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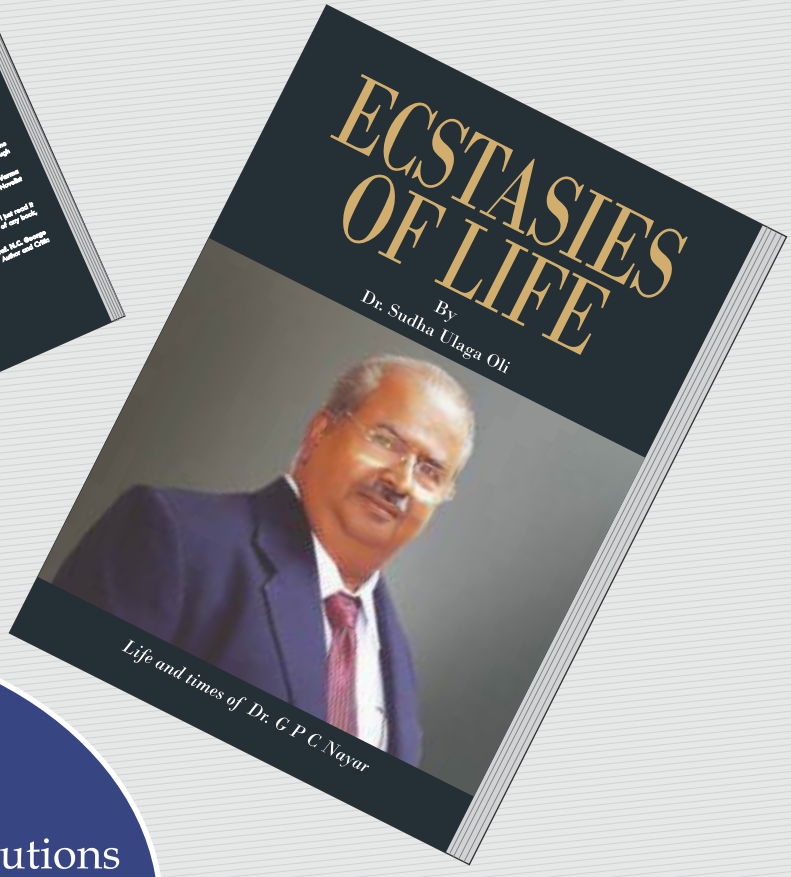

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in an unfriendly environment.
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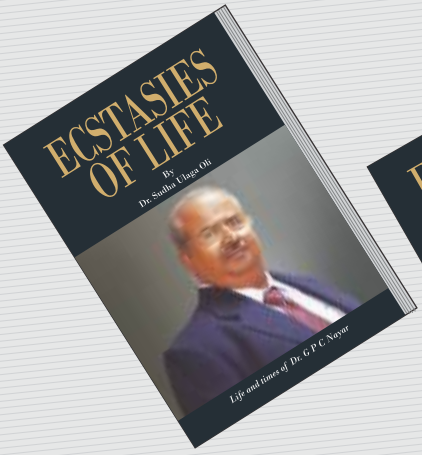

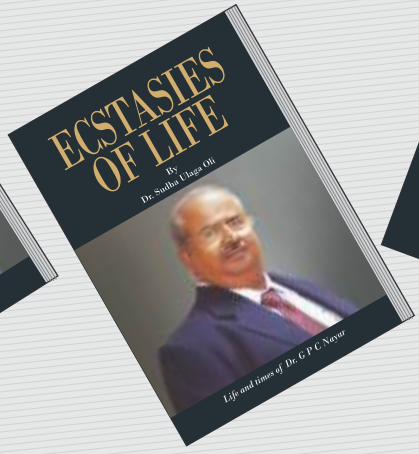

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Chairman's Overview

India is preparing for a landmark exercise in 2026: its first fully digital Census. Beyond being a statistical exercise, the Census reflects the extent to which technology has become embedded in governance, institutions, and everyday life. The transition from paper-based enumeration to digital data collection represents not merely an administrative change, but a significant milestone in India's broader journey of digital transformation.

The move towards a digital Census is not simply about convenience or modernisation. It is about creating a more responsive, efficient, and real-time data ecosystem. Geographic mapping, mobile-based enumeration, cloud storage, and data analytics can improve both the speed and accuracy of Census operations. As data becomes an increasingly valuable resource in decision-making, the Census is no longer viewed only as a government exercise, but also as a foundation for planning and strategy across sectors.

The implications of this transformation extend far beyond public administration. For the world of business and management, access to timely and accurate demographic information is increasingly critical. A company planning to enter a new market must understand the size, income levels, age profile, literacy rates, and consumption patterns of the local population. Retailers, for instance, may identify growing demand in Tier-2 and Tier-3 cities by analysing population growth, rising household incomes, and changing lifestyle aspirations.

Educational institutions can also benefit from demographic information. As industries evolve and new sectors emerge, the demand for specialised skills is changing. Regions with a growing youth population may require greater investment in higher education, skill development, entrepreneurship support, and employability initiatives. In this sense, the Census can play a direct role in shaping the future workforce of the country.

Financial institutions have an equally important stake in Census data. In an economy where digital payments, fintech adoption, and financial inclusion are expanding rapidly, demographic insights are essential for understanding which communities remain underserved and where future opportunities lie.

However, greater reliance on digital systems also raises concerns relating to privacy, accuracy, cybersecurity, ethical data use, and digital inclusion. Citizens must be assured that their data will be protected, used responsibly, and collected in ways that are inclusive and fair.

India's first digital Census is therefore far more than a national counting exercise. It reflects a nation becoming increasingly connected, data-driven, and future-ready. In this evolving context, the SCMS Journal of Indian Management seeks to contribute meaningfully to the discourse by bringing together diverse perspectives, evidence-based research, and contemporary managerial insights to help decision-makers navigate the opportunities and challenges of a rapidly changing environment.

Dr. G. P. C. NAYAR
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Editorial

As the first issue of the year 2026, the SCMS Journal of Indian Management presents ten scholarly articles that engage with contemporary concerns in resilience, sustainability, finance, technology, organisational behaviour, and supply chain management. Together, these contributions combine theoretical depth with empirical rigor and practical relevance across diverse sectors and geographies.

The volume opens with a critical review of risk assessment and management frameworks for SMEs, highlighting the growing importance of resilience and preparedness in uncertain business environments. This is followed by a study on generational differences in sustainable consumption among Indian Millennials and Generation Z, which uses the Theory of Planned Behaviour to examine how younger consumers respond to sustainability concerns.

The issue also features an analysis of direct real estate investment across age groups, employing Structural Equation Modelling to understand how perceived benefits and barriers influence investor intention. Complementing this, a multiphase mixed-method study on dynamic capability explores how organisations can strengthen sustainable business performance through adaptability, learning, and innovation.

Another important theme in this volume is the role of people and organisational culture. A study on hotel employees investigates how cultural intelligence influences turnover intention, with emotional labour acting as a mediating factor. Similarly, research on employer branding in Indonesian higher education demonstrates how organisational justice, employee engagement, and meaningful work shape institutional attractiveness and employee commitment.

Technology and digital transformation form another significant strand of research in this issue. The article on barriers to AI adoption in Singapore's manufacturing sector employs an integrated FDM–ISM–MICMAC approach to identify the structural and organisational challenges that affect implementation. Relatedly, a study on the role of Artificial Intelligence in the Indian retail sector examines how AI is transforming marketing strategies, consumer buying behaviour, and brand engagement.

The volume further includes a systematic literature review on India's agri-business supply chain, with special reference to Jharkhand, highlighting both operational challenges and opportunities within a critical sector of the economy. Concluding the issue is a bibliometric analysis and topic modelling study on impact investing, which reveals the growing emphasis on aligning financial returns with measurable social and environmental outcomes.

Together, these articles contribute to a deeper understanding of evolving managerial challenges and opportunities. We trust that this issue of SCMS Journal of Indian Management will stimulate scholarly dialogue and support informed decision-making in academia, industry, and policy circles.

Dr. Radha Thevannoor

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Toward Resilient SMEs: A Critical Review of Risk Assessment and Management Frameworks

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Abstract

Small and medium enterprises (SMEs) have been the backbone of the global economy throughout history. SMEs are adding value to the economy by innovating, providing jobs and supporting exports. There are numerous impediments to the survival of SMEs as compared to large firms. It has been observed that countries with many SMEs achieve higher economic growth than those with few. The threats and risks to business survival lead to the lack of resilience among SMEs. If ignored, risk factors can make SMEs fragile and lead to mortality. Considering the importance and scope of the topic, this study conducts a comprehensive review of the literature on risk assessment and risk management of SMEs over two decades, from 2000-01 to 2023-24. The existing literature focuses on identifying and categorising the various risk factors that SMEs face. This study enumerates risk factors and the frameworks described in the literature, identifies gaps to uncover new research frontiers, and uses a systematic literature review and PRISMA methodology. A thorough analysis revealed that most of the available literature emphasised the identification and listing of various risk factors that SMEs face, leaving a massive gap in risk assessment and management frameworks, as well as in the application of emerging techniques and tools that would make SMEs more resilient.

Keywords: *SMEs; Risk Assessment; Risk Management Frameworks; Enterprise Risk Management; PRISMA; SME Resilience*

1. Introduction

Small and medium enterprises (SMEs) are vital to the growth of economies worldwide, particularly in emerging countries. SMEs account for 40% of GDP and 50% of total employment worldwide. SMEs are recognised worldwide as a prerequisite for a capable and future-oriented economy (Gonçalves et al., 2016). SMEs establish a mainstay of the economy, contributing to value creation in all industries (Vasnier et al. 2021). SMEs have greater innovation capacity than large organisations (Alcalde et al., 2019). However, compared to larger enterprises, SMEs face numerous threats and risks, including limited growth, low investment, and weak trade, all of which can lead to business collapse. Businesses and risks are inextricably linked, and SMEs are no exception. Business entities require a robust framework to mitigate the ill effects of risk; however, it is crucial for SMEs, as they may not have the wherewithal to sustain and grow due to their small size and other constraints (Wang 2016). Small and medium enterprises (SMEs) are currently exposed to various risks, and reducing these risks is a top priority for new businesses (Agyapong, 2020). Brustbauer (2014) suggested applying risk management techniques to recognise and control hazards before they permanently impair SMEs. Organised risk management is crucial because most SMEs would rather avoid risks altogether or, to a lesser extent, transfer risks through insurance (Smit, 2012).

The study of Pereira et al. (2015) concluded that risk management frameworks exist for major corporations, yet because of their high cost and complexity, SMEs are unable to use them. It is undeniable that elements such as financial, operational, administrative, strategic, and supply chain can create a risky and fragile environment for SMEs; however, proper risk evaluation and the implementation of a management framework will enable SMEs to manage these risks effectively. Numerous studies were conducted over the last two decades across various areas of risk management; however, most focused on risk definition. Limited research has examined risk management in SMEs (Verbano & Venturini, 2013). Risk management procedures (RMPs) have been established; despite this, there is no agreement on what constitutes RM for SMEs (Renault et al., 2018).

Limited studies have focused on how SMEs analyse and manage risks without defining or adopting specific processes (Babu et al., 2020; Sunjka & Emwanu, 2015). Risk Management (RM) in SMEs has received little attention in the academic literature and has been seen as a drawback in these businesses. Given the subject's significance and sensitivity, it is valuable to understand the extent of scholarly research in this domain over the past 20 years of industrial transformation.

Based on the systematic synthesis of prior studies using the PRISMA methodology, it is evident that limited attention has been given to integrative frameworks and their practical applicability. In response to these gaps, the present study sought to address the following research questions, aiming to advance both theoretical understanding and managerial relevance in the domain of SME risk resilience.

1. What conceptual, methodological, and contextual gaps exist in SME risk assessment and risk management frameworks, and how do these gaps limit the development of SME resilience?

2. How do emerging risk assessment and management tools feature in the existing SME literature, and what managerial implications do they offer for improving SME resilience?

To justify the research questions, this study aims to conduct a thorough review of the available literature on risk management in SMEs and to provide a detailed examination of the researcher's approach to risk identification, assessment, and management. The articles under study are extracted from reputable databases in January 2024. The sample of 159 has been included in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) application. The PRISMA model ensured transparency and methodological rigour in the literature selection process, enabling a systematic identification, screening, and inclusion of relevant studies, thereby enhancing the reliability and reproducibility of the review findings in the context of SME risk management. This study provides the most comprehensive PRISMA-based synthesis of SME risk assessment and management literature spanning over two decades, systematically differentiating between risk identification, assessment, and management, and highlighting structural imbalances in existing research.

2. Literature Review

There are various discussions in the literature on the concept of risk. (Small Business Development Corporation, 2022) has defined risk as “An event or circumstance that has a negative effect on your business.” “Risk management is the

process through which firms identify, assess, and treat risks that may have an impact on their business operations" (Small Business Development Corporation 2022)

2.1 *Need for SLR in the SMEs Domain and Novelty of the Study*

The existing literature on SMEs is extensive and fragmented, encompassing diverse approaches and addressing various facets of the SME sector (Flavio and Joao, 2020). This fragmentation necessitates an intensive literature review to categorise and systematise the existing knowledge. Similarly, the literature on SME is diverse, with studies exploring different determinants and yielding contradictory findings (Falkner and Hiebl, 2015). The literature review performed in this paper can help synthesise these findings and identify consistent patterns. This review paper attempted to identify a gap in the literature and provide a roadmap for future research. For instance, the review on risk management in SMEs identified the need for more empirical research on risk identification and strategy implementation. Several SLRs have been conducted in the SME domain, each focusing on different aspects. For instance, Flavio and Joao (2020) have categorised literature into areas such as the internationalisation process and factors influencing internationalisation. The existing SLR on risk management identified various types of risks and the importance of risk management processes (Falkner and Hiebl, 2015). This SLR suggested a further review of specific risk management strategies and their effectiveness. Reviews of SME financing have examined the determinants of banks' credit and profitability (Rao et al., 2023). However, there is room for further research on the impact of different financing models on SME growth. While there are reviews of digital innovation in SMEs, they often highlight gaps in understanding the innovation process and its outcomes (Ramdani et al., 2021).

The current paper aims to differentiate itself by focusing on underexplored aspects of SMEs, identified as gaps in the existing literature, including risk assessment mechanisms and related risk management strategies. This study also offers actionable recommendations for SME managers and policymakers based on the synthesised findings.

2.2 *Risk Assessment*

The literature indicates that some researchers have studied or developed models to identify risk factors. Agyapong's (2020) findings confirmed that financial risks should be assessed, as they have implications for a firm's performance. According to Yang et al. (2021) and Ubarhande and Chandani (2021), the risk of credit default can be reduced through robust risk management. Bilal et al. (2016) developed a model focused on financial risks to evaluate barriers to SME growth. However, Gonçalves et al. (2015) established a framework to assess SMEs' credit risk using an idiosyncratic decision support system. Roy (2021) and Yin et al. (2020) presented a framework for assigning credit scores by assessing SME credit risk. Quintiliani (2017) developed a conceptual framework to identify financial distress among SMEs, thereby helping alleviate the cost of exiting the market.

Besides financial risk, the Supply Chain and Supply Chain Financing are emerging risk factors that have attracted researchers' attention. The study by Temel and Durst (2020) identified technological turbulence as the most significant variable influencing the supply chain, and supply chain risk management as influencing innovation performance. Sutrisno and Kumar (2022) proposed a tool to assess the supply chain sustainability risk. Zhou et al. (2019) implemented Machine Learning for Credit Risk Assessment in SMEs' Supply Chain Finance. Zang et al. (2022) developed a framework to assess the Supply Chain Finance Credit Risk using financial and behavioural data. Games and Rendi (2019) proposed an index to assess credit risk in SCF using the SVM technique. Alora and Barua (2022) developed supply chain risk index using Fuzzy TOPSIS. Tong and Yang (2021) endeavoured to identify, categorise, and prioritise the supply chain risks faced by the manufacturing industry to develop an inclusive supply chain risk index. In this study, Tong and Yang (2021) and Yang et al. (2021) assessed credit risk in supply chain finance.

Vasnier et al. (2021) proposed a method to evaluate how risk affects business strategy. The findings of Hudakova et al. (2018) included an assessment of the determinants of business risk and their effects on firm size. Glowka et al. (2020) analysed the effect of Enterprise Risk Management on SME's performance and its management by SME. The Risk Assessment and Identification had caught the researcher's attention, but the scope is limited to a few risk categories.

2.3 *Risk Management*

Risk management concerning a firm's survival and insolvency is crucial for SMEs. Business risk management has a positive effect on a company's future (Liu & Park

2021). The study on risk management focused on the implementation and availability of risk management practices for SMEs. Sifumba et al. (2017) studied the application of risk management practices by Manufacturing SMEs and found that SMEs had limited awareness of risk management. with the critical elements of risk management practices. Zoghi (2017) investigated the risk management approach of SMEs and its importance; however, he limited risk management to risk identification. The study by Crovini et al. (2020) found that SMEs need to follow specified procedures or a suitable risk management approach. Rostami, Sommerville, Wong, and Lee (2015) investigated the difficulties SMEs face when implementing risk management strategies. Virglerová et al. (2016) investigated how certain elements affect financial risk management and concluded that the "entrepreneurs' and firms' age" is the crucial factor for risk management.

In their study, Kachlami and Yazdanfar (2016) found a positive relationship between financial risk management and entrepreneurial behaviour. Falkner and Hiebl (2015) proposed that, because owners and managers are responsible for risk management, their attitudes affect it. However, the study by Belas et al. (2015) found an insignificant relationship between entrepreneurs' education and the risk management approach, focusing on entrepreneurs' approach to financial risk management amongst SMEs. Ali et al. (2021) and Sunjka (2015) studied the risk management practices implemented by SMEs to address crucial challenges. The aim of the research by Qubtan et al. (2021) was to examine the application of risk management in SMEs, and they found that SMEs are aware of it but lack its implementation. Hudakova et al. (2018) concluded that risk management practices are necessary because risk negatively affects business performance.

Cantonnet et al. (2018) explored the availability of procedures for managing occupational risk in SMEs and recommended the need to design easy ways to implement risk management. Kaassis and Badri (2018) developed a model to evaluate occupational risk management maturity among SMEs. Yang, Ishtiaq, and Anwar (2018) studied the role of competitive advantage among enterprise risk management methods. Implementing or considering ERM methods is associated with initiatives such as establishing a risk management team and developing risk aversion and risk acceptance statements (Ali et al. 2021).

Renault et al. (2018) analysed the risk management practices available for project risk management in construction firms and concluded that SMEs need to raise awareness of these practices. Chowdhury et al. (2019) examined the impact of factors intended to mitigate operational supply chain risk and found that supplier integration, through its positive relationship with social capital, was associated with Operational Supply Risk. Renault et al. (2021) evaluated the impact of demographic variables on risk management practices in project risk management. In contrast, Demertzis and Vatalis (2021) argued that risk management processes are underutilised in project risk management. Catanzaro and Teyssier (2020) implemented a risk management framework for the internationalisation of SMEs and found an association between export promotion programs and the internationalisation risk of SMEs.

The literature describes the development of a risk management framework for SMEs by some researchers during their studies. Marcelino et al. (2014) developed and validated a model of project risk management. The study by Utami et al. (2021) contributed to risk mitigation strategies for SMEs to address natural disasters. Bensaada and Taghezout (2019) developed a conceptual and qualitative framework for ERM.

2.4 *Importance of Risk Management for SMEs*

SMEs are more vulnerable to changes in their surroundings and are exposed to them (Huynh and Lin, 2025). As a result, it is evident that running a business can be risky. In industrialised countries, SMEs are experiencing increasing competition in their local markets, putting many at risk of survival (St-Pierre et al. 2018). Since its outbreak in 2020, the COVID-19 pandemic has impacted industry development (Tong & Yang 2021). Several obstacles hindered the growth of SMEs, driven by globalisation trends (Vijayalakshmi et al. 2022). Unlike huge corporations, SMEs lack procedures and administrative resources and this makes them highly sensitive to the risks arising during various stages of the projects (Demertzis and Vatalis 2021)

For small organisations, identifying risks and developing the requisite counterstrategies is difficult (Temel & Durst 2020). Due to limited experience and understanding, risk management is a serious concern for SMEs (Qubtan et al. 2021). According to Susi and Lukason's (2019) study, sustained value creation is vital for the long-term performance of enterprises, and this depends on the leadership and strong managerial talent of SMEs' decision-

makers. As Liu and Park (2021) note, before implementing any enterprise risk management model, SMEs should evaluate their business size, sector, affiliation, and ownership structure, as the model's effectiveness depends on these factors. SME sustainability and commercial success can be improved with the proper implementation of risk management practices (Brustbauer 2014).

