, prototyping and product development. etc.,	Creating jobs, diversifying local/regional economy, building or accelerating growth of a business/industry, retaining/attracting firms, commercializing technologies, generating complementary benefits for the sponsor, identifying potential spin-in or spin-out business, generating net income for incubator or sponsor, fostering an entrepreneurial climate in community, revitalizing a distressed neighbourhood, encouraging minority or women entrepreneurship.	Incubator quality variables have a stronger causal influence on successful incubation outcomes than regional capacity variables. While regional capacity is a stronger predictor for graduate-firm outcomes than tenant-firm outcomes, incubator quality matters more overall.

7	(Kwiotkowska & Gębczyńska, 2019), Australia	13 accelerators, 44 accelerated startups	N/A	Mentoring, Time-boxed cohort-based entry and exit, Co-location, Seed funding, Structured development program	facilitate start-ups emergence by aiding access to markets and the development of ideas	Accelerators provide tangible and intangible dimensions of start-up infrastructure to form a positively reinforcing cycle of entrepreneurial activities.
8	(Li et al., 2020), Pakistan	567 startups	Respondents' characteristics- Gender, Age, Managerial level, education, experience, province Government regulations for entrepreneurship	Networking support, capital support, training programmes	Entrepreneurship development	Business incubators play an effective mediating role in providing networking services, capital support, and training programs to individuals and entrepreneurs. In contrast, business start-ups positively mediate the relationship between networking services, capital support, training programs, and entrepreneurship development.
9	(Gorączkowska, 2020) ,Poland	1058 industrial enterprise	N/A	Expenditure on R&D,	Product innovation	Tenants of technology incubators are more innovative than entities outside them. Still, their innovations in terms of the level of novelty do not differ from innovations implemented in entities outside incubators.
10	(McAdam & McAdam, 2008), Ireland, UK	Two incubators and 18 firms	Unique resources and Capabilities, Static and dynamic resources in the USI Incubator add to the stock of resources, Proximity to the university	Provision of infrastructure, University services, Credibility with customers and suppliers	Lifecycle development, Entrepreneurial transition, Establishment of entrepreneurial team and gaining independence	The results show that an HTBF's propensity to make effective use of the USI's resources and support increases as the lifecycle stage of the company expands and the small firm searches for independence and autonomy.
11	(Corrocher et al., 2019), Italy	26 Italian science parks and 470 firms	Science parks' features – size, employees, number of firms and universities, number of research projects and research networks Characteristics of tenant firms - patenting activity, turnover, age, and size.	N/A	Fostering firms' innovative activity	Science parks play a remarkable role in stimulating research activity and the development of innovations of tenants, in particular, those with high levels of innovativeness.
12	(Rothaermel & Thursby, 2005a), USA	79 startup firms	N/A	Access to laboratories and other research facilities, business assistance,	Number of full-time employees, cumulative counts of the patents	University link to the sponsoring institution reduces the probability of new

				subsidized space, connections to potential corporate partners, venture capitalists and intellectual property guidance	filed, incremental funding the new venture obtained, industry effects, time in incubator	venture failure and, at the same time, retards timely graduation.
13	(Vanderstraeten et al., 2016) , Brazil	264 operational incubators	N/A	Incubator's service customization strategy	Graduation, number of employees, growth in sales revenue	There is a significant positive direct effect of industry focus on service customization, a significant positive direct effect of service customization on incubatee survival and growth, and a non-significant negative direct effect of industry focus on incubatee survival and growth
14	(Khodaei et al., 2022),Netherlands	9 Spin-off founders,	Opportunity recognition, entrepreneurial commitment, credibility,	Infrastructural support, Business Support, Business plan development, legal support, Networking	Transition to the next growth stage	The results show that founders appreciate milestones and direct interface regarding business support, business plan development, and legal support during the early growth stages. In all stages, in particular, during the later stages, founders appreciate different types of network support (e.g., start-up network and industry) and when facilitators act as intermediaries to guide them in the network.
15	(Schwartz, 2010), Germany	371 startups	N/A	Subsidized rental space, networking, Credibility, Business assistance, collectively shared facilities	Market exits in the form of M&A and closures.	Locating in an incubator – contrasting the widespread rhetoric of policy actors and incubator stakeholders – does not increase the chances of long-term business survival.
16	(Paoloni & Modaffari, 2022), Italy	Case study of single female startup	Personal characteristics of the entrepreneur, environment in which the enterprise operates, organizational and managerial aspects, motivations for starting the new business	Formulation of business model, support in strategic decision making, and operational and managerial aspects to organize the company	Bridging and bonding social capital, Improvement in managerial and organisational aspects, stronger organizational culture Acquisition of	The knowledge transfer from the BI allows the start-up to overcome its main difficulties: the organizational aspect and financial capacity.