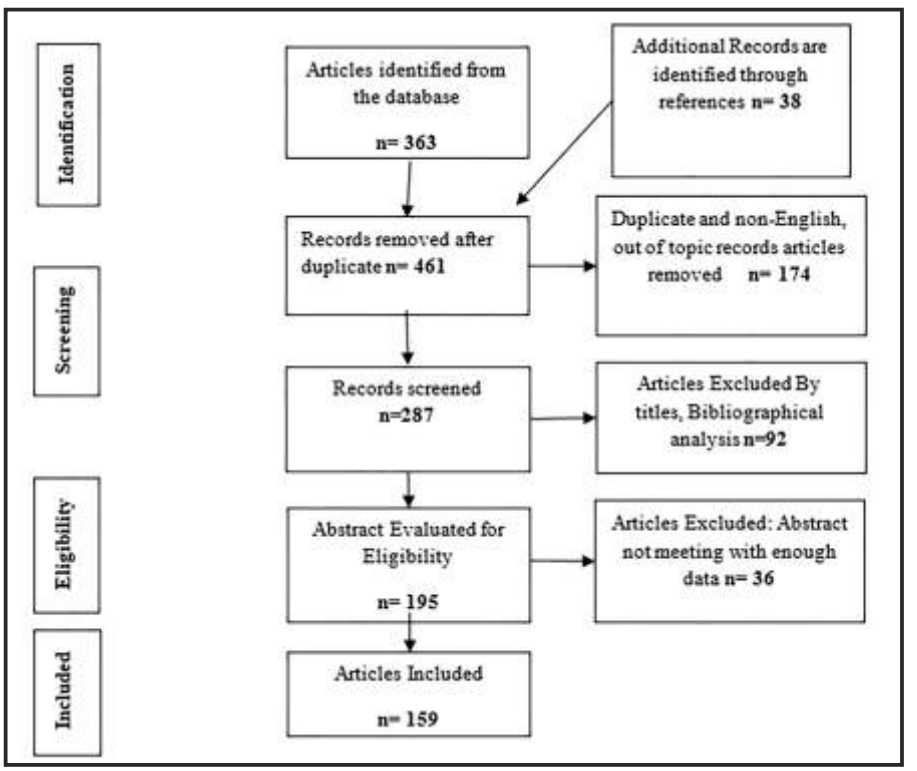
3. Methodology

As stated in the preceding section, the paper's major goal is to provide a comprehensive review of the literature on the development of risk identification, assessment, and management in SMEs. This literature review article also aims to emphasise the methodology and identify the future scope of research on risk management for SMEs. The stated objectives are achieved by considering the literature published over the past two decades, starting in 2002. Given the conceptual heterogeneity of studies on SMEs, a PRISMA-guided qualitative synthesis is the most appropriate method. In review papers, authors widely use bibliometrics and meta-analysis. However, the present review paper on SMEs is likely to be driven by the specific research objectives outlined in the respective section, the chosen methodological approach, and the scope of the study. The authors employed SLR to achieve a comprehensive understanding of risk assessment and management frameworks defined in the existing literature, which is deemed sufficient for said purposes.

For the present study, a Systematic Review was conducted by collecting relevant studies on risk assessment and management in small and medium enterprises, reviewing the methods, and generating the PRISMA flow diagram. Three hundred and sixty-three (363) articles were identified from the database, and they were narrowed down further to 159 following the PRISMA work.

3.1 *Study period and protocol*

The systematic review was executed from 2022 to 2024. A 27-item PRISMA checklist was used to conduct the systematic review, and the study protocol was registered in the Research Registry. The following PRISMA framework enumerates a detailed picture of sample extraction and finalisation.



Source: Author's Creation

Figure 1: Preferred Reporting Items for Systematic Review and Meta-Analysis

3.2 Variables and their Proxies

The primary aspect examined is risk management in SMEs, as captured by studies that explicitly address risk identification, evaluation, or mitigation practices within the SME domain. Along with risk management, risk assessment is treated as a key variable in the present study, reflecting the systematic identification and appraisal of potential risks. Its inclusion is justified by its central role in structured risk management processes. The proxy for this variable is the presence of risk identification methods and assessment frameworks documented in the studies under consideration. The selection of variables and proxies is guided by theoretical relevance, consistency across empirical studies, and alignment with the study's objectives and research questions.

3.3 *Search, Inclusion, and Exclusion criteria*

Research conducted during 2000-2001 and 2023-2024, published in English, was considered for the study. The initial scoping study was conducted by searching articles from reputable publishers' websites and databases, following the procedures outlined by Atkinson and Cipriani (2018). The search was carried out using search strategies to assess the relevance of the study, the completeness of the information, and the research quality, based on the inclusion and exclusion criteria. Table 1 enumerates the search strategy and keywords used to identify the articles included in the study.

Given the heterogeneity of MSME studies in terms of data sources, risk dimensions, and analytical techniques, the application of a single statistical estimation model would not yield meaningful or comparable results. Therefore, a systematic qualitative synthesis under the PRISMA framework is deemed sufficient and appropriate for achieving a comprehensive understanding of risk assessment and management frameworks in existing literature. The published articles which carried out empirical studies on all types of MSMEs along with their risk assessment, risk management, risk analysis, and risk mitigation were included in the study. There were a few articles/studies considered but included separately. For the study only peer-reviewed research articles were considered. The literature excluded research articles in which complete information could not be assessed, and the techniques employed were vague and ineffective. The analysis omitted figures that lacked numerical values. Articles that did not focus strongly on the risk aspects of MSMEs were excluded.

3.4 *Data collection*

The PRISMA flow diagram (Figure 1) explains the criteria used to decide which articles to include and exclude from the research. Only appropriate articles that fulfilled the study parameters were sourced. The complete paper was retrieved in cases where an abstract was deemed appropriate. Each article underwent manual searches to locate more relevant and appropriate articles. The references of the chosen articles were examined and, if suitable, the complete articles were sourced. The data were taken out and recorded in Microsoft Excel sheets/word documents.

Table 1: Keywords applied to find the relevant articles

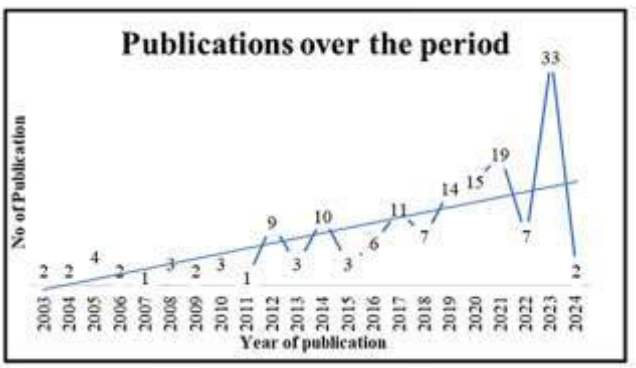
Sr. No	Keywords and Criteria for the search
1	Boolean logic, such as "AND" "OR" "NOT" were applied
2	Risk assessment and Management in small and medium enterprises. Repeating the search by the words "Risk assessment" ", MSME" ", Small and Medium Enterprises", etc.
3	Risk Analysis and Evaluation in small and medium enterprise. Repeating the search by the words “Risk Analysis” “Risk Evaluation” “MSME” “Small and Medium Enterprises” etc.
4	Risk mitigation for small and medium enterprises. Repeating the search by “Risk Mitigation” “MSME” etc.
5	Strategies for managing or reducing risk in small and medium enterprises. Repeating the search by “Risk strategies” “MSME” etc.
6	Credit Risk in small and medium enterprises. Repeating the search by “managing credit risk, “MSME” etc.

Source: Author's Creation

Content analysis of the collected sample is conducted to achieve the research objectives. The analysis of the selected sample is presented in further section. The results for future directions were achieved by incorporating a descriptive, bibliographic study and content analysis.

4 Results and Discussions

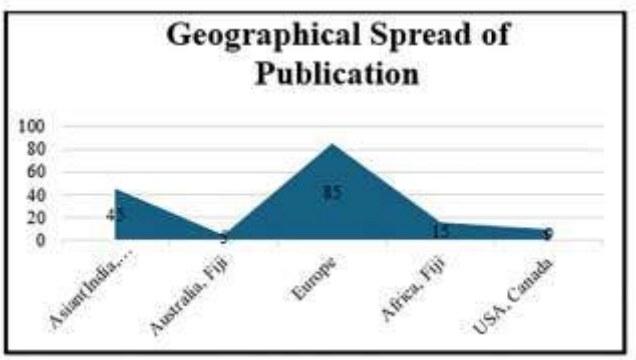
Figure 2 illustrates year-wise research papers contributed to the domain of risk management and the development of publications since 2002, worldwide, focusing on risk management in SMEs.



Source: Author's Creation

Figure 2: Publications over the Period

Figure 2 indicates that there was less research and study in the domain during the initial years, though it was consistent. Research contributions on the subject have reached a recognised level in more recent years. There has been a significant increase in the number of research contributions since 2017,, and 2023 showed the highest number of research articles in the said area. It shows that research on risk and risk management in SMEs is gaining prominence among researchers and underscores the timeliness of the topic.

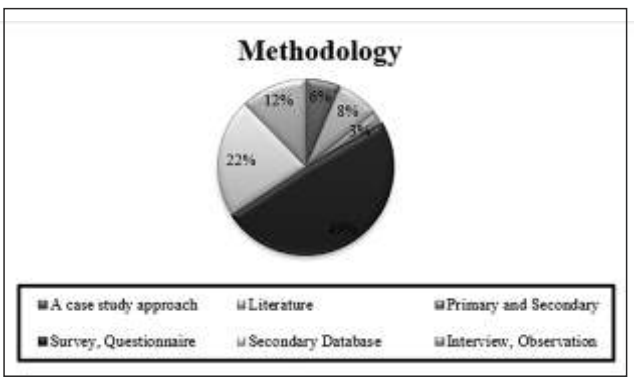


Source: Author's Creation

Figure 3: Geographical Spread

Figure 3 illustrates the geographical distribution of studies in the said area worldwide, grouped by major continents. European countries conducted more studies, accounting for almost 50% of the total research in the domain. Countries such as Germany, France, Italy, Slovakia, the UK, and Spain have undertaken studies in large numbers. In recent years, Asian countries, particularly India and China, have conducted extensive research on the topic. In recent years, these countries have inclined their research toward Risk Management in SMEs. The remaining continents—Africa, Australia, and the USA—have not focused much on the research in this domain. Even though there is variation in the number of studies conducted across countries, the domain has gained attention worldwide. Risk Management in SMEs is proving to be a pressing research need regardless of whether the economy is developed, emerging, or developing.

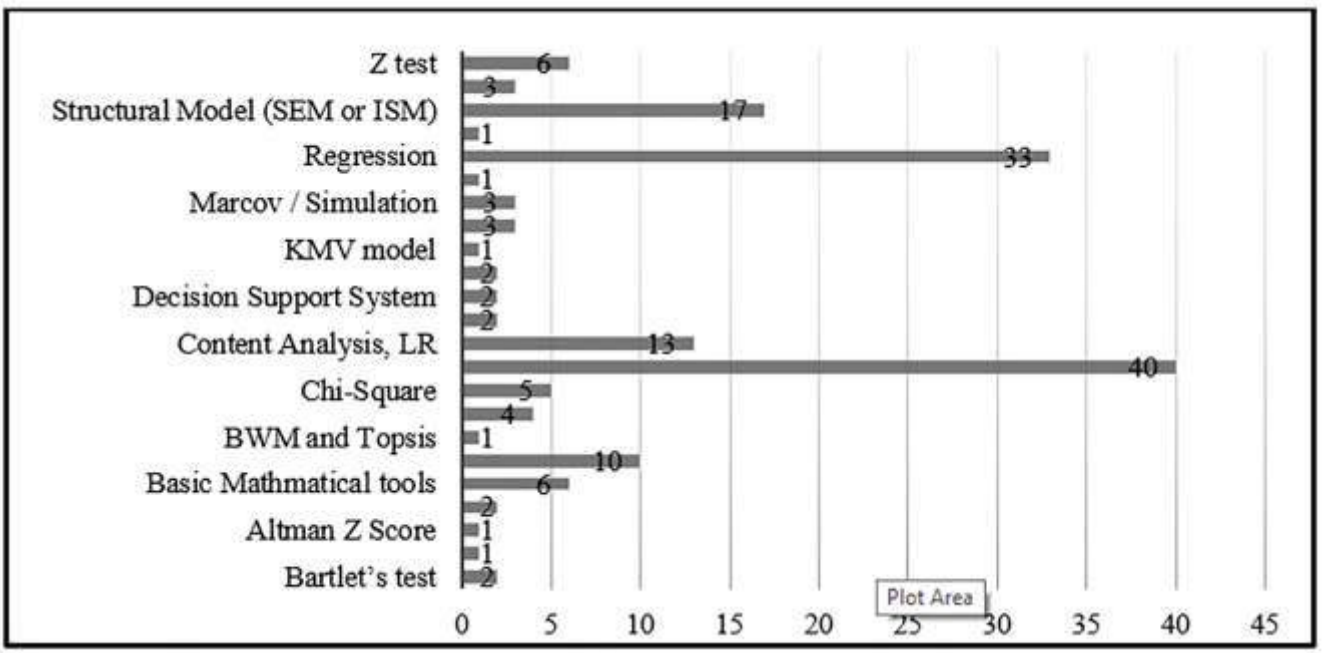
A crucial basis for any research is the methodology used to conduct the research. Figure 4 represents the foremost aspect of research applied by researchers.



Source: Author's Creation

Figure 4: Methodology applied

Figure 4 illustrates the research article's methodological approach to data collection and development. The researcher's methodology is empirical and descriptive. The analysis indicates that many researchers have used primary data, comprising Survey (49%) and Interview-Observation (12%). Few studies (22%) have used Secondary Data from the available database. Some research under the sample is Literature-Based, indicating the gap and scope for further studies in the domain. Prioritisation of factors in this research is done based on their likelihood of occurrence and their impact. It helps to perform risk identification and assessment accurately and precisely.



Source: Author's Creation

Figure 5: Tools applied for analysis

Figure 5 depicts the different techniques and tools applied under the studies for analysis. Researchers use various tools, ranging from basic to advanced. Regression and Conceptual Analysis are the preferred tools by these researchers. Some researchers have used Structural Equation Modelling to conduct factor analysis and to develop models. Few researchers have applied basic mathematical and statistical tools for their research. Few researchers have applied advanced techniques such as Machine Learning and Decision Support Systems.

Source: Author's Creation

Figure 6: Distribution of Focus of Studies

The sample under this study is analysed and categorised as Identification of Risk Factors, Assessment of Risk, and Risk Management. Figure 6 shows that many studies have focused on identifying factors as a primary objective of their research. More than 50% of researchers have identified factors that may pose risks or challenges for SMEs. Some researchers (25%) studied Risk Assessment and Evaluation. Few researchers (17%) have concentrated on risk management in SMEs.

The above discussions and analyses show that researchers need to place greater emphasis on risk management in their studies. Risk identification is crucial, but managing risk is essential once it has been detected, because SMEs may fail due to the non-application of risk management processes and frameworks (Renault et al. 2018). As advocated by Verbano and Venturini (2013), the focus is on identification rather than on early diagnosis and management. There is a dearth of focus on risk treatment.

Table 2 showcases the key authors who have covered risk assessment, analysis, or evaluation in their research articles. Of the total samples studied, 41 articles discussed or conducted risk assessments for SMEs.

Table 2: Risk Assessment covered under Studies

Risk Factors	Key Authors	Performed Risk Assessment	Discussed	Developed Model	Techniques Applied
Credit Risk	(Chen, Wang, & Wu, 2010)	✓			
	(Gonçalves et al., 2016)	✓		✓	Decision Support System
	(Gama and Geraldes 2012)	✓		✓	Logit Scoring Model
	(Laitinen 2008)	✓			
	(Zhang, Hu, & Zhang, 2015)	✓			
	(Yang et al. 2021)	✓			
	(Vasnier et al. 2021)	✓		✓	Marcov
	(Roy & Shaw 2021)	✓		✓	BWM and TOPSIS
	(Yin et al. 2020)	✓			
	(You et al., 2019)	✓		✓	Machine Learning
	(Wen et al., 2022)	✓		✓	Machine Learning
	(Yuan and Wang 2019)		✓		
	(Zhang et al., 2022)			✓	DeepRisk
	S. Li (2024)			✓	BP-KMV and GARCH
Financial Risk (other than Credit Risk)	(Reboud and Tim 2003)	✓		✓	Conceptual
	(Love et al. 2005)	✓			
	(Quintiliani 2017)	✓		✓	Regression
	(Hudáková and Dvorský 2018)		✓		
Operational Risk (Market)	(Grandon and Pearson 2004)	✓			
	(Altman, Sabato, & Wilson, 2010)	✓			
Project Risk	(Pereira et al. 2015)	✓		✓	Conceptual
Strategic & Managerial Risk	(Rehman & Anwar 2019)	✓		✓	PLS-SEM
	(Havierniková, Okreglicka, and Kordoš 2020)		✓		
Supply Chain	(Canbolat et al. 2008)	✓		✓	Simulation
	(Babu et al. 2021)	✓		✓	PLS-SEM
	(Sutrisno and Kumar 2022)	✓			
Innovation	(Raya et al. 2021)	✓			
Business Risk	(Dvorsky & Petrakova, 2021)	✓			
Health Safety	(Fera and Macchiaroli 2010)	✓		✓	AHP Model
	(Jørgensen, Duijm, and Troen 2011)	✓			
	(Kaassis and Badri 2018)	✓			

Source: Author's Creation

Table 2 indicates that the researchers have considered credit risk a crucial risk factor in their risk assessment. Apart from credit risk, other factors such as Supply Chain, Financial Risk, and Occupational Risk have also attracted the attention of a few researchers. The researcher performs the risk analysis rather than merely discussing it. Some of the authors extended their study and contributed substantially to the research by developing a model to assess the risk. However, the developed model encountered at least some of the risk factors faced by SMEs, whereas credit risk is considered the crucial one. The emerging techniques applied for model development are Machine Learning and Decision Support Systems.

Though the factors creating risk to SMEs are vital, their impact on business need to be assessed appropriately. Hence, the strategy for Risk management must be designed to help the organisation accomplish its goals. More studies that concentrate on this requirement are necessary. The risk assessment shall be addressed by risk management techniques to concur with the results for the sustainability and growth of the business.

Table 3 comprehensively depicts research articles that have considered risk management as an integral part of their study.

Table 3: Risk Management (RM) covered under Studies

Type of Risk	Key Authors	Focus of Study	Developed Framework or Model	Framework Tool
Financial Risk	(Jobst ,2006)	Asset Securitisation as RM tool	✓	Qualitative
	(Yiannaki 2012)	Comparative Study of SMEs RM	✓	Balance Scorecard
	(Falkner and Hiebl 2015)	Literature on Importance of RM		
	(Zoghi 2017)	Implementation of RM by SMEs		
	(Kachlami and Yazdanfar 2016)	Specific Factors impacting RM		
	(Virglerova Z et al., 2016)	Factors affecting Financial RM		
	(Belás et al. 2015)	Approach of SMEs to Financial RM		
	(Qubtan et al., 2021)	Approach SMEs to Financial RM		
	(Boom and Boom 2019)	FRM practices adopted by SMEs		
	Meiryani (2024)	Importance of RM		
Occupational Risk	(Cantonnet et al. 2019)	Emerging RM in SMEs		
	(Maenpaa & Voutilainen, 2012)	Insurance of Human Capital Risk		
	(Cañamares et al., 2017)	RM implementation and its integration in SMEs		

Type of Risk	Key Authors	Focus of Study	Developed Framework or Model	Framework Tool
Finance and Market	(Smit, 2012).	Literature on RM in South Africa		
	(Hudakova & Dvorsky, 2018)	Implementation of RM		
Financial and Strategic Risk	(Yang et al., 2018)	Impact of RM on Firm Performance		
	(Marcelino-Sádaba et al. 2014)	Actions to manage project risk	✓	Qualitative
Project Risk Management	(Renault et al. 2018)	RM practices available in construction firm		
	(umanns, Bitter, & Janssen, 2018)	Project Risk Management	✓	DSS
	(Demertzis and Vatalis, 2021)	Current situation of RM in SMEs		
SCM	(Sunjka and Emwanu 2015)	RM practices developed by SMEs		
	(Ritchie and Brindley 2000)	Studied framework available for SMEs		
	(Zailani, Fie, Aghapour, & Marthandan, 2017)	RM practices adopted for SCM risk		
	(Renault et al., 2021)	Impact of Demographic factors on RM practices		
	Qiao and Zhao (2023)	Implementation of SCM in SMEs		
Operational	(Chiarini 2017)	Risk and its management by SMEs		
Market Risk	(Hudakova et al. 2018)	Factors affecting RM practices		
	(Kozubíková et al. 2015)	Impact of Characteristics of entrepreneur on RMP		
	(St-Pierre et al. 2018)	RM mechanism adopted and Managerial Approach		
	(Catanzaro and Teyssier 2020)	RM practices and export capabilities of SMEs		
Strategic Risk	(Sifumba et al. 2017)	RM practices adopted by SMEs		
	(Rostami et al. 2015)	RM practices adopted by construction SMEs		
	(Crovini, Santoro, & Ossola, 2020)	Entrepreneurial approach and RM		

Type of Risk	Key Authors	Focus of Study	Developed Framework or Model	Framework Tool
Managerial	(Henschel 2006)	RM practices adopted by SMEs		
	(Havierniková et al. 2020)	RM practices adopted by SMEs		
	(Panigrahi, 2012)	RM practices adopted by Indian SMEs		
Natural Disaster	(Utami et al. 2021)	Strategies to mitigate risk	✓	Qualitative
ERM	(Bensaada and Taghezout 2019)	RM system for SMES	✓	Qualitative
Literature on Risk Management	(De Araújo Lima, Crema, & Verbano, 2020)	Literature on development of RM in SMEs		
	(Verbano and Venturini 2013)	Literature on RM in SMEs		
	(Crovini et al. 2021)	RM management practices and scope for improvement		

Source: Author's Creation

This study focused on understanding the importance gained by Risk Management in SMEs by researchers worldwide.

Table 3 reveals that only a small proportion (17%) of the studies in the reviewed sample prioritised risk management in the context of SMEs as a central research theme. Among these, the primary focus was on the implementation of risk management practices by SMEs, the necessity of adopting such practices, and the significance of risk management for their sustainability and growth. However, there is a noticeable gap in the literature concerning the development of structured solutions or comprehensive frameworks aimed at facilitating risk management or mitigation specifically tailored to the needs of SMEs.

While exploring Risk Management in their study, researchers considered risk management relating to a few risk factors ranging from Financial Risk, Strategic Risk, and Operational Risk. The framework for risk management is developed for Strategic, Financial, and Project Risk. Project Risk Management is gaining importance from researchers; however, the highly focused area is Credit and Finance Risk. The analysis illustrates that only some types of risk were given importance in risk management; however, the research shall consider all the types of risks that SMEs face (Trajkovski & Antovski 2017).

To develop an effective risk management framework and achieve its intended objectives, it is essential to conduct a thorough analysis of risk-inducing factors and their implications for organisational performance. Among various risk types, financial risk has garnered the most scholarly attention, given its fundamental role in organisational sustainability. However, in the face of an increasingly dynamic business environment, researchers have begun to shift their focus toward strategic and operational risks, recognising their growing relevance. For SMEs to maintain competitiveness, it is imperative to adopt strategies that address these emerging risk dimensions. Factors such as operational inefficiencies, managerial capabilities, limited social and governmental support, natural calamities, and exposure to international markets remain underexplored despite their critical significance. The foregoing analysis suggests that if these commonly identified risk factors are not adequately addressed, they may contribute to heightened vulnerability and instability within the SME sector.

5. Implications

The results of this research are very important for researchers, practitioners and regulators and provide a data-centric basis for strategic decisions. The review of the

literature on risk assessment and management in SMEs reveals several important implications for SMEs. SMEs confront a distinct mix of opportunities and problems when it comes to risk management because of the region's economic diversity, rapid expansion, and growing worldwide interdependence. Following paragraphs enumerate the theoretical and practical implications of the study.

5.1 Theoretical Implications

The present study has contributed to the body of literature by providing an extensive analysis of the literature on risk management and Assessment for SMEs, considering all the types of risk. The study had categorised numerous variables and grouped them into one risk factor. Previous studies have focused on understanding Risk in silos, not in groups. The review shows that traditional Enterprise risk management and resource-based view frameworks are dominating, while dynamic and behavioral aspects shall get more importance. The study extends the current literature by providing the risk assessment and management framework developed for SMEs and reflects the need for the development of advanced frameworks for SMEs.

5.2 Practical Implication

A significant suggestion of this study is an appeal for SMEs to become more conscious and institutionalise risk management procedures. Many SMEs in nations like Vietnam, Indonesia, the Philippines, and India work in semi-formal or informal sectors and frequently lack systematic methods for detecting and reducing risks (Moinak, 2018). Research indicates that this disparity increases susceptibility to changes pertaining to operations, finances, and markets. SMEs if failed to create planned strategies to manage risks, may suffer greatly from supply chain disruptions brought on by disasters or geopolitical unrest, which are frequent in Asia (Guo et. al., 2022). Risk avoidance and a hierarchical decision-making framework are preferred in many developing countries and due to this innovation and proactive risk-taking may hampered. Policymakers and trade associations should support risk education and training that is adapted to regional business

The importance of networking and stakeholder engagement as a risk reduction technique is supported by literature. Forming industry clusters, joining chambers of commerce, and taking part in knowledge-sharing platforms that improve collective resilience are all beneficial for SMEs. Peer-to-peer learning can also help SMEs adopt risk-reduction tactics that have worked for others in comparable situations (Shurukhina et.al., 2018). Strategic interventions adapted to regional contexts encompassing education, technology, and policy can empower SMEs to better anticipate, analyse, and manage risks, thereby building more resilient and competitive business environments.

6. Limitations

The study has certain limitations inherent in a systematic literature review. The study has focused on limited, renowned databases, excluding the non-indexed studies. The research paper considered in the English language from the period of 2000-01, and the semantic studies are included. The study primarily adopts a qualitative approach instead of a statistical meta-analysis. The future research may address these limitations.

7. Conclusion and Future Scope

The application of PRISMA methodology in this study facilitated the systematic identification and extraction of relevant studies by eliminating research that did not meet the predefined inclusion criteria. Through a thorough review of the existing literature, key directions for future research were identified. The critical evaluation provided a holistic overview of scholarly contributions in the areas of risk management and risk assessment within the SME sector. The findings indicate that, although research in this domain is gradually attracting global scholarly interest, a significant proportion of studies originate from European nations. Notably, recent years have witnessed a rise in contributions from Asian countries, reflecting a growing regional engagement with the subject.

A substantial number of studies have focused on identifying and analysing factors containing challenges to the sustainable growth and development of SMEs. Conceptual research appears to dominate the field, often favored over applied research. While literature offers valuable insights into the key risk factors organisations should prioritise, relatively few studies have progressed toward the development or empirical validation of models for risk identification and management. Existing models tend to focus either on risk assessment or risk management and frequently incorporate contemporary methodologies. However, there remains a pressing need for more integrative and comprehensive frameworks that reflect the diversity of industry sectors globally and their broader economic implications.

The research questions proposed in this study are addressed through a rigorous PRISMA-based SLR, which enabled the identification, classification, and critical evaluation of existing SME risk assessment and management literature. By synthesising conceptual, empirical, and methodological evidence across two decades, the study uncovers key gaps in existing frameworks and evaluates the extent to which emerging tools and techniques have been applied.

The study concludes that there is a need for a comprehensive framework to identify and assess all the crucial risk factors with risk management strategies to mitigate the same. Evidence of the prevalence of low mortality and high failure rate among SMEs may be found in industry surveys and academic studies worldwide. Risk aversion, infrastructure, budget deficiencies, and poor leadership talents are all regularly cited as reasons for such circumstances. Despite the inflow of capital and regulatory assistance over the last two decades, research has shown that SMEs' risk management capacities could be improved, resulting in favorable conditions for the sector. By embedding a systematic approach to enterprise risk management into SMEs, potential benefits such as reduced risk as well as management and organisational alignment toward the SME's mission can be accomplished (Smit, 2012). The framework with quantitative as well as qualitative approaches may lead to addressing the issue of risk management and improving the sustainable resilience of SMEs. SMEs significantly contribute to a country's economic development; hence their growth and low mortality should be priorities.

A thorough evaluation of risk-generating factors and their organisational impact is essential for formulating effective management strategies aimed at achieving desired outcomes. Financial risk continues to receive the most extensive attention in scholarly research, reflecting its critical role in organisational stability. However, given the complexities of the current business landscape, reliance on financial metrics alone is insufficient. Strategic risks are increasingly being recognised by researchers as equally significant, as they encompass variables that influence long-term competitiveness and sustainability.

For SMEs, it is imperative to adopt strategies that foster a sustainable competitive advantage. One area of concern is the limited preparedness of SMEs to effectively manage the consequences of natural disasters identified by Wedawatta and Bingunath (2012). This concern highlights the need for proactive risk management frameworks to address such unpredictable events. Additionally, strategic risks such as innovation demands, market competition, and evolving consumer expectations are becoming increasingly relevant.

Despite their importance, several operational and external risk factors, such as production disruptions, inventory control, inadequate government support, exposure to natural hazards, and entry into international markets, remain underexplored in the context of SMEs. The prevailing literature suggests that these commonly identified yet insufficiently addressed risks contribute to an increasingly vulnerable and unstable business environment for SMEs if not systematically mitigated.

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Generational Differences in Sustainable Consumption: A Theory of Planned Behaviour Perspective on Indian Millennials and Generation Z

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Abstract

Sustainability has, in recent times, been a key driver of consumer behaviour, influenced by emerging economies such as India. There remains a significant gap in research on generational cohorts in India and their sustainable consumption intentions. This study addresses this knowledge gap by examining the determinants of Millennials' and Generation Z's behaviour in light of the "Theory of Planned Behaviour (TPB)". Further, it develops this based on the generational cohorts theory. This study utilised a quantitative approach and applied "Partial Least Squares-Structural Equation Modelling (PLS-SEM)" to examine the influence of subjective norms, attitude, and perceived behavioural control on purchasing intentions, with age group taken as a moderating factor (i.e., Millennial and Generation Z). 324 respondents from India were surveyed. The results indicate how all TPB variables affected sustainable purchasing intentions, with Generation Z found to be more sensitive than Millennials to attitude and subjective norms. This study shows that generational cohorts are important and can determine consumers' adoption of sustainability-fuelled behaviour and habits. In practice, this research shows that marketers can frame their sustainability messaging to navigate generational traits: Generation Z is more drawn to emotional and peer behaviours, while Millennials respond to value-based appeals. Policymakers could also use generationally segmented programs to promote sustainability in any capacity, which may help drive sustainable behaviours across India's consumer landscape.

Keywords: *Sustainable Consumption, Theory of Planned Behaviour (TPB), Generational Cohort Theory, Indian Millennials, Generation Z, Sustainable Marketing*

1. Introduction

The UN has defined sustainability as "meeting the needs of the present without compromising the ability of future generations to meet their own needs." Sustainability has become a key driver of consumer behaviour globally, including in India, where fast urbanisation, growing environmental awareness, and heightened awareness of ethical consumption are transforming market trends. Understanding consumer behaviour towards sustainability in India is increasingly vital as Indian consumers' willingness to invest in sustainably produced goods is changing. According to PwC's 2024 Voice of the Consumer Survey (PwC research, 2024), consumers in India are willing to pay an average premium of 13.1% for sustainably produced or sourced products, exceeding the global average of 9.7% (surveyed more than 7,000 consumers across 11 Asia Pacific countries). This increased willingness presents a significant business opportunity for companies that incorporate sustainability into their operations and product portfolios. The rising occurrences of climate change disruptions also affect consumer purchase decisions. The same PwC survey states that 88% of consumers across Asia Pacific, including India, have directly felt the effects of climate change in their everyday lives, leading 50% to purchase more sustainable products. As more conscious consumers make an effort to live sustainably, businesses are under pressure to transition by prioritising sustainability and offering products that resonate with this growing awareness. McKinsey's 2024 report confirms that consumers in emerging economies such as India are more than likely to double their expenditure on well-being products and services than their counterparts in mature economies (McKinsey, 2024). This trend reflects the growing link between sustainability and individual well-being, motivating companies to develop products that address health and environmental issues.

A generation is defined as "an identifiable sect of individuals who share birth years, experience similar life events, and socio-economic developments" (Kupperschmidt, 2000; Ordun, 2015). Millennials, who are also known as Generation Y, have been described variously as "people born between 1980-1990, the first generation of so-called 'digital natives' " (Cord et al., 2015, pp. 158-9); born between 1977 and 1996 (Valentine & Powers, 2013); born between 1981 and 1995 (Solka et al., 2011); or between 1977 and 1994 (Neuborne, 1999; Williams & Page, 2011). Therefore, a general knowledge of Millennials is that they would be no younger than 28 and no older than 48 years of age today in 2025. The post-millennial Generation Z (Tapscott, 2009) is defined as individuals born between the mid-1990s and the early 2010s, and hence can be aged 15 to 30 in 2025. Therefore, based on definitions for each generational category's start and end birth years, there may be some overlap between younger Millennials and older Generation Z.

According to Strauss and Howe (1991), ageing around the same period and witnessing the same socio-economic phenomena during the development stage (typically between 17 and 23 years) results in corresponding values, orientations, and lifestyles among cohort members. Thus, marketers must understand all generations thoroughly, including their differences and similarities across regions, so they can position their goods and services to suit them. Previous studies confirm that one method for determining how customer values change is to compare the features of the new generation with those of past generations (Debevec et al., 2013; Ordun, 2015; Chaney et al., 2017).

Understanding consumer sustainable behaviour in India is crucial given its unique cultural, economic, and social environment. Unlike individualist U.S. consumption, Indian purchasing behaviour is influenced by societal values, prices, and saving ('jugaad' mentality). With India expected to be the world's third-largest consumer market in 2030, businesses and policymakers need localised data to drive sustainability. Most studies on sustainability (Maniatis, 2015; Nguyen et al., 2020; Cheah & Phau, 2011) focus on Western markets, where income levels, lifestyle priorities, and consumption patterns differ from those in India. Convenience may be a preference among U.S. consumers, while Indian consumers consider affordability and sustainability. Factors such as external climate impacts and regulatory systems have varying effects on purchasing behaviour across these markets.

This study bridges the knowledge gap by identifying what drives Indian Millennials and Gen Z to adopt sustainability. It provides realistic insights for companies to strategise sustainable campaign launches and governments to develop programs relevant to India's socio-economic landscape. Millennials and the subsequent generation, i.e., "Generation Z," represent a large share of the population in India and globally. Due to their sheer size, they wield immense power in society. While much international research has been conducted on sustainability and consumer behaviour (Maniatis, 2015; Nguyen et al., 2020; Cheah and Phau, 2011), a considerable gap exists in this

context in the Indian setup, particularly concerning generational groups. Most generational research focuses on developed economies like the U.S. and Europe. However, one cannot generalise about the characteristics and nature of a generation worldwide, as the factors and events that influence each region differ. Such studies cannot be applied to comprehend Indian needs because socio-economic and other conditions do not match those of the Western world. This study matters because it fills a major knowledge gap in sustainability research by identifying Indian consumer decision-making across generations. Although many studies on sustainable consumption have been conducted, most are conducted in Western markets whose socio-economic profiles, consumption values, and regulatory frameworks differ from those in India. Since India is set to be the third-largest consumer market in 2030, businesses, governments, and stakeholders must know how Millennials and Generation Z understand and respond to sustainability so that they can position their products, policies, and campaigns in harmony with the values and aspirations of these powerful demographic groups. The research will inform effective strategies to drive sustainable consumption in a culturally and economically appropriate way.

The Theory of Planned Behaviour (TPB) has been used to predict behaviour related to sustainable consumption across many contexts (Naskar et al., 2025; Sapkota et al., 2025). Recently, researchers have begun to understand that the relationship between the variables in the TPB can vary depending on several factors, including demographics and socio-cultural backgrounds, which suggests that understanding boundary conditions is an important area of study if we want to improve the explanatory power of the theory (Husnatarina et al., 2026; Kumar et al., 2021; Kumar et al., 2026). One example of a potentially useful boundary condition is generational cohort, because generations share common formative experiences and therefore socio-technologically relevant experiences. Therefore, because attitudes and beliefs about what others think you should do (subjective norms) are social constructions, and because each generation will have developed these beliefs based on their unique experience with technology and sustainability awareness, there will likely be systematic differences in how they develop from cognition to behavioural intention (Djafarova & Bowes, 2021; Dabija, 2018).

Following the above discussion, the subsequent research questions are formulated:

- What are the key drivers of sustainable consumer choices among Millennials and Generation Z in India?
- How do generational differences influence the perceptions of sustainability in consumer purchasing decisions?
- What are the biggest hurdles to making sustainable consumption the norm?
- How can policymakers and businesses use this knowledge to help fuel sustainable consumption in the Indian market?

This research contributes to the theoretical and applied knowledge of sustainability in emerging markets by presenting a generationally segmented analysis of Indian consumers. Unlike previous work based on Western contexts, this study presents localised evidence of the values, social factors, and perceived barriers underlying sustainable action in India. Our research will assist companies in crafting effective, culturally relevant sustainability campaigns and enable policymakers to create interventions that overcome motivational and structural barriers. Additionally, this study contributes to theoretical application within sustainability research by applying generational cohort theory and the Theory of Planned Behaviour. It forms a solid basis for subsequent research in comparable markets.

2. Literature Review & Framework

Researchers have widely explored the determinants of sustainable consumer behaviour, with the most critical influences including personal values, social norms, and perceived behavioural control (Ajzen, 1991). The “Theory of Planned Behaviour (TPB)” and the “Value-Belief-Norm (VBN)” model have been used in various studies to explain how consumer attitudes toward sustainability are converted into purchasing behaviour. The attitude-behaviour gap is the other key topic of study, indicating that consumers may have strong sustainability attitudes but ultimately do not follow through with environmentally friendly purchases due to various obstacles, including high costs, inaccessibility, and reservations about the company's claims. Studies suggest overcoming this gap requires businesses to improve trust through transparent communication and credible eco-labelling. Generational differences have also been examined, with studies showing that younger consumers, such as Millennials and

Generation Z, have stronger pro-sustainability preferences than their elderly counterparts. However, whereas Millennials are more likely to support brands with robust CSR programs, Gen Z consumers expect greater transparency and accountability from companies and are highly wary of greenwashing. All in all, the available literature highlights that companies need to take a general approach to sustainability, making ecologically friendly goods not only socially responsible but also affordable and readily accessible. More research would be required to map how the above global shifts play out across particular regional economies, such as India, where economic and socio-cultural considerations will influence sustainable consumption differently.

2.1 Theoretical Framework

2.1.1 Theory of Reasoned Action

"Theory of Reasoned Action (TRA)" (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) states that behavioural intentions, which are the immediate determinants of behaviour, are a function of salient information or beliefs regarding the probability that doing a specific behaviour will result in a particular consequence. TRA is mainly concerned with subjective norms and attitudes as the primary determinants of behaviour, assuming that individuals always have complete control over their behaviour. Nonetheless, this presumption is unrealistic in most cases, as many behaviours, particularly those related to sustainability, face barriers such as budget constraints, inaccessibility, or societally imposed limitations. TPB addresses this gap by considering perceived behavioural control (PBC), which accounts for external barriers and one's perceived ability to overcome them. This added variable makes TPB more relevant to everyday situations in which people may plan to perform a behaviour but are constrained by external factors.

Conversely, Social Identity Theory (Tajfel & Turner) presumes that individuals derive their self-concept from group membership and does not fully explain personal attitudes or perceived constraints on decision-making. TPB is superior to Social Identity Theory (SIT) for research on consumer behaviour toward sustainability because it provides a formal model of individual decision-making that accounts for attitudes, social influence, and perceived control. Consumer choice, especially regarding sustainability, will be guided by individual beliefs and environmental limitations rather than group identity. Unlike SIT, TPB includes PBC, which can predict an individual's likelihood of engaging in a behaviour based on their sense of control over it. TPB, therefore, is a more practical and richer theoretical framework for investigating sustainability decisions in which both intrinsically motivational elements and external obstacles affect consumers' behaviour.

2.1.2 Theory of Planned Behaviour

TPB by Ajzen (1985) is a universal psychological model of human action. TPB broadens the TRA by including perceived behaviour control as the primary determinant of intention and behaviour. TPB states that an individual's likelihood of enacting a certain behaviour is based on three key determinants: subjective norms, attitude towards the behaviour, and perceived behavioural control. Attitude is the degree to which an individual has an opinion for or against the behaviour. Subjective norms convey social pressure to perform or not perform the task. On the contrary, perceived behavioural control entails personal belief about the ease of performing the act, based on the individual's past performances and anticipated obstacles.

TPB has been widely applied in sustainability research, particularly in the analysis of green and sustainable consumer behaviour. According to Joshi & Rahman (2015), the theory explains the "green attitude-behaviour gap" well, as individuals express concern about environmental issues but do not necessarily exhibit sustainable shopping behaviour. This difference is most often attributed to external barriers, such as the prohibitive costs of environmentally friendly products, limited availability, and uncertainty about green claims (greenwashing). Despite consumers' positive attitudes towards sustainability, they may not engage in sustainable consumption if they perceive significant barriers, which is why perceived behavioural control is important for green consumption behaviour.

Several studies have demonstrated TPB's viability in understanding green consumption behaviour. In their study, Nguyen et al. (2020) found that environmental awareness, health consciousness, and altruism positively influence green purchase intentions. Consumers who are health-conscious and concerned about others' welfare tend to buy green products because they find these actions useful at both the individual and social levels. In addition, perceived control over behaviour (e.g., financial resources and the availability of sustainable goods) influences whether consumers turn their green attitudes into actual buying habits.

Subjective norms are essential in sustainable consumerism among Millennials and Generation Z, who are socially influenced by social media, peer networks, and business sustainability practices. Evidence suggests that 74% of consumers use social media to find sustainable brands, and 76% use online reviews before making green purchases. Greater visibility of environmentally friendly lifestyles on internet platforms strengthens the power of subjective norms, leading young consumers to follow more sustainable consumption practices. However, research also shows that social pressure alone is not always enough to motivate behaviour unless structural constraints, such as affordability and accessibility, are removed.

TPB describes how the three chief factors, i.e., subjective norms, attitude toward the behaviour, and perceived behavioural control, determine behavioural intention. Positive social norms and favourable attitudes give the impetus for a behaviour to be performed, but only if individuals feel that they have control over it can the intention materialise. Attitude toward the behaviour is based on behavioural beliefs—an individual's perception of the expected outcomes of behaviour. A positive attitude forms when the anticipated results are favourable; if they are undesirable, the attitude becomes negative. The stronger the belief in a particular outcome, the more it influences overall attitude. Subjective norms are perceived social pressures to perform a behaviour. They are derived from two sources: injunctive norms, which capture whether significant others (e.g., family, friends, or co-workers) support or oppose the behaviour, and descriptive norms, which capture whether others in one's social group perform the behaviour. The degree to which one cares about one's opinions controls one's influence on behaviour. Control beliefs determine PBC factors that enable or hinder the behaviour, including skills, resources, time, and external support. If individuals believe they have the resources and ability to implement the behaviour, they are more likely to take action on their intentions. PBC also controls the influence of subjective norms and attitude on intention, i.e., even if a person holds a positive attitude and social support, they will not act unless they believe they can. When there is no control over behaviour, perceived control is a good predictor of whether the behaviour will be enacted.