					startup by a larger company	
17	(Peña, 2004), Spain	114 startup firms	Owner's formal education and business experience, talent and motivation, passive experiences Organizational factors -firm age, size, resources, and strategies External factors- Location economies, industry characteristics, macroeconomic conditions and public policies	Training programs, savings due to use of space and equipment at below market prices, exchange activities carried out with other tenants, networking.	Annual sales, Profits, and firm employment	Human capital attributes of entrepreneurs and specific start-up firm characteristics seem critical to explaining business success.
18	(Shih & Aaboen, 2019), Sweden	Nineteen respondents comprised incubator managers and business advisors, science park managers, business advisors at the university's technology transfer office (TTO), support organisations' representatives and incubator firms' managers.	N/A	Direct and indirect Mediating role of business incubators	Development of startups' business networks	The incubator described in this paper can facilitate a relationship, directly and indirectly, initiation and development between the innovation support actors and the incubator firms (i.e. in the micro net).
19	(van Rijnsoever, 2020), Spain	100 startups	N/A	Community-building, Field-building, Peer-coupling, Infrastructure support, VC-networking, Deal-making, Business Learning	Bridging a strong financial support network among startups	Different incubator support mechanisms influence the meeting and mating process, which contributes to overcoming weak network problems in the FSN.

20	(Pato & Teixeira, 2020),Portugal	408 newly created ventures	Institutional factors- Policy-related, Economic, Socio-cultural, and technology-related. Human Capital- Entrepreneur characteristics. Business traits- Sector's size, worker's education Innovation- Product, Process, Organizational, Marketing	Institutional support from knowledge and technology infrastructures, such as universities, incubators/ science parks and R&D centres	Sales, Gross Value Added, Exports	Certain institutional factors, namely EU policy support, financial support from sources other than not banks, business advice for starting up/ ongoing activities and collaboration to access new markets, are critical for new venture export performance, particularly those located in rural settings.
21	(Dourado Freire et al., 2022), Brazil	3 TBI managers and 30 Startup founders	Characteristics of TBI and Startups	Physical resources, human resources, organisational resources, technological resources, financial resources	Startup development and continuity	Resources are the linkage between startups and TBIs, promoting the development and continuity of these organizations. Among the resources offered by TBIs, the most representative is physical resources due to the early stage of startups
22	(L. Zhang et al., 2019), China	71 ventures	Entrepreneurship Specific Human Capita- Entrepreneurial experience, Family background, Entrepreneurial competence	Entrepreneurs Network Involvement	Tenants' graduation or exit because of failure	Network involvement strengthens the influence of entrepreneurial experience on tenants' successful graduation but does not impact the relationship between entrepreneurial family background and tenants' graduation.
23	(Van Rijnsoever et al., 2017), Western Europe and North America	935 early-stage technology-based entrepreneurs.	Startup characteristics-Team size, start-up maturity, industry experience, entrepreneurial experience, age, gender, sector and country	Hit maker-direct transfer of resources and organizational or business knowledge from the incubator Network broker connection to external funding sources through the incubator's network	Investments raised by startups, the ability of the startups to attract funding from formal investors and banks	Incubators positively affect (1) the amount of funding that start-ups attract and (2) the ability of start-ups to attract funding from formal investors and banks.
24	(Blank, 2021)	59 student startups	Teams prior managerial experience, sector, full-time work experience, founder's age	Mentoring	Survival of startup	The survival chances of startups whose founding teams have high levels of managerial experience or low levels of entrepreneurial experience are low when