Recent research indicates that the TPB constructs, i.e., attitude, subjective norms, and perceived behavioural control, consistently forecast individuals' intentions to purchase green items, irrespective of the category of product or cultural context (Deniz, 2026; Kumar et al., 2021). Researchers are increasingly arguing that demographic moderators, such as age and generational identity, should be incorporated to enhance contextual sensitivity and predictive accuracy (Dabija, 2018). This perspective aligns with efforts to refine the Theory of Planned Behaviour by specifying the conditions that intensify specific psychological motivations.

In summary, the TPB provides a robust framework for understanding the complexities of sustainable consumer behaviour. Although attitudes towards sustainability are positive, adopting environmentally friendly behaviours is contingent on social influences, perceived control, and structural factors that facilitate or impede green purchasing decisions. To bridge the attitude-behaviour gap, businesses must prioritise affordability, accessibility, and consumer education, while policymakers should implement regulations that support sustainable practices and reduce greenwashing. As sustainability shapes global consumption patterns, TPB remains a critical tool for designing effective interventions that drive long-term behavioural change toward a more sustainable future.

2.1.3 Generational Cohort Theory

The term "generation" has had a changing meaning over the years, and its exact origin is hard to identify. However, according to Robert (1979), the French philosopher Émile Littré first used the term in 1863 to mean "all persons living in the same period." The relevance of generational differences began to gain momentum towards the end of the 19th century, especially with changes in communication technology, such as the World Wide Web. These changes played a role in bringing about a change in social structures, minimising the role of family—particularly parental control—over younger generations. In 1977, Inglehart presented the "Generational Cohort Theory" (GCT), which was further developed by Strauss and Howe (1991) in their highly respected book Generations. In their model, a generation lasts around 20 to 25 years, i.e., the time it takes for a cohort to be born, mature, and begin having children. Generational cohorts are characterised by people born in the same year who experience comparable life events and significant historical events at the same stages of their early lives. These experiences form their values, attitudes, and outlook, making one cohort different from another (Strauss & Howe, 1991; Ismail et al., 2020).

Schewe and Meredith (1994) also hypothesised that events between the ages of 17 and 21 permanently shape a person's central beliefs about career, money, social tolerance, and personal behaviour. These core values are relatively stable throughout life and are not influenced by age or subsequent life stages. As distinct nations and regions undergo distinct historical dynamics, forging their respective generations in different ways (Reetu, 2016), India, for example, has transformed in response to economic reforms under the Prime Minister P.V. Narasimha Rao's administration during 1991-1996. Those reforms have fundamentally remapped the nation's economy by reducing government regulation, facilitating deregulation of foreign investment and trade, and streamlining administration.

Generational cohort theory posits that individuals experiencing similar socio-economic and technological changes during their formative years develop enduring value systems and consumption behaviours (Strauss & Howe, 1991). According to research, Generation Z cares more about the environment, prefers to buy ethical products, and is more likely to respond to sustainability messages than older generations (Francis & Hoefel, 2018; Dabija, 2018). Also, Generation Z's increased use of social media makes them more aware of peer norms and conversations about sustainability, which could make normative influences on behaviour stronger (Djafarova & Bowes, 2021).

2.2 Proposed Theoretical Framework

This research develops a theoretical model based on TPB to examine psychological and social determinants of sustainable consumer behaviour, as shown in Figure 1. TPB offers a systematic framework to explain how subjective norms, attitudes, and perceived behavioural control drive a person's decision-making. Based on this model, the current research attempts to explain the behavioural intentions of Millennials and Generation Z toward sustainable consumption. The research model presented in this research, shown in the figure, is based on the TPB. Intention refers to future behaviour and attitudes that directly impact it. In addition, the relationship between perceived behavioural control and subjective norms is also considered direct. Three hypotheses were formulated to analyse the relationships among the independent variables—subjective norm, attitude, and perceived behavioural control—and the dependent variable, intention to make sustainable consumer choices. The directionality of these hypotheses is informed by prior research conducted within the TPB framework. Therefore, this research will find out whether there's a direct positive relationship between independent variables- subjective norm, attitude, perceived behavioural control, and dependent variable- behavioural intention.

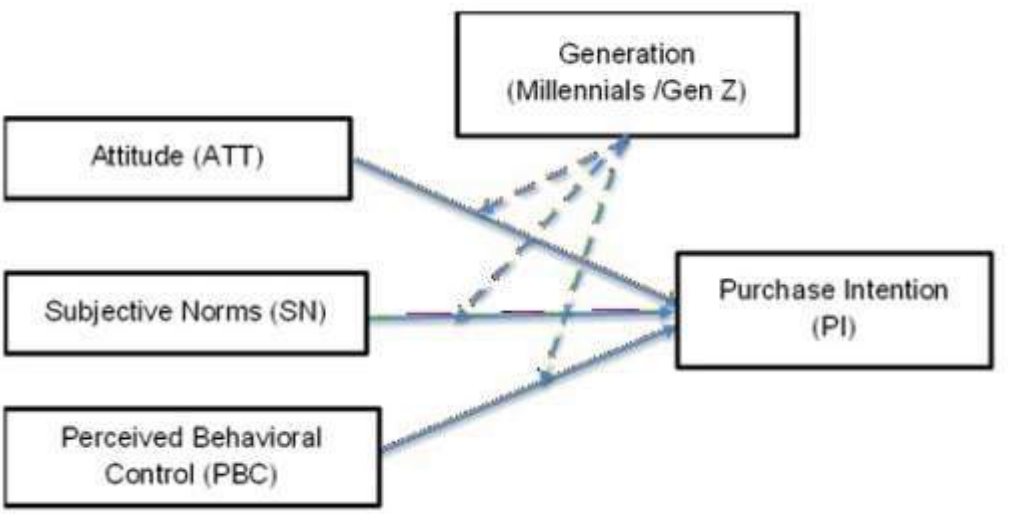

Figure 1: Proposed Theoretical Framework

Attitude

Attitude is a person's assessment of engaging in a particular behaviour related to an activity, like purchasing a product (Blackwell et al., 2006). It indicates the degree to which a person holds positive or negative thoughts towards the conduct. Generally, a subject's perceived behaviour control and intention to perform a given behaviour are positively related to their attitude and subjective norm towards behaviour. The relative predictive power of attitude, subjective norm, and perceived behaviour control is expected to vary across behaviours and situations (Ajzen, 1991). Based on the expectancy-value model, the set of beliefs about behaviour that can be used to connect a behaviour to various outcomes and other attributes indicates an individual's attitude toward the behaviour. In line with this, attitude also helps explain human behaviour (Ajzen, 1988). Thus, the following hypothesis is presented:

H1. There's a significant positive relationship between attitude and intention to make sustainable consumer decisions.

Subjective Norm

Subjective norm is social pressure to conform to expectations about adopting a behaviour, which affects someone's intention to participate in or abstain from the behaviour. If social expectations hold that individuals are supposed to enact the behaviour in question, they are more likely to do so. Conversely, when social norms are that individuals shouldn't engage in the behaviour, then the person should be less inclined to do so. Here, when buying sustainable products is socially desirable behaviour, depending on what others say, the person is more inclined to make a sustainable purchase. In this research, the subjective norm refers to perceived social pressure that influences consumers to buy sustainable products. For this, we postulate the following hypothesis:

H2. There's a significant positive relationship between subjective norms and intentions to make sustainable consumer decisions.

Perceived Behaviour Control (PBC)

Ajzen (1991) explained PBC as the degree to which an individual can perform the behaviour. It encompasses two elements: how much control an individual has over their behaviour, and to what extent they believe they can perform or refrain from performing the behaviour. It is determined by the individual's beliefs about how capable internal and situational factors render the behaviour less complicated. One would be more likely to adopt sustainable products if one feels more in charge. Perceived behavioural control in this research is the ability to purchase sustainable products. Thus, the following hypothesis is posited:

H3. There's a significant positive relationship between perceived behaviour control and intention to make sustainable consumer decisions.

Moderating Hypothesis

When investigating the psychological and social factors behind sustainable consumer behaviour, it is important to consider demographic factors, such as age, that may modify these relationships. Age isn't just an individual factor; it may reflect differing values, priorities, life experiences, or exposure to education or media on sustainability. Collectively, these differences may affect consumers' decision-making. The current research sought to understand whether consumers' age group influenced the relationships between the primary behavioural modulators of subjective norms, attitude, and perceived behavioural control, and their intention to sustainably consume. The research offered an analysis in which age served as an additional moderating variable and provided insight into the detailed differences among generations, considering sustainability influences. This insight will be useful for designing targeted and effective marketing or policy initiatives.

The generational cohort is a boundary condition in the Theory of Planned Behavior (TPB), influencing both how important and intense the attitudinal and normative components of the model are for younger generations, including Gen Z's interactions with social media and technology, suggesting that their perceptions of social norms may have a significant influence on the formation of intentions based on their perception of their peers' actions and visible social validation (Djafarova & Bowes, 2021). We expect Gen Z to internalise sustainability-related attitudes, leading to stronger relationships between attitudes and intentions compared to millennials (Dabija, 2018). In principle, membership in a particular generation can affect the relationship between TPB constructs and purchase intentions for sustainable products. Based on the above discussion, the following moderating hypotheses are proposed:

H4a. Age group significantly moderates the relationship between attitude and intention to make sustainable consumer decisions.

H4b. Age group significantly moderates the relationship between subjective norm and intention to make sustainable consumer decisions.

H4c. Age group moderates the relationship between perceived behaviour control and intention to make sustainable consumer decisions significantly.

3. Design and Methodology

This research has employed a quantitative, cross-sectional study design to explore consumers' intention to buy sustainable products using the TPB framework and has analysed the moderating effect of generational cohort (Millennials versus Generation Z). Data were collected through an online systematic questionnaire circulated across various parts of India between February and May 2025. Respondents were selected through purposive sampling to ensure participation from defined demographic groups: Millennials (born between 1981 and 1996) and Generation Z (born between 1997 and 2012).

The survey tool was developed based on validated measurement scales adapted from earlier studies. All items were measured using a five-point Likert-type scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Attitude (ATT) was measured using four items, subjective norms (SN) using three items, and perceived behavioural control (PBC) using three items. All the items were adopted from Kaiser and Gutscher (2003). Purchase Intention (PI) was measured with four questions adapted from Liang et al. (2022). Subtle adjustments were made to align the items with the context of sustainable products in India. The questionnaire underwent pre-testing with 20 participants to ascertain clarity, and requisite modifications were implemented before comprehensive dissemination.

Three hundred twenty-four valid responses were collected after eliminating incomplete or incorrect submissions. Among the respondents, 160 (49.4%) identified as Millennials, while 164 (50.6%) identified as Generation Z, thus achieving a balanced generational representation. The gender breakdown consisted of 53% male and 47% female respondents. Most participants reported having a university-level education and living in urban or semi-urban regions of India, suggesting a digitally literate, sustainability-conscious consumer demographic.

4. Results

A PLS-SEM approach was used to analyse the determinants of customers' inclination to buy sustainable items. Reflective indicators assessed the constructs, and the validity and reliability of the assessment approach were confirmed. The structural model was examined using the SEMOPY 2.3.11 package in Python for data analysis. Table 1 presents the comprehensive analysis of the constructs.

Table 2 illustrates the correlation among the constructs. All constructs exhibit a positive and significant correlation. The most important correlation exists between Perceived Behavioural Control (PBC) and Purchase Intention (PI) ($r = 0.723$), indicating that consumers' perception of ease or control in acquiring sustainable products is closely linked to their intention to purchase. The correlation between PI and attitude is significant ($r = 0.703$), highlighting the impact of positive evaluations on behavioural intent. No multicollinearity issues are detected, with all correlations remaining below 0.85.

Table 1. Descriptive Statistics

Construct	Items	Mean	SD
Attitude (ATT)	ATT1 – ATT5	3.6	0.9
Subjective Norms (SN)	SN1 – SN3	2.9	1.1
Perceived Behavioural Control (PBC)	PBC1 – PBC4	3.8	0.8
Purchase Intention (PI)	PI1 – PI4	3.5	1.0

Table 2. Correlation Matrices

	ATT	SN	PBC	PI
ATT	1.000			
SN	0.665	1.000		
PBC	0.612	0.624	1.000	
PI	0.703	0.675	0.723	1.000

4.1 Measurement Model Evaluation

Cronbach's alpha and composite reliability (CR) were computed for each concept to guarantee reliability and validity. All item loadings surpassed 0.70, indicating adequate indicator reliability. The CR values ranged from 0.85 to 0.89, whereas the average variance extracted (AVE) ranged from 0.55 to 0.66, thus confirming convergent validity (Table 3). Discriminant validity was confirmed through the application of Heterotrait-Monotrait (HTMT) ratios. Discriminant validity was established by the HTMT criterion, with all values remaining below the 0.85 threshold (Table 4).

Table 3. Construct Reliability and Internal Consistency

Construct	Cronbach' s Alpha	CR	AVE
ATT	0.88	0.91	0.66
SN	0.84	0.87	0.55
PBC	0.85	0.88	0.60
PI	0.86	0.89	0.65

Table 4. Construct Validity (HTMT

Constructs	ATT	SN	PBC	PI
ATT	1			
SN	.45	1		
PBC	.51	.43	1	
PI	.68	.59	.62	1

4. Structural Model Evaluation

The proposed model's goodness-of-fit (GoF) is calculated using the formula GoF = SQRT($AVE_{mean} \times R2mean$). The GoF value is 0.615. According to Wetzels et al. (2009), a Goodness of Fit (GoF) of more than 0.10 is considered modest, greater than 0.25 is medium, and greater than 0.36 is high. Our model's goodness-of-fit (GoF) is 0.597, indicating a robust overall fit. The model explained 58% of the variance in purchase intention (R^2 = 0.58). All hypothesised relationships were supported, as shown in Table 5.

Table 5. Hypothesis Testing

Hypothesis	Path Coefficient (β)	t-value	p-value	Result
H1: ATT → PI	0.42	6.21	< 0.001	Supported
H2: SN → PI	0.29	4.85	< 0.01	Supported
H3: PBC → PI	0.21	2.98	< 0.05	Supported

Further, PI's predictive relevance (Q^2) value was 0.39, indicating good predictive ability.

4.2.1 Moderating Role of Generation (Multi-Group Analysis)

A multi-group analysis is suitable for examining moderating effects of generational cohorts, as it permits researchers to compare structural parameter estimates across the predetermined groups while allowing for the possibility that each group's process may be different (Sarstedt et al., 2011). The use of a multi-group analysis in previous studies on sustainability has allowed researchers to examine whether there are generational differences in green consumerism, providing further evidence for the appropriateness of this method for studying generational cohorts (Dabija, 2018). A multi-group analysis was conducted to examine generational differences. Path coefficients for Millennials and Gen Z are shown in Table 6.

Table 6. Moderating analysis

Path	Millennials (β)	Gen Z (β)	Difference	Significant?
ATT → PI	0.38	0.51	0.13	Yes (**p < .05**)
SN → PI	0.19	0.37	0.18	Yes (**p < .01**)
PBC → PI	0.25	0.18	-0.07	No

The findings show that generation strongly influences the relationship between subjective norms and purchase intention, with more pronounced effects for Gen Z.

5. Discussion

This research aimed to analyse the factors affecting consumers' intentions to purchase sustainable products through the lens of TPB and evaluate the moderating impact of generational cohorts (Millennials compared to Gen Z). The PLS-SEM results substantiate the proposed correlations and provide important insights into generational differences in sustainable consumption intentions. The Theory of Planned Behaviour (Ajzen, 1991) suggests that attitudes toward sustainable items significantly influence purchase intentions. This outcome aligns with previous studies indicating that favourable evaluations of sustainability initiatives—such as eco-friendly packaging, ethical sourcing, and brand transparency—increase consumers' propensity to adopt sustainable behaviours (Paul et al., 2016; Joshi & Rahman, 2015). The large attitude coefficient (β = 0.42, p < 0.001) indicates that cognitive appraisals and positive feelings toward sustainability have a strong influence on behavioural intentions. Subjective norms were also a significant predictor (β = 0.29, p < 0.01), implying that social pressure and peer, family, and influencer expectations contribute to consumers' sustainable actions. This result is consistent with previous studies that found normative

influence to be an essential factor in pro-environmental consumption, particularly in collectivist societies (Yadav & Pathak, 2017). During the age of social media, peer confirmation and social desirability would likely enhance the effect of subjective norms (Gentina et al., 2019). In addition, perceived control over behaviour had a considerable influence on intention ($\beta = 0.21$, $p < 0.05$), reflecting that consumers who are confident they can recognise, pay for, and obtain environmentally friendly products are likely to have the intention to buy them. This finding is consistent with prior PLS-SEM investigations of green consumption (Chen & Deng, 2016), as it illustrates internal and external factors of control, including availability and price, that influence behavioural intention. The moderating influence of generational cohorts indicates that Generation Z has a greater impact on attitude and subjective norms on purchase intention than Millennials. The impact of attitude was more significant among Gen Z ($\beta = 0.51$) than among Millennials ($\beta = 0.38$). Further, subjective norms had a significantly more significant influence on Gen Z ($\beta = 0.37$) than on Millennials ($\beta = 0.19$). The findings align with current research on generational marketing, which characterises Gen Z as having higher ethical motivation, social commitment, and environmental consciousness compared to previous generations (Francis & Hoefel, 2018; Djafarova & Bowes, 2021). A stronger connection between Gen Z's attitudes toward sustainability and their intentions to behave sustainably may indicate a greater alignment between Gen Z's values, beliefs, and self-identity and those related to sustainability. Research indicates that Gen Z consumers are more likely to connect their consumption with the expression of ethical and environmentally responsible behaviour than prior generations (Dabija, 2018; Francis & Hoefel, 2018). Given the greater alignment between Gen Z's values and their consumption behaviour, we should see a faster transition from positive views of sustainability to intentions to act in an environmentally friendly manner than for other generations. Additionally, as a result of Gen Z having a larger variety of social influences (peers and online communities) available to them to inform their purchasing decisions, the social normative influence may be even stronger with regard to the sustainable actions of Gen Z. According to Djafarova & Bowes (2021), peer pressure will increase when Gen Z sees others exhibiting environmentally friendly behaviors on social media, which will increase the likelihood of Gen Z conforming to perceived social norms. This effect is particularly pronounced in collectivist cultures, such as India, which emphasise social harmony and cooperative behaviour (Yadav & Pathak, 2017).

Higher exposure to digital media and commitment to socially responsible causes can perhaps account for their higher vulnerability to internal evaluation and external social pressures. The effect of perceived control for behaviour was not reduced significantly due to generation, which implies that access and self-efficacy for sustainable products are perceived similarly for both groups. This means that structural barriers or enablers, such as price and product availability, have similar impacts on both generations, regardless of their attitudinal or normative perspectives. The Goodness-of-Fit (GoF) measure of 0.597 and the R^2 of 0.58 indicate good model fit and high explanatory power. The results confirm the relevance of the TPB in sustainability and highlight the importance of including psychological and demographic variables to forecast ecologically conscious consumer behaviour.

6. Study Implications

6.1 Theoretical Implications

This research offers important theoretical and practical contributions to understanding and promoting sustainable consumer behaviour. The results theoretically enhance the TPB's applicability to sustainable product use. All three variables, i.e., subjective norms, attitude, and perceived behavioural control, were strong predictors of customers' intention to buy sustainable products. This supports TPB as an effective model to explain pro-environmental behaviours (Ajzen, 1991). The study further extends the TPB by integrating generational cohorts as a moderating variable, demonstrating that Generation Z is more strongly influenced by attitudes and subjective norms than Millennials. This investigation highlights the necessity of incorporating demographic segmentation into behavioural models and emphasises the need for more sophisticated, cohort-specific frameworks to understand green consumerism.

6.2 Practical Implications

The research presents practical recommendations for marketers, sustainability advocates, and policymakers. Due to Generation Z's heightened sensitivity to attitudinal and normative cues, sustainability marketing strategies aimed at this demographic should prioritise emotionally engaging content, influencer-driven campaigns, and social proof. Emphasising peer approval and communal advantages via social media can encourage sustainable behaviours in younger consumers. Millennials exhibit reduced susceptibility to social norms; thus, messaging should emphasise personal benefits, long-term value, or alignment

with lifestyle to promote sustainable choices. The notable influence of perceived behavioural control in both generations highlights the necessity of minimising obstacles to sustainable consumption. Businesses and policymakers must enhance product accessibility, affordability, and consumer knowledge by implementing transparent labelling, certification, and digital tools. These strategies can improve consumers' self-efficacy and confidence in sustainable choices. Furthermore, governmental and educational entities can develop programs tailored to specific generations to instil sustainability values early on and foster enduring pro-environmental behaviours. This study highlights the necessity of customising sustainability interventions according to psychological and generational factors to enhance responsible consumption.

Since Generation Z is more sensitive to attitudes and social norms than other generations, sustainability campaigns for Generation Z need to focus on a person's values, authenticity, and how their peers endorse sustainability. Campaigns that use influencers and user-generated sustainability content will help create a social norm (Djafarova & Bowes, 2021). Both groups are likely to be affected by lower obstacles, such as price and access, as feeling in control plays a big role in buying sustainable products.

7. Conclusion, Limitations, and Future Scope

This study examined the determinants of customers' intention to buy sustainable products using the TPB paradigm. It analysed the moderating influence of generational cohorts—Millennials and Generation Z. The results indicate that attitude, subjective standards, and perceived behavioural control substantially affect sustainable purchasing intention, confirming the Theory of Planned Behaviour's applicability in sustainable consumption. The study emphasises that Generation Z demonstrates a more pronounced behavioural reaction to attitudinal and normative influences than Millennials, signifying a generational disparity in psychological motivators. These findings improve understanding of green consumer behaviour and underscore the need for tailored solutions based on demographic-specific differences. The model has high explanatory power and offers fundamental insights for marketers, sustainability advocates, and regulators attempting to encourage environmentally friendly consumer behaviour in a generationally differentiated market.

Limitations and Future Scope

This research presents great insights; however, there are many limitations that call for consideration. The cross-sectional design limits the capacity to infer causality between the constructs. A longitudinal study may elucidate alterations in sustainable consumption behaviour over time and across various life stages. Secondly, the data were obtained through self-reported surveys, which may be prone to social desirability bias, particularly regarding ecologically responsible conduct. Future studies may integrate behavioural tracking or experimental methodologies to corroborate self-reported intentions. The study concentrated solely on Millennials and Gen Z within a defined geographic and cultural framework. Given the variability in generational traits and sustainability consciousness between areas, subsequent research should investigate cross-cultural comparisons and incorporate additional age cohorts, such as Generation X or Baby Boomers, to improve generalizability.

This research utilised the Theory of Planned Behaviour (TPB) framework, which focuses on rational and deliberate actions. Incorporating affective or value-oriented theories—such as the Value-Belief-Norm (VBN) theory or habit-related constructs—into future models may include sustainable decision-making's emotional and automatic aspects. Ultimately, the study investigated purchase intention rather than actual purchasing behaviour. Future studies may examine the intention–behavior gap by analysing post-purchase satisfaction, repeat activity, and long-term adherence to sustainable habits. Rectifying these shortcomings will enhance the theoretical model and yield a more thorough comprehension of consumer engagement with sustainability.

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Navigating Direct Real Estate Investment Perspectives Across Age Groups: Use of Structural Equation Modelling to Analyse the Effects of Perceived Benefits and Perceived Barriers on Investor Intention

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Abstract

This study examines the relationships between perceived benefits& investment intentions, and between perceived barriers & investment intentions, with age as a moderating variable. Utilising a quantitative research approach, data were collected through structured surveys and analysed using multinomial logistic regression with bootstrapping (N = 5000). The analysis reveals a significant relationship between perceived benefits and investment intentions, suggesting that individuals who perceive higher benefits are more likely to invest. Furthermore, age is identified as a significant moderator, altering the strength and direction of this relationship across different age groups. Interaction-effect plots reveal non-parallel slopes, reinforcing the moderating influence of age. Structural equation modelling indicates that Perceived Benefits (PBF) has a stronger path coefficient with Investment Intention (II) when Age is not included as a moderating variable.

Meanwhile, if Age is considered a moderating variable, then Perceived Barriers (PBR) have a stronger path coefficient. The results provide valuable insights for policymakers, financial institutions, and investors, highlighting the need for age-specific investment strategies to enhance financial decision-making. Future research should explore additional moderating variables to deepen the understanding of investment behaviour dynamics.

Keywords: *Real Estate Investment, Multinomial Logistic Regression, Bootstrapping, Structural Equation Modelling, Age*

1. Introduction

In India, Direct Real Estate investing and property ownership have been a key constituent of investor portfolios for decades. From residential and commercial investments to paying guests and co-living spaces, direct real estate investing offers a wide range of opportunities for investors with diverse goals, thereby accounting for a major share of the wealth of Indian households. According to IBEF, the Indian real estate market has the potential to reach US$ 5-7 trillion by 2047, with the possibility of surpassing US$ 10 trillion. As per Gill et al. (2012), the major factors behind the growth are the entry of multinational corporations, an increasing population base, rising disposable income, the growth of nuclear families, and rapid urbanisation. This has led to a surge in real estate demand over the past decade, making it an attractive investment avenue.

As the Indian economy progresses, it offers emerging opportunities for investors whose participation plays an important role in the development of the real estate market, in particular and the Indian economy, in general (Gill et al. (2012a)). This makes it important for us to understand the perceptions and the variables that influence their investment decisions.

Based on a Confirmatory Factor Analysis, these variables can be categorised into two broad factors: Perceived Benefits and Perceived Barriers. These have been shown to significantly influence perceptions of investing directly in real estate. Understanding these perceptions is also crucial, as it helps policymakers and real estate industry stalwarts adopt policies that improve participation in real estate investments.

This research study simultaneously examines perceived benefits and perceived barriers to identify their relationship with investment intentions across various age demographics. We consider one variable, i.e., age, which, as identified by Gill et al. (2012), influences investment decisions. This research contributes to the existing literature and informs policy frameworks that enhance financial inclusion and resilience in real estate investment.

2. Review of Literature

An array of past studies analyse investors' perceptions of real estate investment, identifying the drivers and barriers to such decisions. This study can be further augmented by the following works done in India and abroad. Tamilmathi and Priya (2023) divided the real estate market into residential and commercial sectors, noting that demographic and socio-economic factors influence investment decisions. Kumar and Priya (2019) categorise investors in Chennai into individual investors and return seekers, and identify economic considerations, livelihood factors, and growth factors as the primary determinants of investment decisions. Kumari and Kumar (2025) found that investors in Delhi NCR prefer residential properties over commercial ones and are influenced by economic conditions, government policies and regulations, returns on investment, and location. Mydhili and Dadhabai (2018) also consider location and environment to be the most significant factors. Anastasia (2015) analyses various rational and irrational factors influencing property-buying behaviour. Kapadia (2017) categorises real estate investors into five categories based on factors ranging from investment price, volatile market, government policies, tax benefit, interest rate, location, profit percentage, low risk, economic growth etc. which influence their decisions regarding real estate investments Gill et al., (2012) conduct regression analysis to confirm that investor expertise, advisory motivation, investment propensity, and age influence perception of Indian real estate investors.

Some international studies include Cheng Lim et al. (2002), who conducted a comparative study of Singapore and UK investors to identify significant differences in behavioural patterns between the two groups regarding real estate investments in Southeast Asia. Otty et al., (2023) analysed the factors driving real estate investment decisions among private investors in South-East Nigeria using fundamental statistics. For Kenya, Chol (2017) identifies financial, population, and housing costs as factors affecting real estate investment decisions, while Muli (2013) identifies macro factors such as GDP growth, interest rates, and inflation as driving real estate market growth. In UAE markets, Abdallah et al. (2021) capture key factors influencing real estate investor behaviour. In Northern Thailand,, Biamukda and Tan (2016) examine the roles of financial, legal, and environmental factors, reference groups, location, and trust in influencing high-involvement behaviours among real estate companies.

Konieczna (2024) investigated Generation Z's perceptions of real estate investment and found that affordability and price per square meter are factors influencing their perceptions. It studies the preferences of this previously overlooked age group. Eze and Lim (2013) focus on the factors influencing the purchase of housing properties in Malaysia, omitting the post-purchase factors which have a significant impact on future decisions. This is explicitly captured by Ullah and Sepasgozar (2020), who analyse post-purchase regrets and identify complex buy-sell processes, inaccurate information, and financial constraints as key concerns in smart real estate investments. Baum and Murray (2010) identified a list of formal and informal barriers to real estate investment in developing economies.

Similarly, Swanzy-Impraim et al., (2022) studied the barriers to institutional investment in rental housing, thereby identifying poor landlord-tenant relations, hassle of maintenance, low profitability, regulatory constraints, and unreliable market information as inhibitors. Galuppo and Tu (2010) examine perceptions among lenders, equity investors, and developers to identify the perceived risks and barriers to sustainable real estate investment, noting a lack of consumer awareness and incentives as major impediments. Pires et al. (2018) employ fuzzy cognitive mapping to develop a model capable of identifying location constraints, tenant risk behaviour, and high ownership costs as challenges for real estate investments in residential rental properties. Nguyen et al. (2022) reveal that basic factors such as institutions and laws, economic factors, cultural and community factors, and other markets and investment opportunities have the same influence despite the Covid-19 pandemic.

To understand the interactions and interrelationships among the factors, Kaiser et al. (2023) employed a moderation analysis to examine the impact of COVID-19-related governmental restrictions on the risk perception of commercial real estate investors. Devi et al. (2025) inferred that real estate investor behaviour is dynamic and combines rational and irrational elements, driven by evolutionary psychology.

Tan (2013) measured homebuyers' intention to purchase green and sustainable homes in Malaysia using Structural Equation Modelling (SEM) and Confirmatory Factor Analysis to assess the reliability and validity of the factors. Reddy and Khandai (2025) used SEM to identify convenient location, financial aspects, housing amenities, etc., as influences on buyers, while housing features do not. Omrane and Bag (2022) used partial least squares SEM and found that value consciousness, which includes price, healthiness and quality, affects residential property buying decisions in Kolkata.

3. Research Objectives

This research aims to contribute to the existing body of knowledge and overcome the identified gaps in the following ways:

- By simultaneously capturing both the perceived benefits and barriers across different age demographics.
- By identifying and mapping the perceived benefits and barriers to real estate investment with Investment intentions.
- Using a modelling approach to explore the role of Age (as a moderator variable) in influencing Investment perceptions and subsequent Investment intentions.

4. Research Methodology

The research has been structured in the following manner:

1. To determine whether Perceived Benefits positively influence Investment Intentions
2. To determine whether Perceived Barriers negatively influence Investment Intentions
3. To test whether Age acts as a moderator variable in influencing the relationship of Perceived Benefits and Barriers to Investment Intentions.

4.1 Data Collection Methods

The target population for the research includes individuals across various age groups. The respondents were required to indicate their perceptions through a structured questionnaire on perceived benefits, barriers, and investment intentions, using a Likert Scale.

4.2 Sampling Strategy

The convenience sampling method was employed in this study, as respondents were approached based on the researcher's accessibility and availability.

4.3 Statistical Tests

We have finally conducted a series of statistical tests and measures to reach the research objectives.

1. **Descriptive Statistics and Frequency Distribution:** First, the mean, Median, and standard deviation for each Likert-scale response have been presented. Also, the demographic data has been summarised using frequency distribution tables.
2. **Normality Test:** After the Reliability tests, the data were checked for normality to determine the appropriate test for analysis.
3. **Fixed Factor Analysis:** we applied Confirmatory Factor Analysis, fixing the number of factors to 2 to confirm the categorisation of perceived benefits and perceived barriers into their respective factors.
4. **Regression Analysis**: It is important to conduct a regression analysis to understand the cause-and-effect relationship and identify the impact of interaction terms. This helps conduct a moderation analysis and determine whether age acts as a moderator variable.
5. Smart PLS follows **the two-stage analytical procedure** as suggested by Anderson and Gerbing (1988)

Stage 1: Measurement Model Assessment (Outer model in Smart PLS): This involves evaluating the validity (convergent and discriminant) and reliability (internal consistency) of the constructs to ensure the measures are robust and accurate.

Stage 2: Structural Model Evaluation: This tests the hypothesised relationships between variables to assess the model's predictive capabilities and examine path coefficients.

To test the significance of path coefficients and factor loadings, a bootstrapping procedure with 5000 resamples was used, as suggested by Hair et al. (2017).

6. In Partial Least Squares Structural Equation Modelling (PLS-SEM), the measurement model assessment is a critical step in ensuring the reliability and validity of the constructs. This involves evaluating two types of validity: convergent and discriminant.

5. Result Analysis

5.1 Descriptive Statistics

Annexure 2 provides an overview of the data collected through the survey. It indicates the Mean, Standard Deviation, and Kurtosis for the Likert-scale responses, thereby helping us understand the characteristics of each variable.

5.2 Frequency Distribution Tables

Age_G

Annexure 3 describes the demographic variable Age_G by indicating that 35.9% of respondents were 18- 24 years old, 16.8% of respondents were 25-34 years old, 14.5% of respondents were 35-44 years old, 15.3% of respondents were in the 45-54 years category, while 17.6% being 55+years old.

Gender

Annexure 4 describes the demographic variable Gender, indicating that 55% of respondents were Males and 45% were Females.

Do_you_currently_own_any_Real_Estate_asset

Regarding Direct Ownership, respondents were required to record a Yes/No answer, as indicated in Annexure 5. 54.2% of respondents were already invested directly in real estate, while 45.8% had no exposure to the real estate market.

What_percentage_of_your_portfolio_is_Direct_Real_Estate

Annexure 6 describes the respondents by Portfolio share of Direct Real Estate Investments. It indicates that 58.8% of respondents have a portfolio share of less than 5%, 16.8% between 5% and 10%, 13.7% between 10% and 15%, and 10.7% more than 15%.

These test results help us get a broad overview of the nature of respondents and their behaviour towards direct real estate investing.

5.3 Factor Analysis

Since we have compiled and categorised the list of variables from various literature reviews, it is important to explore whether these variables can be grouped into distinct factors. Table 1 presents the SPSS Rotated Component Matrix, which uses Principal Component Analysis as the Extraction Method and Varimax rotation when the number of factors is set to '2'. The results indicate that all the identified barriers starting with the prefix 'BR' are categorised in Component 1, while the benefits marked 'BF' are grouped in Component 2. This helps to define the model structure by categorising Component 1 as Perceived Barriers and Component 2 as Perceived Benefits.

Based on this analysis, the variables BF_SUM and BR_SUM have been determined, representing the sums of perceived barriers and perceived benefits across all responses, respectively.

5.4 Structural Equation Modeling

Stage 1: OUTER MODEL

1. Convergent Validity:

Convergent validity ensures that the items (indicators) intended to measure the same construct are indeed correlated. It is assessed using the following criteria:

Indicator Loadings: Each item should have a loading of at least 0.7 on its respective construct (Ghazal et al., 2018), indicating a strong association.

Average Variance Extracted (AVE): AVE measures the proportion of variance captured by the construct relative to the variance due to measurement error. An AVE value of 0.5 or higher indicates sufficient convergent validity. AVE values of 0.527 or higher indicate adequacy (Gholami et al., 2013; Rahman et al., 2015). Annexure 7

Composite Reliability (CR): CR values between 0.7 and 0.9 indicate adequate internal consistency reliability for the construct. All the values are higher than 0.9, aligning with the standard set by Hair et. al. (2021) (Annexure 7)

Annexure 7 collectively shows that all constructs meet the criteria for convergent validity. Each item has a loading above 0.7, and the reliability metrics (Cronbach's Alpha,

Table 1: Fixed Factor Analysis

—Rotated Component Matrix	Component	
	1	2
BR_5_Legal_Complexities	0.833	-0.164
BR_8_Limited_Investment_Experience	0.807	-0.262
BR_14_Long_Gestation_Periods	0.769	-0.091
BR_9_Lack_of_Price_Transparency	0.764	-0.074
BR_10_Uncertain_Lifesyles_or_Transferable_Jobs	0.762	-0.262
BR_7_Lack_of_Financing_Options	0.756	-0.257
BR_1_Huge_Amount_of_Capital	0.752	-0.241
BR_2_Lack_of_Liquidity	0.740	-0.190
BR_6_Hassle_of_Manitaining_Physical_Properties	0.717	-0.075
BR_13_Risk_of_Property_remaining_Vacant	0.688	-0.085
BR_4_Lack_of_Proper_Market_Knowledge	0.688	-0.043
BR_3_Potential_Market_Fluctuations	0.682	-0.181
BR_11_Climate_Change	0.637	-0.290
BR_12_Political_Instability	0.458	-0.163
BR_15_Experience_of_Past_Market_Crashes	0.443	0.198
BF_7_Sense_of_Stability	-0.245	0.773
BF_14_Offers_Autonomy	-0.288	0.771
BF_9_Sense_of_Psycological_Security	-0.300	0.766
BF_13_Leave_Behind_a_Valuable_Asset_for_Future_Generations	-0.384	0.754
BF_15_Flexibility_among_Investment_Avenues	-0.063	0.710
BF_11_Multi_Purpose_advantage	-0.159	0.709
BF_3_Availability_of_Tax_Incentives	-0.052	0.703
BF_6_Safeguard_against_inflation	-0.008	0.696
BF_5_Potential_to_earn_Rental_Income	-0.024	0.683
BF_12_Ability_to_Customize	-0.232	0.680
BF_8_Sense_of_Financial_Sophistication	-0.398	0.673
BF_2_Long_Term_Capital_Appreciation	0.003	0.662
BF_4_Emotional_Satisfaction	-0.288	0.605
BF_10_Advantage_of_Leverage	0.013	0.577
BF1_Diversification_of_Portfolio	-0.122	0.523
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation.		

rho_A, CR, and AVE) are all above their respective thresholds. This indicates that the items are effectively measuring the intended constructs and that the constructs themselves are reliable.

2. Discriminant Validity:

Recent developments in assessing discriminant validity with structural equation modelling have demonstrated that the traditional Fornell-Larcker criterion of 1981 has its limitations. For instance, Henseler et al. (2014) criticised the fact that a traditional Fornell-Larcker criterion might be unable to detect discriminant validity flaws in advance under common research conditions.

To fill the gaps in the former methods, Henseler et al. (2014) provided the heterotrait-monotrait ratio of correlations

Table 2: Fornell-Larcker criterion

	Age	Investment Intention (II)	Perceived Barrier (PBR)	Perceived Benefit (PBF)
Age	1.000			
Investment Intention (II)	0.431	0.868		
Perceived Barrier (PBR)	-0.524	-0.549	0.726	
Perceived Benefit (PBF)	0.277	0.817	-0.482	0.732

The diagonal values of Table 3 represent the square root of the Average Variance Extracted (AVE) for each construct. The AVE is a measure of the amount of variance captured by a construct relative to the variance due to measurement error. A higher AVE indicates that the construct explains a significant amount of variance in its indicators, and the Off-Diagonal values represent the correlations between different constructs. Values below the diagonal represent the correlations between different constructs. These values indicate the strength of the relationship between two constructs.

Diagonal Value for Age is 1; since it is binary (1 for Male and 0 for Female), the square root of the AVE for Age is 0.816. Moreover, the Off-Diagonal Value for the Age and Investment Intention (II) correlation is 0.432, indicating a moderate relationship between these two constructs.

The diagonal value (square root of AVE) must be greater than all the corresponding off-diagonal values in its row and column. As the diagonal value for Age is 1, it is greater than the correlations with II (0.431), PBR (-0.524), PBF (0.277), and so on.

For all the constructs, the diagonal value is greater than the values below it (the Off-diagonal values), so all the constructs meet the discernment validity. This means that the constructs are distinct and measure different concepts.

Table 3: HTMT Ratio

	Age	Investment Intention (II)	Perceived Barrier (PBR)	Perceived Benefit (PBF)	Age x Perceived Benefit
Age					
Investment Intention (II)	0.476				
Perceived Barrier (PBR)	0.511	0.590			
Perceived Benefit (PBF)	0.275	0.890	0.471		
Age x Perceived Benefit	0.275	0.062	0.310	0.081	
Age x Perceived Barrier	0.284	0.398	0.248	0.312	0.486

No pairs of constructs, HTMT value is more than 0.90, and hence HTMT values are within the threshold limit

Table 4: Normality Analysis

Grouped Variables	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BF_SUM	.115	131	<.001	.951	131	<.001
BR_SUM II_SUM	.100	131	.003	.957	131	<.001
	.167	131	<.001	.929	131	<.001

5.5 Normality Test

Before proceeding with various tests and analysis it is important to conduct the test of Normality to determine whether the grouped variables follow a normal distribution.

We define the hypothesis in the following manner:

H0=Grouped Variables follow Normal Distribution

H1= Grouped Variables do not follow normal

Based on the analysis of the results presented in Table 4, the Sig. values for BF_SUM, BR_SUM, and II_SUM are less than 0.05. Therefore, the Null hypothesis (H0) is rejected, and the data are not normally distributed. Furthermore, based on these results, it is evident that non- parametric tests must be adopted for conducting inferential analysis.

5.6 Regression Analysis

To test the moderation effects of Age, a detailed Regression Analysis has been conducted. Since the dependent variable, II_SUM, is not normal, a Multinomial Logistic Regression Model has been applied for regression analysis. The dependent variable II_SUM was converted to nominal categories based on the recorded values. The categories were defined in Table 5 as follows:

Table 5: Categorisation of Investment Intentions

Range	Nominal Category	Indicator
3-6	1	Low Investment Intention
7-10	2	Neutral Investment Intention
11-15	3	High Investment Intention

The interpretation of the model is summarised below:

Model Information

Dependent Variable- II_CTG (Nominal Values for II_SUM)

Independent Variables- BF_SUM and BR_SUM (Scale)

Factor- Age_G (Nominal)

ReferenceCategory-Category3

Model Evaluation

Before testing for moderation, it is important to evaluate the reliability of the predictors used in the model. In this regard, the Model Fitting Information summarised in Table 6 indicates that Sig. The value of the Model is <0.001 (<0.05), indicating that the Model is significantly better than an Intercept-only model. Thus, the inclusion of independent variables significantly improves the model fit.

Since the reliability of the variables used in the final model has been confirmed, it is important to assess how well the regression model fits the data. This is tested using the Goodness-of-Fit statistic, which provides significance values for the Pearson and Deviance measures. As summarised in the Table 7, the Sig. value is 1.00 for both the statistics at 222 degrees of freedom. Since the p-value is greater than 0.05, the model fits the data adequately, with no significant discrepancy between observed and predicted values.

Table 6: Model Fitting Information

Model Fitting Information				
Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2Log Likelihood	Chi-Square	df	Sig.
Intercept Only	260.041			
Final	78.116	181.925	28	<.001

Table 7: Goodness of Fit

Goodness -of-Fit			
Statistic	Chi -Square	df	Sig.
Pearson	91.448	222	1.000
Deviance	78.116	222	1.000

Since the model is an improvement over the Null Model and adequately fits the data, it is important to understand the significance of each variable in the model. This is estimated through the Likelihood Ratio Tests.