						they do not take advantage of the incubator's mentoring program.
25	(Chen et al., 2023), China	6400 incubators and 471,686 incubated enterprises for five consecutive years,	Firm-level includes firm age, length of incubation, registered capital, whether it is a high-technology firm, whether it contacts a business mentor, the number of employees, employee structure, the amount of angel or venture capital received, R&D investment, and patent output incubator level include incubator age, the number of employees, office space, incubator revenue, market-based investment share, revenue structure (nonproperty revenue share), government funding, the number of incubatees, and the number of business mentors in place.	Entrepreneurial service support – Funding resource support, technical resource support, Human resource support, Knowledge resource support,	*Corporate Performance*- Total enterprise revenue, enterprise net profit, firm growth length *Employment contribution*- the number of employees, the number of college students employed, the number of doctoral and foreign students employed *Innovation output*- the number of intellectual property applications, licenses, and the cumulative number of effective intellectual property rights in the current year.	The development of the digital economy in cities helped improve the revenue capacity of startups, and the more developed the digital economy is, the better the financial performance of startups. From a resource-based view, resource service support from incubators, such as capital, technology, human resources, and knowledge, is an essential channel through which the digital economy promotes the performance of startups.
26	(Woolley & MacGregor, 2022), USA	419 firms	Firm-level variables-year of founding, the number of founding team members, the firm's industry and patenting activity, the influence of founder experience and education, and the founder obtaining a doctorate before starting the firm	Portfolio of resources and service offerings by Venture development programs	Closure due to bankruptcy, asset sale, or under-performance. obtaining government small business innovation grants, and raising venture capital (VC)	There is no significant benefit to participating in a private incubator, while firms participating in a university incubator were over 50% less likely to experience a negative closure than other firms.
27	(Alvarez Salazar, 2021), Peru	21 respondents	*Human capital*- studies and experience, demographic, attitudinal, entrepreneurship team *Social capital*-linking to networks, network maintenance	Organisation process Incubation	Startup survival-break-even point, accelerated growth, cash stock and continuous operation	Survival is a reflective construct. In human capital, international exposition, optimism and global vision are highlighted; in social capital, the possession of the family and friendly networks; in entrepreneurial capital, the risk profile of the investor; and in the case

			Organisational capital, *Entrepreneurial capital*- Monetary, Non-monetary, knowledge generation			of the incubation process, although the variables are the same as shown in previous studies, it should be noted that in the Peruvian case, they are only appreciated by the novice founders.
28	(Xiao & North, 2017) , China	27 founders, two incubator directors,	TBI level- size, age, No. of universities	Direct funding, technical support, and entrepreneurial mentoring	City's socio-economic development, Graduation performance	Technical support facilities and entrepreneurial mentoring from TBIs have significantly and positively influenced the early development of the firms in the four most affluent tier 1 cities, whilst these effects become less pronounced for the tier 2 and tier 3 cities.
29	(Patton & Marlow, 2011)	27 firms	Number of employees, Age, Sector	Business planning, development of the management team, and securing appropriate investment.	Commercialisation process of early-stage technology firms	Business incubation effectively aligns a balance of learning approaches that support future growth prospects and add competitive advantage to young, fragile firms.
30	(Rubin et al., 2015) , Australia and Israel	215 TBI's and their incubated firms	Provision of key resources from local organisations	Technical service support, financial service support, Entrepreneurial service support, Professional service support	Level of innovation	Technical service support from an incubator was found to have positively influenced all levels of innovation activity across all regions, whilst financial support positively affected the making of more advanced innovations.
31	(Klingbeil & Semrau, 2017), Germany	276 tenants	Venture team size, Industry Incubator age, specialization,	N/A	Venture growth	Venture team size serves as a moderator for the effect of incubator size on tenant growth. Incubator size positively affects the growth of tenants with smaller venture teams. Tenants with larger venture teams may suffer from being located in a larger incubator.
32	(D. P. Soetanto & Jack, 2013), UK	62 tenants	Type, size, product, performance and initial motivation for being located at the incubator	Networking of firms- Tangible and Intangible resources, external and internal	Firm innovation, Job growth	There is no significant difference between highly innovative firms and medium to low innovative firms in terms of networks they develop with internal (other