The hypothesis is as follows:

H0: The interaction terms have an insignificant impact on the dependent variable

H1= The interaction terms have a significant impact on the dependent variable

As per Table 8, the Sig.value for interaction terms Age_G*BF_SUM and Age_G*BR_SUM are 0.021 and 0.002, which are less than 0.05, thereby indicating that interaction terms have a significant impact on the dependent variable (II_CTG).

Thus, including Age significantly improves the model, suggesting that Age moderates the relationship between BF_SUM and BR_SUM and II_CTG. However, to understand the effect across each group, it is important to analyse the Parameter Estimates Table. (Annexure 8 and Annexure 9)

Table 8: Likelihood Ratio Test

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2LogLikelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	78.116[a]	.000	0	.
Age_G	101.261	23.144	8	.003
BF_SUM	78.116[a]	.000	0	.
BR_SUM	78.116[a]	.000	0	.
Age_G* BF_SUM	96.134	18.018	8	.021
Age_G* BR_SUM	102.516	24.400	8	.002

The chi-square statistic is the difference in the -2 log-likelihoods between the final and reduced models. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

As the sample size is very small so simple bootstrapping has been performed. Bootstrapping creates simulated samples by resampling a single dataset, when the sample size is very small. It helps smooth out outliers and remove random fluctuations in the observed data, making the model more reliable. In this case, a sample size of 5000 has been used to test the change in Sig. values across Age_G.

Annexures 8 and 9, respectively, present the parameter estimates without and with bootstrapping. The model results without bootstrapping indicate that several interaction terms are not significant. This is compared with the parameter estimates from bootstrapped results to check whether Sig. falls. values. A fall in Sig. values indicates statistical significance for the interaction terms. The model results with bootstrapping do indicate a fall in Sig. values across all the interaction terms. Furthermore, it is observed that the Sig. values for interaction terms involving Age_G 2 and 4 are statistically significant ($p < 0.05$) in almost all cases, indicating that certain Age groups modify the relationships between BR_SUM and BF_SUM and II_CTG.

Interpretation of Results with Bootstrapping:

Category1 vs. Category3 (Reference Category)

With respect to the main effects, the Sig. The values for BF_SUM and BR_SUM are 0.660 and 0.874, respectively, which are greater than 0.05, indicating that the parameter estimates are not significant. However, the B value for BF_SUM is -1.936, indicating that increasing benefits decreases the odds of being in Category 1 compared to Category 3. Hence, as we increase the perceived benefits,

more respondents who had low intention show interest of moving towards high intention of investing in real estate

At the same time, for interaction term BF_SUM*AGE_G, the Age Group 2 and Age Group 4 yield conclusive results. For Age Group 2 the significance value is less than 0.05, thereby indicating parameter significance. Moreover, the B value is -93.232, indicating a significant reduction in the odds of staying in Category 1 relative to Category 3. This suggests that perceived benefits increase the likelihood of investing for this age group. Respondents in the 25-34 age group are at the peak of their careers. Most of them are single and are looking for avenues to invest their savings. So, increase in perceived benefits will surely lure them towards this lucrative investment in real estate

Similarly, for Age Group 4, the significance value is close to 0.05 (i.e., marginally significant), and the B value is -8.892, which is significantly negative, indicating that higher perceived benefits encourage investment from people across the age group. Respondents in the 45-54 age group have fulfilled most of their family obligations. In the latter half of this age group, when respondents turn 50, they are planning for their retirement. One of the safest avenues of investment is real estate. Most of them have accumulated wealth by the early 50s, available for investment. However, for Age Groups 1 and 3, the parameter estimates are insignificant, and the B value is positive, indicating an increase in the odds of staying in Category 1 despite increasing benefits for these age groups. This contrasts with the behaviour of individuals across Age Groups 2 and 4. This is because respondents in the 18-24 age group are mainly students. They may intend to invest but lack the means. Moreover, real estate investments require substantial accumulated wealth, which they may not have; hence, an increase in perceived benefits has no impact on their intention to invest in real estate. The 35-44 age group is bogged down by family responsibilities. They have to think about children's education, provide for their aged parents and their medical needs, and invest in a house for their own residential use. These people may not have the money to invest in real estate.

With respect to the interaction term, BR_SUM*AGE_G, for Age Group 2, the parameter estimate is significantly below 0.05, and the B value is also negative, indicating that, despite increasing barriers, the odds of being in Category 1 decrease relative to Category 3. The 25-34 age group is on the lookout for profitable investment avenues, and real estate offers the opportunity to earn high returns at low risk. Moreover, the locking period is 5-10 years, during which they can reap high returns from their real estate investment. However, for Age Group 1 and Age Group 3, although the parameter estimates are insignificant, the B value is positive, indicating higher odds of being in Category 1 than in Category 3 with an increase in Perceived Barriers. They have a low intention to invest in real estate, and the increase in perceived barriers further discourages them from doing so.

Therefore, it can be summarised that individuals in Age Group 2 have a higher inclination towards Real Estate investing than individuals in Age Group 1 and Age Group 3.

Category2 vs. Category3 (Reference Category)

Similarly, the Neutral Category is compared with High Investment Category across various age groups. For the main effects, the Sig. values for BF_SUM and BR_SUM are 0. 245 and 0.086 which is greater than 0.05, thereby indicating that the parameter estimates are not significant. At the same time, the B value for BF_SUM is 2.476, which is significantly positive and indicates that, despite increasing perceived benefits, the odds of staying in the Category 2 increase. Likewise, the B value for BR_SUM is 3.878, indicating that individuals remain neutral even as the effect of perceived barriers increases. Hence, respondents with neutral intentions are not affected by changes in perceived benefits or perceived barriers.

However, for the interaction term BF_SUM*AGE_G, the Sig. value is less than 0.05 for Age Group 2 and Age Group 4, indicating statistical significance for the parameters. At the same time, the B values are -97.428 and -8.257, i.e., negative, indicating that the odds of being in Category 2 decrease as the effect of Perceived benefits increases across these age groups. Hence, just like the Category 1 respondents, the Category 2 respondents in the Age Group 2 and 4 intend to move to Category 3 with the increase in perceived benefits. Though their initial intention to invest in real estate is neutral, with savings in hand and increasing perceived benefits of the investment, they are drawn towards this lucrative investment avenue. On the other hand, for Age Groups 1 and 3, the parameter estimates are not significant, but the B values are less than 1, which implies a reduction in odds of staying in the neutral category compared to Category 3. Thus, for individuals in neutral category there is a higher likelihood of investment intention with increasing effects of Perceived Benefits across all age groups.

On the other hand, with the interaction term BR_SUM*AGE_G for Age Group 2, the parameter Sig. value is less than 0.05 thereby confirming statistical significance. Furthermore, the B value is -44.985, indicating a likelihood towards Category 3 despite the increasing effect of Perceived Barriers. Since this Age Group is young and has ready funds, the increase in perceived barriers does not deter them from investing in real estate. A similar behaviour is observed across other Age Groups where the parameter estimates are not significant.

Thus, for individuals in the neutral category, Perceived Benefits override the effect of Perceived Barriers and increase the inclination to invest in Real estate across all age groups. However, we observe a significant difference between the direct and interaction effects, indicating that Age plays an important modifying role in the relationship.

Furthermore, differences across age groups for individuals in Category 1 and Category 2, compared with Category 3, suggest that Age acts as a moderator variable.

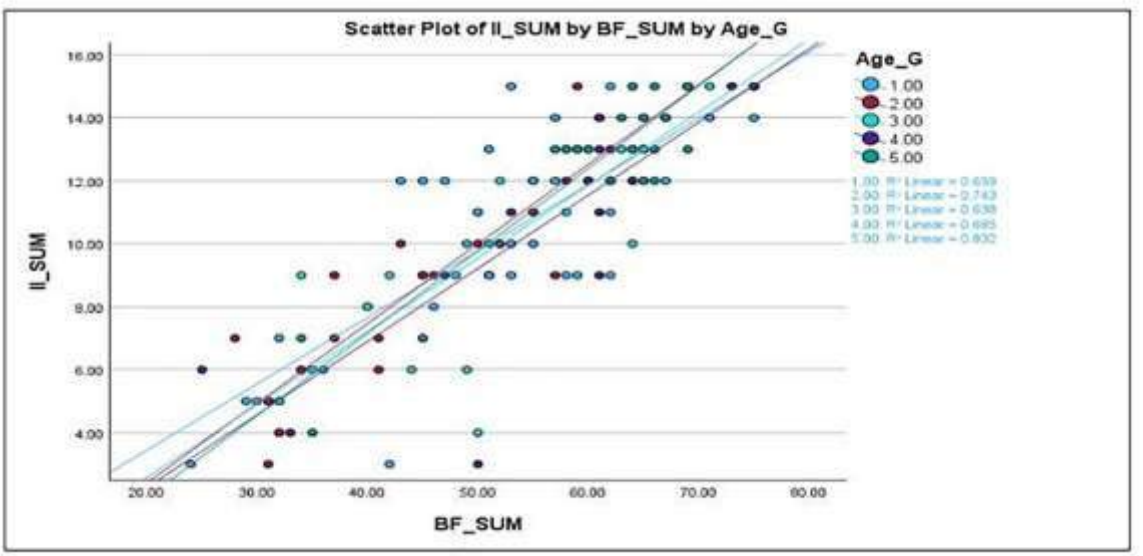

Figure 1: BF_SUM vs. II_SUM with AGE_G as Moderator

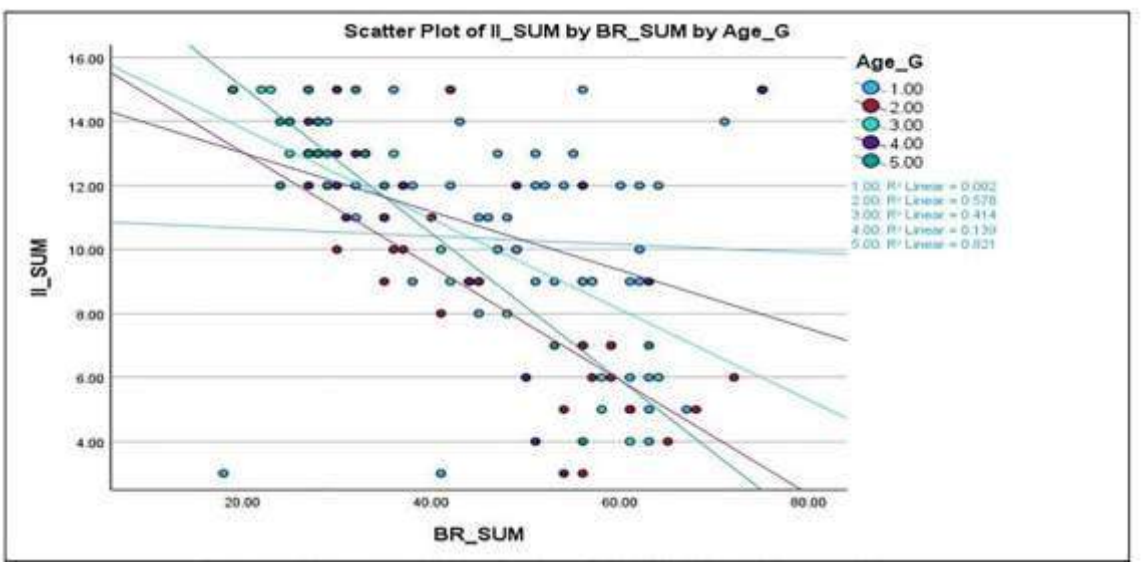

Figure 2: BR_SUM vs. II_SUM with AGE_G as moderator

In addition to Multinomial Logistic Regression results, the interaction plots have been used to support the results indicated by the regression model. The Figure 1 represents the relationship between BF_SUM and II_SUM across Age groups. The linear trend represents a direct relationship between the two variables, and the non-parallel slopes across age categories indicate that the effect of BF_SUM varies across age groups.

Similarly, Figure 2 shows relationship between BR_SUM and II_SUM across Age groups. The linear trend represents an indirect relationship between the two variables and the non-parallel slopes for age categories show that the effect of BR_SUM varies across the age groups. Thus, confirming the moderating effect of Age_G on investment behaviour.

4.1 Stage 2: Inner Model (Structural Model Evaluation)

To assess the structural model, Hair et al. (2017) suggested looking at the R^2, beta (β) and the corresponding t-values via a bootstrapping procedure with a resample of 5,000. They also suggested that, in addition to these basic measures, researchers should report the predictive relevance (Q^2) and the effect sizes (f^2). As asserted by Sullivan and Feinn (2012), while a p-value can inform the reader whether an effect exists, the p-value will not reveal the size of the effect. In reporting and interpreting studies, both the substantive significance (effect size) and statistical significance (p-value) are essential results to be reported.

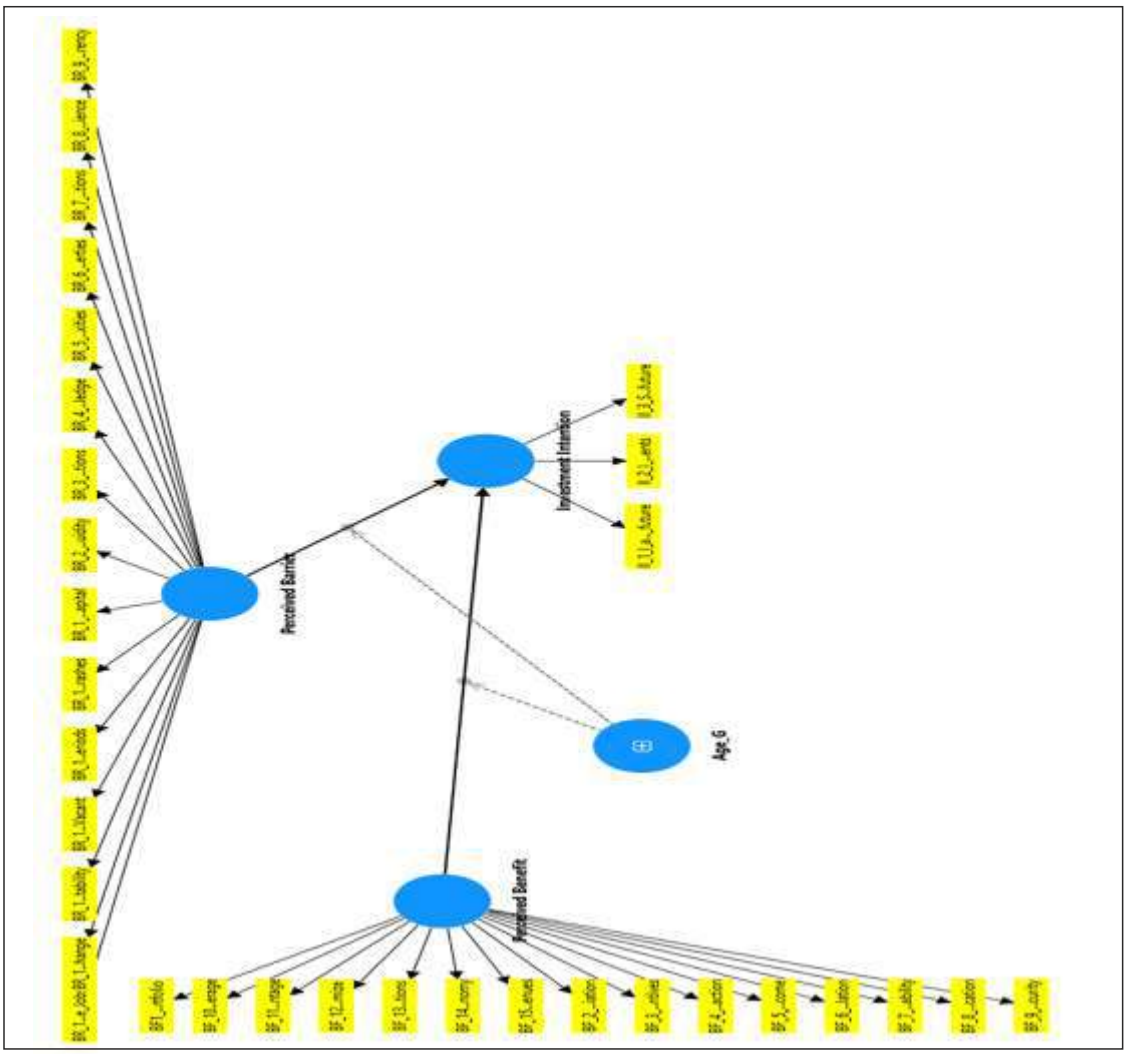

Figure 3: Significance Testing of Proposed Hypotheses

The significance of the proposed hypotheses was determined by examining the t-values of the path coefficients using 5,000 bootstrapped resamples (Henseler, 2021). The results are summarised in Table 9 along with the diagram in figure 3 with corresponding confidence intervals and p-values.

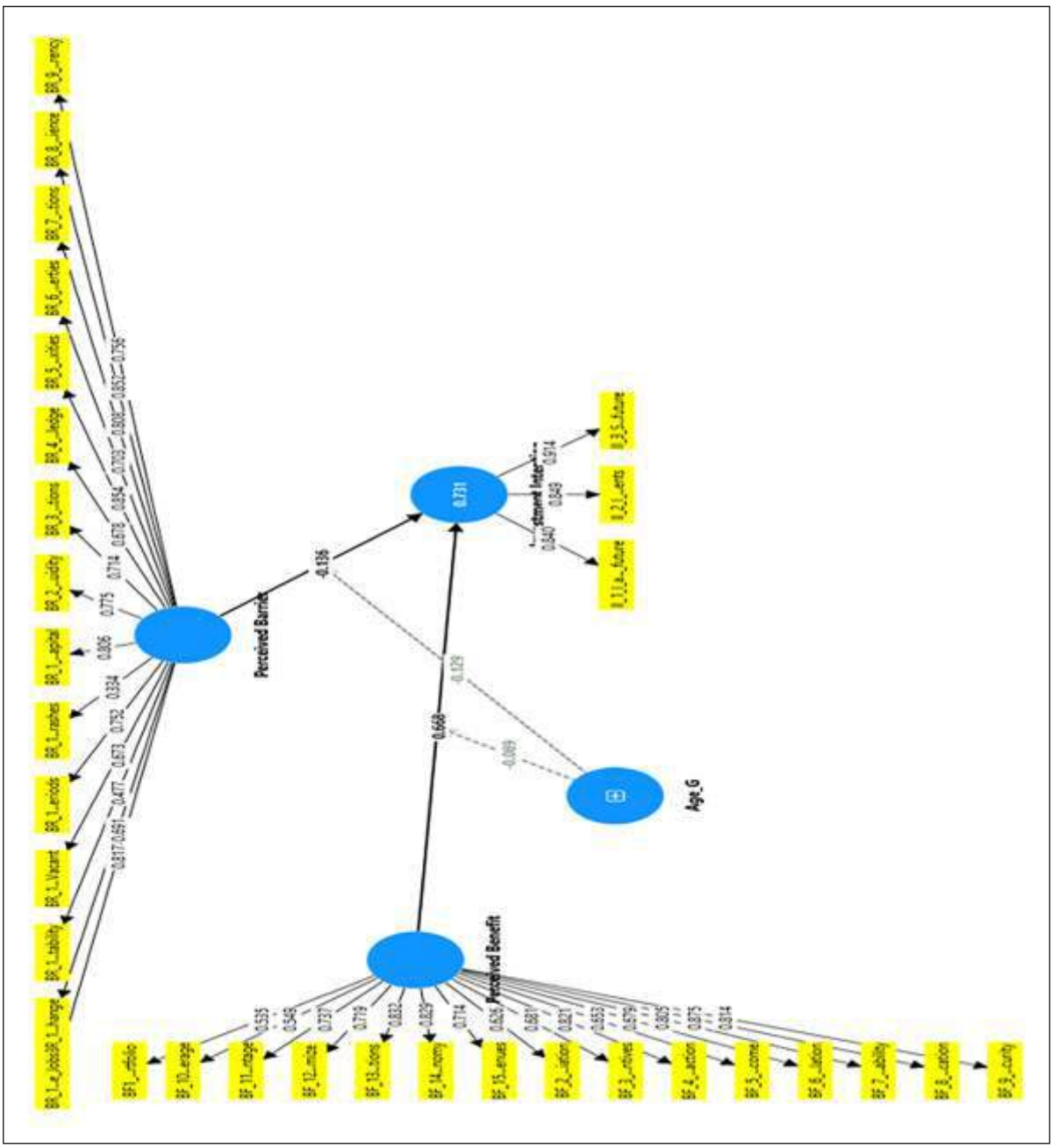

Figure 4: Effect Sizes and Confidence Intervals for Path Coefficients in the Structural Model

Table 9: Result of Inner Model (Hypothesized Path)

Hypothesised Path	Std. Beta	t-value	p-value	Decision	f^2	R^2
PBF↓ II	0.668	11.118	0.000	Supported	1.079	0.731
PBR↓ II	-0.136	2.071	0.038	Supported	0.038	
Age x PBF ↓ II	-0.089	1.275	0.202	Not Supported	0.016	0.722
Age x PBR ↓ II	-0.129	2.115	0.034	Supported	0.035	0.727

The above table 9 suggests that, out of the two dependent variables (i.e., PBF and PBR), PBF has a better path coefficient with II without Age as a moderating variable, and if Age is considered as a moderating variable, then PBR has a better path coefficient.

6. Discussion and Implications

6.1 Discussion

Our findings indicate that age does act as a moderator in influencing investment intentions. An important observation is that younger individuals differ from older investors in how BF_SUM and BR_SUM interact to influence their investment intentions. This signifies that age can either strengthen or weaken the direct effects, depending on the variables. Furthermore, these results advance the analysis presented in previous research by Gill et al. (2012), reinforcing the importance of age in behavioural analysis. Interestingly, younger participants in our study appeared more apprehensive about real estate investing, awarding higher scores to barriers and lower scores to benefits than the older age group. The people in the 18-24 age group are students who do not have the means to invest in real estate. Moreover, the age group 35-44 years is also not very interested in investing in real estate, as they have various family responsibilities, which act as a deterrent to investment despite the perceived benefits of real estate. This difference suggests that it is important to understand the role of age in devising appropriate policies.

It thereby makes it essential for businesses, policymakers, and organisations to consider age as a moderator while designing marketing campaigns or executing appropriate initiatives to stimulate investment. The age groups 25-34 years and 45-54 years should be the focal point while selling real estate as avenues of investment. The real estate agents should approach this group as they have the positive intention as well as the funds with them for investment. Even the people of this group with low intention of investment can be convinced to invest by reinforcing the perceived benefits. The marketing strategy should be to properly counsel the prospects belonging to these age groups about the benefits of this lucrative avenue in order to convert them into investors of real estate. Tailoring strategies to the behaviour of different age groups can make them more effective at resonating with people at different life stages.

6.2 Implications

1. Theoretical Implications

This study makes a valuable contribution to the literature on investment behaviour by explaining that investment intentions are not only driven by perceived benefits or barriers but also shaped by age as a moderating variable. The findings challenge the previous literature that assumes uniform cognitive processing across demographic groups.

The incorporation of age-based heterogeneity into behavioural investment models will enhances the explanatory power of behavioural models and provides a more refined understanding of how investors evaluate risk, return, and barriers across different life stages.

The combined findings from multinomial logistic regression and structural equation modelling (SEM) further support the following theories.

(I) The strong direct impact of Perceived Benefits (PBF) on Investment Intention (II) in the absence of moderation supports the rational choice and expectancy-value theories. According to these theories, a rational individual chooses the option that provides the higher perceived gains for a given level of risk.

(ii) With age as the moderator, the dominance of Perceived Barriers (PBR) supports the life-cycle theory and behavioural finance perspectives. They suggest that the aversion to risk and constraint increase with age.

2. Practical Implications

(i) For Financial Institutions and Advisors

The findings suggest that universal investment strategies will not be effective. Investors in the lower age

bracket respond positively to perceived benefits such as returns, growth potential, and innovation. In contrast, older investors are more apprehensive about perceived barriers, including risk and financial security concerns. Based on this, financial advisors need to develop age-segmented advisory models and investment plans with different product design, and risk frames that are customised for specific age groups.

(ii) For Investors

Investors can make informed investment choices with greater awareness of how age-related insights and behavioural factors influence their decisions. They need to be aware of the distinct motivational drivers of different age groups. Younger investors will be attracted to investment avenues that offer greater perceived benefits, irrespective of risk, while older investors will be attracted to risk-averse investment options with limited benefits.

(iii) For Product Design and Marketing

Investment products and advertising content need to be designed so that they are age-sensitive. Younger demographics will be attracted towards marketing messages that highlight long-term perceived benefits and growth opportunities. Whereas for older demographics, minimising perceived barriers through guarantees, greater transparency, and risk mitigation mechanisms may be more effective. This will ensure more inclusive participation in investment markets, helping develop these markets in an emerging country like India.

3. Policy Implications

Policymakers and regulatory bodies need to emphasise the importance of age-specific financial literacy and inclusion initiatives when developing the structure of such programmes. Specific financial education programs emphasising opportunity awareness for younger individuals and risk management for older individuals should be designed and implemented.

Moreover, regulatory frameworks that enhance transparency and protect older investors, thereby mitigating barriers, may encourage increased participation by older demographics in investment markets.

7. Limitations and further scope for research

This study is subject to certain limitations. Most importantly, it relies on a small sample size, which prevents us from generalising the results to the whole population and from proving significance across all Age groups. Future research may focus on a more diverse set of samples to ensure its broad applicability.

Additionally, this research focuses solely on the moderating effects of age and does not consider the potential influence of other moderators. So, future research could incorporate other moderator variables to provide a comprehensive and deeper understanding of this investment behaviour. By employing modelling techniques and conducting detailed analysis, this study opens the door for similar research across other asset classes, such as equities or gold, to evaluate behavioural patterns across different investment avenues.

Overall, the study highlights the strategic value of age-specific approaches in promoting real estate investment. By aligning policy initiatives and marketing strategies with the behavioural profiles of specific age groups, stakeholders can magnify the effectiveness of their efforts to foster greater participation in the real estate investment segment.

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Annexure

Annexure 1:

Variable Classification

Variable	Type	Coding	Representation
BF_SUM	Independent	Scale	Sum of 15 Likert-Scale Perceived Benefits Responses
BR_SUM	Independent	Scale	Sum of 15 Likert-Scale Perceived Barriers Responses
II_SUM	Dependent	Scale	Sum of 3 Likert-Scale Investment Intention Responses
Age_G	Moderator	Nominal	It represents the categorical age groups*
Interaction terms	BF_SUM × Age_G and BR_SUM × Age_G		
*Age Groups have been defined as follows: 18 -24 as Category 1, 25 -34 as Category 2, 35 -44 as Category 3, 45-54 as Category 4, 55+ as Category 5			

Annexure 2:

Descriptive Statistics

Variables	Minimum	Maximum	Mean	Std.Deviation	Kurtosis	StandardError
BF1_Diversification_of_Portfolio	1.00	5.00	3.7405	.95746	.038	.420
BF_2_Long_Term_Capital_Appreciation	1.00	5.00	4.0305	.98402	.602	.420
BF_3_Availability_of_Tax_Incentives	1.00	5.00	3.4275	1.13700	-.480	.420
BF_4_Emotional_Satisfaction	1.00	5.00	3.4427	1.35964	-1.164	.420
BF_5_Potential_to_earn_Rental_Income	1.00	5.00	3.6183	1.15331	-.728	.420
BF_6_Safeguard_against_inflation	1.00	5.00	3.1756	1.29781	-1.032	.420
BF_7_Sense_of_Stability	1.00	5.00	3.5115	1.25494	-1.009	.420
BF_8_Sense_of_Financial_Sophistication	1.00	5.00	3.4733	1.49011	-1.189	.420
BF_9_Sense_of_Psycological_Security	1.00	5.00	3.6489	1.24606	-.789	.420
BF_10_Advantage_of_Leverage	1.00	5.00	3.3893	1.11336	-.619	.420
BF_11_Multi_Purpose_advantage	1.00	5.00	3.7710	1.12020	-.707	.420
BF_12_Ability_to_Customize	1.00	5.00	3.6718	1.13302	-.442	.420
BF_13_Leave_Behind_a_Valuable_Asset_for_Future_Generations	1.00	5.00	3.5802	1.39203	-1.055	.420
BF_14_Offers_Autonomy	1.00	5.00	3.4733	1.22994	-.636	.420
BF_15_Flexibility_among_Investment_Avenues	1.00	5.00	3.1374	1.22011	-.791	.420
BR_1_Huge_Amount_of_Capital	1.00	5.00	3.3511	1.51365	-1.312	.420
BR_2_Lack_of_Liquidity	1.00	5.00	3.1832	1.28782	-1.094	.420
BR_3_Potential_Market_Fluctuations	1.00	5.00	2.9618	1.21785	-.920	.420
BR_4_Lack_of_Proper_Market_Knowledge	1.00	5.00	3.1069	1.32579	-1.069	.420
BR_5_Legal_Complexities	1.00	5.00	2.8855	1.39582	-1.372	.420
BR_6_Hassle_of_Manitaining_Physical_Properties	1.00	5.00	3.2061	1.36842	-1.202	.420
BR_7_Lack_of_Financing_Options	1.00	5.00	2.8168	1.41313	-1.312	.420
BR_8_Limited_Investment_Experience	1.00	5.00	2.8702	1.48530	-1.439	.420
BR_9_Lack_of_Price_Transparency	1.00	5.00	2.9618	1.27342	-1.035	.420
BR_10_Uncertain_Lifesyles_or_Transferable_Jobs	1.00	5.00	2.8550	1.50447	-1.431	.420

BR_11_Climate_Change	1.00	5.00	2.7405	1.33352	-1.061	.420
BR_12_Political_Instability	1.00	5.00	3.0916	1.19261	-.746	.420
BR_13_Risk_of_Property_remaining_Vacant	1.00	5.00	3.1145	1.25662	-.982	.420
BR_14_Long_Gestation_Periods	1.00	5.00	2.8321	1.33677	-1.061	.420
BR_15_Experience_of_Past_Market_Crashes	1.00	5.00	2.5954	1.22649	-.979	.420
II_1_I_am_considering_investing_into_real_Estate_in_future	1.00	5.00	3.6260	1.17889	-.739	.420
II_2_I_am_open_to_accepting_risks_with_Real_Estate_investments	1.00	5.00	3.2595	1.26240	-.801	.420
II_3_Share_of_Real_Estate_investments_shall_increase_in_future	1.00	5.00	3.5267	1.30872	-.914	.420

Annexure 3:

Descriptive Statistics- Age

Variables	Frequency	Percent	Valid Percent	Cumulative Percent
1.00-18-24	47	35.9	35.9	35.9
2.00-25-34	22	16.8	16.8	52.7
3.00-35-44	19	14.5	14.5	67.2
4.00-45-54	20	15.3	15.3	82.4
5.00-55+	23	17.6	17.6	100.0
Total	131	100.0	100.0	

Annexure 4:

Descriptive Statistics- Gender

Variables	Frequency	Percent	Valid Percent	Cumulative Percent
1- Male	72	55.0	55.0	55.0
2- Female Total	59	45.0	45.0	100.0
	131	100.0	100.0	

Annexure 5:

Descriptive Statistics- Do_you_currently_own_any_Real_Estate_asset

Variables	Frequency	Percent	Valid Percent	Cumulative Percent
1- Yes	71	54.2	54.2	54.2
2- No	60	45.8	45.8	100.0
Total	131	100.0	100.0	

Annexure 6:
Descriptive Statistics- What_percentage_of_your_portfolio_is_Direct_Real_Estate

Variables	Frequency	Percent	Valid Percent	Cumulative Percent
Less than 5%	77	58.8	58.8	58.8
5%-10%	22	16.8	16.8	75.6
10%-15%	18	13.7	13.7	89.3
Moretha n15%Tot al	14	10.7	10.7	100.0
	131	100.0	100.0	

Annexure 7:
Convergent Validity

Constructs	Items	Loadings (>0.6)	Cronbach α (> 0.7)	rhoA (> 0.7)	CR (> 0.7)	AVE (>0.5)
Perceived Benefit (PBF)	BF_1	0.534	0.936	0.951	0.944	0.535
	BF_2	0.627				
	BF_3	0.681				
	BF_4	0.821				
	BF_5	0.653				
	BF_6	0.679				
	BF_7	0.805				
	BF_8	0.875				
	BF_9	0.627				
	BF_10	0.549				
	BF_11	0.737				
	BF_12	0.719				
	BF_13	0.832				
	BF_14	0.829				
	BF_15	0.714				
Perceived Barrier (PBR)	BR_1	0.806	0.932	0.950	0.942	0.527
	BR_2	0.775				
	BR_3	0.714				
	BR_4	0.678				
	BR_5	0.854				
	BR_6	0.703				
	BR_7	0.808				
	BR_8	0.852				
	BR_9	0.756				
	BR_10	0.816				
	BR_11	0.691				
	BR_12	0.477				
	BR_13	0.674				
	BR_14	0.752				
	BR_15	0.335				
Investment Intention (II)	II_1	0.844	0.837	0.846	0.902	0.754
	II_2	0.844				
	II_3	0.915				

Annexure 8:
ParameterEstimates

Parameter Estimates

II_CTG		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
1.00	Intercept	111.235	24113.355	0.000	1	0.996			
	BF_SUM	-1.936	311.405	0.000	1	0.995	0.144324361	1.2334E-266	1.6888E+264
	BR_SUM	-0.515	230.202	0.000	1	0.998	0.597759067	6.7398E-197	5.3016E+195
	[Age_G=1.00]	-82.541	24113.36	0.000	1	0.997	1.42243E-36	0	.b
	[Age_G=2.00]	6739.3	21007.332	0.103	1	0.748	.b	0	.b
	[Age_G=3.00]	-111.76	24113.35	0.000	1	0.996	2.88223E-49	0	.b
	[Age_G=4.00]	74.924	24472.28	0.000	1	0.998	3.4617E+32	0	.b
	[Age_G=5.00]	0c			0				
	[Age_G=1.00] * BF_SUM	1.363	311.405	0.000	1	0.997	3.909487151	3.3405E-265	4.5754E+265
	[Age_G=2.00] * BF_SUM	-93.232	286.940	0.106	1	0.745	3.23569E-41	1.8447E-285	5.6756E+203
	[Age_G=3.00] * BF_SUM	1.600	311.405	0.000	1	0.996	4.952893128	4.2323E-265	5.7961E+265
	[Age_G=4.00] * BF_SUM	-8.892	332.001	0.001	1	0.979	0.000137444	3.4521E-287	5.4723E+278
	[Age_G=5.00] * BF_SUM	0c			0				
	[Age_G=1.00] * BR_SUM	0.434	230.202	0.000	1	0.998	1.542701379	1.7393E-196	1.3683E+196
	[Age_G=2.00] * BR_SUM	-40.309	173.402	0.054	1	0.816	3.11938E-18	7.8353E-166	1.2419E+130
	[Age_G=3.00] * BR_SUM	0.845	230.202	0.000	1	0.997	2.326823	2.623E-196	2.0641E+196
	[Age_G=4.00] * BR_SUM	8.032	240.894	0.001	1	0.973	3079.081734	2.7489E-202	3.4489E+208
	[Age_G=5.00] * BR_SUM	0c			0				
2.00	Intercept	-302.35	14622.12	0.000	1	0.984			
	BF_SUM	2.476	150.684	0.000	1	0.987	11.88833063	6.5E-128	2.1744E+129
	BR_SUM	3.878	159.965	0.001	1	0.981	48.34450888	3.3255E-135	7.0281E+137
	[Age_G=1.00]	307.14	14622.12	0.000	1	0.983	2.4526E+133	0	.b
	[Age_G=2.00]	7161.2	12909.40	0.308	1	0.579	.b	0	.b
	[Age_G=3.00]	313.08	14622.12	0.000	1	0.983	9.3691E+135	0	.b
	[Age_G=4.00]	426.37	15136.93	0.001	1	0.978	1.49E+185	0	.b
	[Age_G=5.00]	0c			0				
	[Age_G=1.00] * BF_SUM	-2.610	150.684	0.000	1	0.986	0.073500754	4.0186E-130	1.3443E+127
	[Age_G=2.00] * BF_SUM	-97.428	238.274	0.167	1	0.683	4.86822E-43	7.3764E-246	3.2129E+160
	[Age_G=3.00] * BF_SUM	-2.732	150.684	0.000	1	0.986	0.0650889	3.5583E-130	1.1906E+127
	[Age_G=4.00] * BF_SUM	-8.257	177.230	0.002	1	0.963	0.000259448	3.5965E-155	1.8716E+147
	[Age_G=5.00] * BF_SUM	0c			0				
	[Age_G=1.00] * BR_SUM	-3.834	159.965	0.001	1	0.981	0.02161235	1.4866E-138	3.1419E+134
	[Age_G=2.00] * BR_SUM	-44.985	0.000		1		2.907E-20	2.907E-20	2.907E-20
	[Age_G=3.00] * BR_SUM	-3.810	159.965	0.001	1	0.981	0.022150248	1.5236E-138	3.2202E+134
	[Age_G=4.00] * BR_SUM	-0.081	166.568	0.000	1	1.000	0.922204202	1.5191E-142	5.5985E+141
	[Age_G=5.00] * BR_SUM	0c			0				

a. The reference category is: 3.00.

b. Floating point overflow occurred while computing this statistic. Its value is therefore set to system missing.

c. This parameter is set to zero because it is redundant.

Annexure 9 :
Parameter Estimates

II_CTG		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
1.00	Intercept	111.235	340.980	0.106	1	0.744			
	BF_SUM	-1.936	4.403	0.193	1	0.660	0.144325208	2.57684E-05	808.346226
	BR_SUM	-0.515	3.255	0.025	1	0.874	0.597761656	0.00101317	352.674425
	[Age_G=1.00]	-82.540	340.980	0.059	1	0.809	1.42308E-36	0	2.49E+254
	[Age_G=2.00]	6739.381	297.059	514.701	1	0.000	.b	.b	.b
	[Age_G=3.00]	-111.768	340.980	0.107	1	0.743	2.88355E-49	0	5.045E+241
	[Age_G=4.00]	74.925	346.056	0.047	1	0.829	3.46328E+32	9.47E-263	.b
	[Age_G=5.00]	0c			0				
	[Age_G=1.00] * BF_SUM	1.363	4.403	0.096	1	0.757	3.909464212	0.00069800	21896.43799
	[Age_G=2.00] * BF_SUM	-93.232	4.058	527.960	1	0.000	3.23571E-41	1.1381E-44	9.19937E-38
	[Age_G=3.00] * BF_SUM	1.600	4.403	0.132	1	0.716	4.952864066	0.00088430	27740.36573
	[Age_G=4.00] * BF_SUM	-8.892	4.695	3.588	1	0.058	0.000137443	1.38661E-08	1.362357368
	[Age_G=5.00] * BF_SUM	0c			0				
	[Age_G=1.00] * BR_SUM	0.434	3.255	0.018	1	0.894	1.542694695	0.00261477	910.1782119
	[Age_G=2.00] * BR_SUM	-40.309	2.452	270.241	1	0.000	3.11938E-18	2.55211E-20	3.81275E-16
	[Age_G=3.00] * BR_SUM	0.844	3.255	0.067	1	0.795	2.32681292	0.00394379	1372.804274
	[Age_G=4.00] * BR_SUM	8.032	3.406	5.560	1	0.018	3079.068395	3.88037208	2443235.333
	[Age_G=5.00] * BR_SUM	0c			0				
2.00	Intercept	-302.356	206.768	2.138	1	0.144			
	BF_SUM	2.476	2.131	1.350	1	0.245	11.8883706	0.18255827	774.1821608
	BR_SUM	3.878	2.262	2.940	1	0.086	48.34469625	0.57399659	4071.818014
	[Age_G=1.00]	307.141	206.768	2.207	1	0.137	2.4535E+13	2.44834E-43	.b
	[Age_G=2.00]	7161.24	182.549	1538.932	1	0.000	.b	.b	.b
	[Age_G=3.00]	313.087	206.768	2.293	1	0.130	9.3723E+13	9.35221E-41	.b
	[Age_G=4.00]	426.377	214.047	3.968	1	0.046	1.4905E+18	945.929140	.b
	[Age_G=5.00]	0c			0				
	[Age_G=1.00] * BF_SUM	-2.610	2.131	1.501	1	0.221	0.073500507	0.001128676	4.786425111
	[Age_G=2.00] * BF_SUM	-97.428	3.369	836.125	1	0.000	4.86827E-43	6.5971E-46	3.59249E-40
	[Age_G=3.00] * BF_SUM	-2.732	2.131	1.644	1	0.200	0.065088681	0.00099950	4.2386448
	[Age_G=4.00] * BF_SUM	-8.257	2.506	10.855	1	0.001	0.000259448	1.909E-06	0.035260903
	[Age_G=5.00] * BF_SUM	0c			0				
	[Age_G=1.00] * BR_SUM	-3.834	2.262	2.874	1	0.090	0.021612266	0.00025660	1.820287139
	[Age_G=2.00] * BR_SUM	-44.985	0.000		1		2.90701E-20	2.90701E-20	2.90701E-20
	[Age_G=3.00] * BR_SUM	-3.810	2.262	2.837	1	0.092	0.022150162	0.00026298	1.865592155
	[Age_G=4.00] * BR_SUM	-0.081	2.355	0.001	1	0.973	0.922200627	0.00911810	93.27091793
	[Age_G=5.00] * BR_SUM	0c			0				

a. The reference category is: 3.00.

b. Floating point overflow occurred while computing this statistic. Its value is therefore set to system missing.

c. This parameter is set to zero because it is redundant.

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Dynamic Capability for Sustainable Business Performance: A Multiphase Iterative Mixed Method Study

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Abstract

The present study uses a multiphase, iterative, mixed-methods approach to identify the dynamic capability for sustainable business performance. Dynamic capabilities and sustainability have been studied separately so far. However, research has, to some extent, recognised certain dynamic capabilities that support sustainable business performance in emerging markets. This creates a clear research gap that this study addresses. This study advances the mixed-methods approach. It shows a new approach to developing the best practices for sustainable business by mixing primary and secondary qualitative and quantitative data sources. The study is divided into phases: (i) Creating Sustainable Business Performance Index (SBPI) through qualitative content analysis, (ii) Quantitative comparison of the top ten NIFTY consumer index companies from 2014 to 2023 using SBPI, and (iii) Writing a qualitative case study to identify the dynamic capability of the most sustainable firm.