						incubator firms) and external partners (the STFC, universities)
33	(D. Soetanto & Jack, 2018), Netherlands, Norway and the UK	141 small technology-based firms	Firm size, Founding date of the firm	Incubation supports the perform exploratory and exploitative innovation	Job Growth	That neither slack resources nor innovation activities alone explain firm performance. Instead, small technology-based firms fit their innovation activities to their slack resources.
34	(Fernandes et al., 2017), Brazil	108 respondents from incubated companies 31 incubation managers	Location of incubates in TBIs that have a relationship with universities and research centres, Number of formal agreements concluded between TBIs and universities and research centres and financing provided by promotion agencies and external institutions to incubatees	Strategic assets provision- supply of knowledge assets, creation of relationship assets	New Product launches	TBIs' strategies focusing on the supply of knowledge assets and the creation of relationship assets are more effective than strategies focused only on the supply of physical infrastructure for firms located in incubators.
35	(Nair & Blomquist, 2019), Sweden	26 entrepreneurs, three incubation managers	Scalable business idea, a good team	Value creation	Failure prevention and management by incubator	Business incubation practices could help prevent and mitigate failure at personal, organisational, and social levels towards value creation for the startups and their stakeholders and channel the effects of failure towards social benefit.
36	(Smilor, 1987a),USA	50 incubators	N/A	Leveraging business know-how into tenant companies support, administrative assistance, facilities support, business expertise, including management, marketing, accounting and finance; and access to financing and capitalization	Develop credibility of startups, shorten the learning curve, solve problems faster, and provide access to an entrepreneurial network.	Incubators can spur new technology-based ventures by providing a practical mechanism for taking and sharing risks in the early stages of business development.
37	(Clausen & Korneliussen, 2012), Norway	207 incubator firms	Firm size, Age, prior entrepreneurial experience, entrepreneurial orientation	N/A	New product speed to market	Entrepreneurial orientation has a statistically significant positive effect on the ability to bring technology and products quickly to the market.

38	(Chan & Lau, 2005),Hong Kong	6 cases	The duration of joining the incubation programme, the nature of the business, the location of the firm	Pooling and sharing resources, consulting, networking, clustering and funding, geographic proximity costing	Venture creation and development	Incubators' services and support should be prioritised in accordance with the development process of the technology firms.
39	(H. Zhang & Sonobe, 2011), China	62 STBI's	Infrastructure as well as the human and financial resources, firm size in terms of employment and value-added, labour productivity FDI inflow	Infrastructural support, financial support, human resources, etc	Employment size, value-added, labour productivity	The number of graduates from an incubator is closely associated with the human resources, infrastructure, and financial resources of the incubator but not with the variables characterizing the location of the incubator, such as the inflow of FDIs, proximity to universities, and the diversity and scale of industrial activities in the locality.
40	(Sá & Lee, 2012) , Canada	29 tenants	The nature of tenants' businesses, the roles they play in the incubator	Networking-Advisory networks, Spin-off networks, strategic networks	Business collaboration, access to essential sources of knowledge, skills, and R&D facilities	This study points to the variegated nature of networks, suggesting that greater attention is needed to conceptualise inter-organizational interactions in technology-based incubators.
41	(Sung, 2007), Korea	118 tenants	Starting year, Industry, Association with previous experience, venture type, the focus of innovation	Basic, administrative, secretarial, additional, financial	Annual sales, number of employees, R&D/capital ratio, Internal Rate of Return, employee growth rate	Korean entrepreneurs think financial services are most needed. Government policy on incubation is not adequate. Future functions/services of incubators should concentrate on additional and financial parts/services.
42	(Redondo et al., 2022), Spain and Netherlands	101 responses	Complementarity and supplementarity of resources	Transferability of knowledge	Knowledge exchange, entrepreneurial commitment, knowledge generation	Complementarity, supplementarity and transferability of resources, and incubator predisposition towards business are fundamental for exchanging knowledge, developing entrepreneurial spirit and generating innovation.
43	(Lopes et al., 2018), Portugal	15 incubation managers, 28 incubated company managers	N/A	infrastructures, technical consultancy and access to information on sources of funding.	Economic growth through the process of transferring and commercialising	Not only the importance of RDI cooperation networks but also how the consequent commercialisation of new products and services generates positive consequences for economic growth.

					knowledge and technology	
44						
45	(Habiburrahman et al., 2022), Indonesia	41 respondents from incubators 59 respondents from the startups	Domicile location, type, and business turnover of the startups	N/A	Synergy products; processes; innovation management; communication; culture; experience; information technology; innovation skills; functional skills; and implementation skills	Incubators and startups agree on eleven critical factors to building their business success, but there are differences in the priority scale between incubators and startups on these eleven factors.
46	(Loganathan & Bala Subrahmanya, 2022), India	73 startups	Age at incubation, entrepreneurial experience, Product or Service, geographical area, customer	Networking, Specialization and Infrastructure	Technological capacity development	The specialisation of incubators, alignment with the university knowledge base and the extent of utilisation of the networking services provided by the incubator are significant factors in helping start-ups achieve technological outcomes.
47	(Bacalan et al., 2019), Philippines	17 incubatees	N/A	Enabling factors like concise milestones with clear policies and procedures, technology transfer and R&D, etc.	Employment growth, Profit growth, Sales growth, Survivability	On-site business expertise, the suggested ideas on situational experiences (technology/ ideas), and the confidential techniques or information that would assist the incubatees (know-how) are the most relevant enabling factors for incubates success.
48	(Löfsten, 2016), Sweden	131 NTBF’s	Incubator level-incubator environment contributed to the firm’s ability to perform, obtain resources, and handle its environment.	Business planning and localization resources, business location and proximity.	Firm survival- Growth rates, patent records, copyrights and licenses and technological development	This study shows that the latent business plans variable has a significant positive connection with firm survival. Also, patent development during firms’ initial years is critical to firm survival.
49	(Sedita et al., 2019b), Italy	243 firms	Intellectual property protections, R&D expenditure, geographical area, industry specificity, firm	Incubation, capabilities, collaboration breath,	Innovation performance of new ventures	The incubation effect is significant in shaping the innovation performance of new experiences (measured as a percentage of sales of new-to-market

			size and age, type of new venture, internationalization			innovations). Moreover, it positively moderates the impact of (1) the internal technical capabilities and (2) the adoption of a limited portfolio of collaborations for innovation.
50	(Löfsten et al., 2022), Sweden	241 NTBF's	N/A	Entrepreneurial networks, geographical proximity	Early NTBF growth-profit, sales growth, employment growth	Professional networks have a positive and significant effect on NTBFs' growth, which indicates that utilizing these networks benefits both young and growing firms.
51	(Özdemir & Şehitoğlu, 2013) Turkey	48 on-incubator and 41-off incubator firms	N/A	office space with shared office services, consultancy services (technical, administrative, and managerial), training, access to university facilities, access to financing and networking	Reinforcement of R&D functions, establishment of technology-oriented enterprises, extension of the production and utilization of advanced technologies	Turkey's Technology incubators are important in supporting start-ups in their vulnerable stages. 60% of the firms found the services provided critical to firms' development.
52	(Studdard, 2006) , USA and Finland	52 firms	NA	Business knowledge sharing process	New Product development, technological competence development, reputation, reduction in sales costs	It is suggested that the increased knowledge acquired by the firm through its interaction with the incubator manager would increase the firm's new product development increases the firm's technical competence, improves its reputation and decreases the cost of sales to customers.
53	(Colombo & Delmastro, 2002) Italy	45 Italian NTBFs	Personal characteristics of founders of NTBFs, the motivations of the self-employment choice, the growth and innovative performances of firms, propensity towards networking, and access to public subsidies	N/A	Growth rate, adoption of advanced technology, participation in international R&D programs, collaboration with universities	Italian parks attracted entrepreneurs with better human capital, as measured by educational attainments and prior working experience. On-incubator firms show higher growth rates than their off-incubator counterparts.

54	(Mian, 1996a), USA	47 client firms	NA	Shared office services, business assistance and networks,	Development of new technology-based firms	several UTBI services, specifically some of the university-related inputs such as university image, laboratories, equipment, and student employees add significant value to the client firms, making the UTBI a viable strategy for nurturing NTBFs.