The study identifies and explores the dynamic capabilities of the most sustainable company in the Indian Fast Moving Consumer Goods (FMCG) sector. It assesses the sustainable business performance of the top ten companies in the National Stock Exchange of India's NIFTY Consumer Index from 2014 to 2023. **The comparative findings show that Hindustan Unilever Limited (HUL) superseded other firms across all environmental, social, and financial aspects of the Triple Bottom Line Approach from 2014 to 2023, emerging as the most sustainable company in the industry.** The study guides overcoming challenges and implementing innovation to achieve a sustained competitive edge.

Keywords: *Dynamic capabilities, Collaboration, sustainability, sustainable business performance, mixed methods research, FMCG, Triple Bottom Line*
Type: Research paper

1. Introduction

Unique dynamic qualities provide durability and growth, enabling long-term success (Chevrollier and Kuijf, 2023). A company with dynamic capabilities can take advantage of opportunities to rethink its business model and adapt to unforeseen circumstances. Businesses can adjust to changing market conditions and consumer preferences by sensing, seizing, and reconfiguring resources (Ledi et al., 2024). The culture of continuous learning, experimentation, and innovation, along with proactive response to market changes, helps develop organisational dynamic capabilities (Priyono and Hidayat, 2024).

In the context of India, exploring dynamic capability in the FMCG industry is not easy due to the unique challenges and opportunities. A rapidly growing market, Variety in consumer tastes, and the need for sustainability could be driving various challenges. A dense population and a resource-limited setting also add to the difficulties. The lack of detailed studies on the utilisation of dynamic capabilities in the Indian FMCG market makes the present study more interesting and valuable.

In the ever-changing business environment, sustainable business performance is a constant challenge, and organisations with dynamic capabilities have the potential to overcome it (Ali *et al*., 2019). In today's volatile business environment in India, we need to identify and explore specific dynamic capabilities (Khurana, 2022) which provide a competitive edge to the firms.

The focus of this paper is to spotlight the top-performing company in the Indian FMCG industry and identify its unique dynamic capability that enables it to maintain a high level of corporate sustainability. To evaluate the performance of FMCG companies in India, a mixed-method approach has been used. Hindustan Unilever Limited (HUL) has come out as the most sustainable company. 'Collaboration' has been identified as HUL's dynamic capability after scrutiny of its practices.

By understanding how HUL integrates collaboration and sustainability, other FMCG firms can benchmark and adapt similar practices, thereby improving sustainable business performance. The findings of this study can help policymakers formulate sustainability policies for the FMCG sector.

Previous research has examined dynamic capabilities in the context of green innovation and CSR. Limited empirical research has identified specific dynamic capabilities that develop sustainable business performance, as measured using the TBL approach. Few research studies have applied sustainability in the emerging market aspect by operationalising it into a composite index. The mentioned gaps have been addressed in the study by a) developing SBPI, b) recognising the most sustainable company in the FMCG industry using longitudinal comparison and c) empirically identifying the dynamic capability underlying the sustainable business success.

The paper is organised into the following four sections.

1. **An overview of relevant literature on**
   - i) dynamic capability
   - ii) sustainable business performance
   - iii) dynamic capabilities for sustainability.
2. **Research design**
   - i) data collection
   - ii) data analysis methods used in the study.
3. **A case analysis on the business practices of HUL, examining**
   - i) How collaboration acts as a dynamic capability for the company.
4. **The findings suggest**
   - i) Implications for future research
   - ii) Practice related to collaboration, and draws conclusions based on these findings.

2. Theoretical Background

2.1 Dynamic Capabilities

Dynamic capabilities help in adapting to environmental changes by developing, combining, and reconfiguring their resources (Kareem and Alameer, 2019). Scholars have proposed the resource-based view as one of the notable theoretical foundations amongst various others (Miller, 2019).

There are two main viewpoints on the concept of dynamic capabilities (Peteraf *et al.,* 2013) - one presented by Teece *et al.* (1997) and another by Eisenhardt and Martin (2000). Teece and colleagues view dynamic capabilities as a means for companies to survive in unpredictable situations, while Eisenhardt and Martin view them as best practices in turbulent environments.

Teece *et al.* (1997) built on the resource-based view (RBV) introduced by Barney (1991). They noticed that RBV did not fully explain how companies gain an edge in uncertain situations (Barney, 2021). They suggest that managers should combine internal and external strengths, continuously develop and adjust them to deal with uncertainty, and gain an edge over competitors. Dynamic capabilities are more specifically associated with change (Warner & Wäger, 2019). It enables a firm to stretch beyond current routines to solve problems differently (Zahra *et al.,* 2006).

Dynamic capabilities leverage four essential resources: people involved (actors), tangible assets (physical resources), organisational setup (structure and systems), and shared values and practices within the company (company culture). These resources enable product innovation through dynamic capabilities (Kaur, 2019).

Dynamic Capabilities are a continuously changing process, just as nature evolves through variation, selection, and retention (Galvin *et al.*, 2014). Teece (2018) proposes studying dynamic capabilities from a systems-theoretic perspective. He explains that dynamic capabilities are like systems that operate across different parts of the company and cannot be developed in isolation.

At the core of dynamic capabilities lie three essential components: sensing, seizing, and reconfiguring (Arndt, 2019). Sensing involves identifying changes occurring in the external environment, while seizing entails taking decisive action based on the insights gathered during the sensing phase. Reconfiguration involves integrating and modifying organisational resources to address environmental changes (Ortiz-Avram, 2024). In the volatile business environment, dynamic capabilities are essential for sustainable business performance (González-Ramos et al. in 2023).

The practical application of dynamic capabilities spans domains such as strategic management (Eisenhardt and Martin, 2000), innovation management (Teece, 2017), and international business (Ambos *et al.,* 2010). These capabilities can be developed continuously to gain a competitive advantage.

2.2 Businesses Sustainability

Balanced economic, social, and environmental objectives are essential to business sustainability (Evans *et al.,* 2017; Fernando *et al.,* 2019; Danladi *et al*., 2023). It helps organisations achieve a competitive edge in a challenging business environment. (Haseeb, 2019). Organisations must adopt a triple bottom line (TBL) approach (Elkington and Rowlands, 1999), continually innovate their business models, prioritise customer-centricity, and establish a world-class delivery capability through operational excellence and high-performance teams to achieve sustainable business performance (SBP). Adopting the TBL business approach aligns with economic, social, and environmental objectives (Tjahjadi *et al.,* 2021).

The economic dimension focuses on maximising shareholder wealth through sustainable business practices (Alonso-Martinez *et al*., 2021). Sustainability reporting and financial performance are positively related (Yousefinejad *et al.,* 2022).

The company's employee well-being and stakeholder engagement practices demonstrate its social sustainability. Corporate social responsibility (CSR) is the key driver of business performance (Halme *et al.,* 2020; Ng *et al.,* 2022). The literature suggests a positive relationship between CSR and firms' financial performance (Awaysheh *et al.,* 2020).

Environmental sustainability aims to preserve the natural environment. It is a critical factor in the sustainable growth of a business, which is often compromised by activities such as the use of natural resources and the emission of harmful substances (Fan *et al.,* 2023). Consumer behaviour tends to be hostile toward businesses that disregard environmental concerns, and even low prices may not be able to sway consumers in favor of such firms (Naini and Reddy, 2023).

2.3 Dynamic Capabilities for Sustainability

Researchers are now examining how dynamic capabilities relate to sustainability, including environmental, social, and economic factors (Vo Thai, 2024). Marcus and Anderson (2006) studied how dynamic capabilities can help businesses gain both business and social skills. Sensing, seizing, and reconfiguring have a positive impact on sustainability innovations (Mousavi *et al.,*2018). The application of dynamic capabilities to sustainability helps the firm achieve economic, environmental, and social goals simultaneously (Wu *et al*., 2012).

Dynamic Capabilities focuses on sustainability aspects (Amui *et al.,* 2017) such as green product development (Chen and Chang, 2013), business models for sustainability

(Bocken and Geradts, 2020), and sustainable supply chain management (Kähkönen *et al*., 2018). Innovation and collaboration have been discussed in studies related to Dynamic Capabilities for Sustainability (DCsS) (Dangelico *et al*., 2017). Other concepts discussed in these studies are process innovations (Kabongo and Boiral, 2017; Kumar *et al*., 2018), business-model innovations (Inigo *et al*., 2017; Bocken and Geradts, 2020), collaborative approach (Yu *et al*., 2017), and strategy content (Garud and Gehman, 2012; Bianchi *et al*., 2022).

DCsS work as a part of business strategy (Buzzao and Rizzi, 2020). The effect of dynamic capabilities on firm performance is positive a significant research focus; with scholars predicting a positive impact (Protogerou *et al*., 2011).

Chen and Chang (2013) distinguish sustainability-specific dynamic capabilities, e.g., "Green Dynamic Capabilities," from traditional dynamic capabilities. Some researchers have used traditional dynamic capabilities constructs in the sustainability context (Zhu *et al*., 2013; Mousavi *et al*., 2018), while others use sustainability-specific dynamic capabilities (Chen and Chang, 2013; Neumann and Snoeren, 2016).

Researchers have examined how dynamic capabilities affect sustainability concepts, like green innovation (Dangelico *et al.,* 2017, Ullah *et al.,* 2024), social innovation (Repo and Matschoss, 2019; Kamaludin *et al*., 2024) and circular economy (Raji *et al*., 2024), etc., but haven't studied their overall impact on sustainable business performance. Therefore, there is a need to explore how dynamic capabilities help balance economic, environmental, and social performance.

2.4 Conceptual Link: Dynamic Capabilities, Collaboration and Sustainable Business Performance

Collaboration is a higher-order dynamic capability, as it helps a firm sense stakeholder needs, seize opportunities through partnerships, and reconfigure organisational resources to develop shared value. In the present study of the FMCG industry, recognising rural market needs and sustainability challenges shows sensing capability; developing partnerships with self-help (SHGs) and Project Shakti of HUL, which redesigned the distribution system and supply chain of the company and adoption of sustainable packaging shows the reconfiguration aspect of dynamic capability done by the company. Thus, collaboration is not only operational cooperation but also

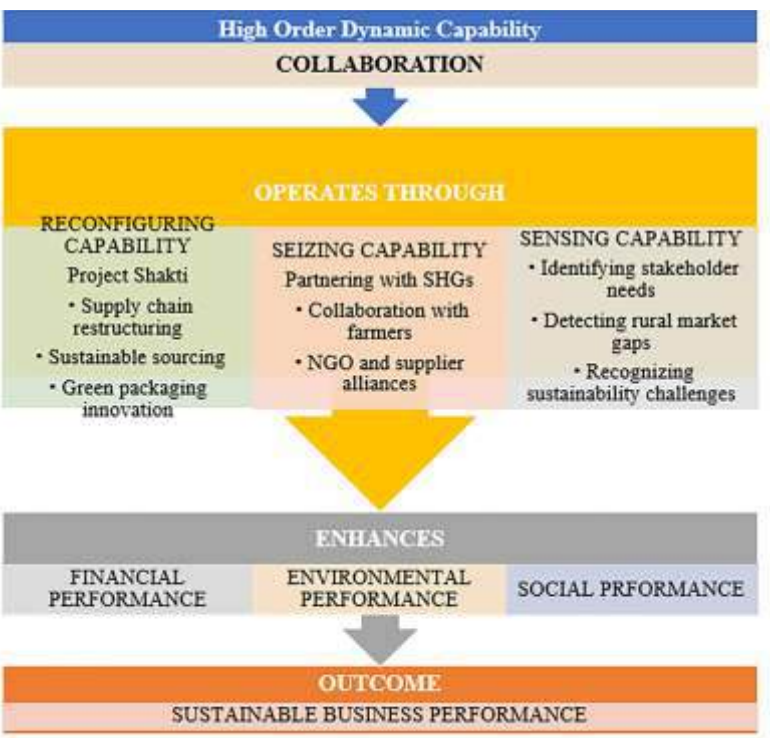


Figure 1: Conceptual Framework of Collaboration as a Dynamic Capability Driving Sustainable Business Performance

an effective mechanism for integrating firm resources with triple bottom line results. Figure 1 presents the conceptual framework of this study, showing that collaboration serves as a higher-order dynamic capability through sensing, seizing, and reconfiguration. These aspects, together, enhance social, environmental, and financial performance, thereby improving sustainable business performance (SBPI).

3. Research Method

The purpose of this research is to shed light on sustainability practices within the Indian FMCG industry with a particular focus on identifying and analysing the most sustainable firm in this sector. This research study adopted a mixed-methods approach to identify the dynamic capability of the most sustainable company in the Indian FMCG industry. Researchers using a mixed-methods approach employ different methodologies, data sources, collection techniques, and analytical strategies, all harmonised to achieve the objectives of their investigation (Creswell & Creswell, 2017).

We used a multiphase iterative mixed-methods research design. "A multiphase iterative design includes three or more phases, with early ones providing foundational data on which later phases can build. The design is iterative in that the researcher moves back and forth among quantitative and qualitative methods, with each new body of data informing the conceptualisation and implementation of subsequent phases" (Leedy & Omrod, 2015).

The mixed method research question (RQ) in our study is: What is the dynamic capability of the most sustainable company in the Indian FMCG industry?

To explore this question, we need to:

(1) Define clear metrics for sustainable business performance.

(2) Identify a method to compare the sustainability performance of various firms.

(3) Conduct a detailed study to outline the dynamic capabilities of the company identified as the most sustainable in the industry.

In this endeavour, we drafted the following three interrelated research questions:

RQ-1 How to measure the sustainable business performance (SBP) of the firm?

RQ-2 Which firm in the Indian FMCG industry has the most sustainable business performance?

RQ-3 What ensures the sustainable business performance of the most sustainable firm in the Indian FMCG industry?

To answer the above RQs, we adopted a multiphase QUAL QUAN QUAL iterative mixed-method research design (Kimmons, 2022). Table 1 presents the mixed-method approach used to address the mixed-method RQ in our study.

To compare the companies, we identified three broad dimensions of sustainability (Elkington & Rowlands, 1999; Székely & Knirsch, 2005; Stubbs & Cocklin, 2008; Wikström, 2010; and Adams *et al*., 2012) from the literature: social, environmental, and financial. The dimensions represent people, planet and profit dimensions of the Triple Bottom Line (TBL) framework (Elkington & Rowlands, 1999).

Table 1: Multiphase Iterative Mixed Method Approach

[QUAL → QUAN → QUAL Research Design]		
Phase	**Nature of the study**	**Research Question**
Phase I	Qualitative study to propose a conceptual framework for measuring sustainable business performance (SBP)	**RQ-1** How to measure the SBP of the firm?
Phase II	Quantitative study for measuring and comparing the SBP of FMCG firms.	**RQ-2** Which firm in the Indian FMCG industry demonstrates the most sustainable business performance?
Phase III	Qualitative study to identify the dynamic capability of the most sustainable firm.	**RQ-3** What ensures the sustainable business performance of the most sustainable firm in the Indian FMCG industry?

In the first phase, we conducted a qualitative content analysis (QCA) of the sustainability reports of the NIFTY 50 (a benchmark Indian stock market index that represents the weighted average of the 50 largest Indian companies listed on the National Stock Exchange) firms. QCA is "a research method for the subjective interpretation of the content of text data through the systematic classification process of coding and identifying themes or patterns" (Hsieh & Shannon, 2005).

QCA aimed to identify indicators for measuring sustainable business performance. SBP is the ability of a business to achieve long-term success while simultaneously contributing to social, environmental, and economic sustainability. It involves creating a positive impact on society and the environment while generating profits and value for stakeholders. In this qualitative study, we developed a sustainable business performance index (SBPI) by identifying sustainability indicators from the content of the evaluated reports (see Table 2).

It shows that indicators for environmental sustainability are carbon footprint reduction, waste recycling, energy conservation, and water efficiency. For social sustainability, the indicators are education initiatives, poverty alleviation, skill development, health care, women's empowerment, and employment generation. ROCE was chosen as the economic sustainability indicator because it shows long-termlong-term capital efficiency and profitability and and aligns with the economic aspect of the Triple Bottom Line approach. Unlike other profitability ratios, ROCE considers managerial effectiveness across both equity and debt capital, thereby supporting cross-company comparisons from 2014 to 2023.

Table 2: Sustainable Business Performance Index (SBPI)

Dimension*	Indicators**	Definition	Bottom Line
Social	Education Initiatives	The company's performance in education initiatives such as school supply donation drives, employee volunteering, career workshops, adult education support, STEM education sponsorship, and teacher training workshops.	**People**'s bottom line focuses on employees and local communities. It measures the firm's social performance.
	Poverty Alleviation	The company's performance in poverty eradication, rural development projects and vocational training.	
	Skill Development	The company's performance in skill development, including engineering training and skill development centres.	
	Employment Generation	The company's performance in employment-generation initiatives, including recruitment drives, entrepreneurship support programs, internship and apprenticeship programs, and diversity and inclusion initiatives.	
	Health Care	The company's performance in health care initiatives, such as asthma care and sanitation, and the establishment of health care centres.	
	Women Empowerment	The company's performance in women's empowerment, including gender diversity programs, flexible work arrangements, and women's leadership development.	

Dimension*	Indicators**	Definition	Bottom Line
Environment	Carbon Footprint Reduction	The company's performance on emission-reduction targets.	**Planet**'s bottom line focuses on reducing the company's ecological footprint. It measures the firm's environmental performance.
	Water Efficiency	The company's performance in water efficiency measures and sustainable water sourcing.	
	Energy Conservation	Company's performance in renewable energy adoption, energy management system (use of different technologies)	
	Waste Recycling	The company's performance in waste reduction, minimisation, and recycling infrastructure and facilities	
Economic	Return on Capital Employed (ROCE)	The company's performance in generating profits from capital provided by the equity shareholders and the debenture holders.	**The profit** bottom line focuses on generating returns for investors of capital. It measures the firm's financial performance.

*Based on triple bottom line (TBL) approach (Elkington & Rowlands, 1999)

**Based on qualitative content analysis of the sustainability reports of NIFTY 50 Indexed firms. NIFTY 50 is a benchmark Indian stock market index that represents the weighted average of fifty of the largest Indian companies listed on the National Stock Exchange (NSE).

Table 3: Reliability Statistics for Sustainable Business Performance Index

Environmental Performance Scale				
Cronbach's Alpha = 0.950 No of Items=4	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Carbon Footprint Reduction	10.24	13.889	0.924	.920
Water Efficiency	9.89	14.814	0.889	.931
Energy Conservation	9.92	16.278	0.831	.949
Waste Recycling	9.83	14.346	0.880	.934
Social Performance Scale				
Cronbach's Alpha = 0.927 No of Items=6	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Education Initiatives	16.29	21.529	0.735	.921
Poverty Alleviation	16.08	20.168	0.784	.915
Skill Development	16.01	21.495	0.793	.914
Employment Generation	16.13	20.222	0.802	.912
Health Care	16.13	20.332	0.837	.907
Women Empowerment	16.14	20.945	0.790	.914

In the second phase, we used a quantitative method. For quantitative comparison of SBP, we used the Sustainable Business Performance Index (SBPI) developed in the first phase. Based on market capitalisation in the NIFTY Consumer Index, the top ten companies were selected. It was done to ensure comparability among top-notch firms with effective reporting practices and market presence. This enhances the reliability of sustainable disclosure and ensures longitudinal data availability from 2014 to 2023. This approach provides a robust representation and a uniform industrial context.

Miles *et al.* (2014) suggest, "A researcher might use rating scales to assign rough indicators of magnitude or intensity to discrete pieces of qualitative data". Likewise, Halevi Hochwald *et al.* (2023) developed a Likert-type numerical scoring system to quantify qualitative data.

Two independent expert evaluators with expertise in this area were requested to assign scores to the sustainability indicators (as per Table 2) on a seven-point Likert scale. The criteria for selecting the experts include their academic background in sustainability and strategic management, 10 years of experience in sustainability reporting and ESG practices, and familiarity with sustainability frameworks such as the GRI standards. This helped in consistent scoring across companies.

One of the expert evaluators observed, "Most of the firms are consistently reporting their sustainability performance directly or indirectly in their sustainability reports, annual reports or in the integrated reports". Reliability of the environmental performance scale and the social performance scale was assessed through the internal consistency measure of Cronbach's Alpha (*refer* to Table 3) and found to be satisfactory (> 0.70).

We used Krippendorff's alpha, a measure of inter-rater reliability, to assess the ratings' reliability (Krippendorff, 2018). Krippendorff's alpha coefficient of 0.74 indicated substantial inter-rater agreement. This shows that the ratings were dependable, giving us confidence to use them for further analysis.

The average sustainability performance score was calculated by taking the 10-year (2014-2023) average of environmental, social, and financial performance scores for each company (see Table 4). Average environmental and social performance was assessed based on scores assigned by the two independent expert evaluators, and economic performance scores were retrieved from the financial databases for 2014-2023.

The following formula was used to calculate SBPI

SBPI = (Average Social Performance Score + Average Environmental Performance Score + Normalized Financial Performance Score) / 3

Where:

- Social Performance Score = Mean of six social sustainability indicators
- Environmental Performance Score = Mean of four environmental sustainability indicators
- Financial Performance Score = Ten-year average ROCE (normalised for comparability)

Equal weightage was assigned to social, environmental, and financial dimensions to maintain alignment with the Triple Bottom Line framework.

Statistical Analysis of Sustainable Business Performance

Along with average sustainability performance scores for the period 2014–2023 given in Table 4, additional statistical analysis was conducted to examine performance consistency, trends of growth, and year-wise comparative positions across firms.

Standard deviation of the Sustainable Business Performance Index (SBPI) was calculated for each firm using the formula:

$$SD = \sqrt{[\Sigma (Xi - \bar{X})^2 / (n-1)]}$$

where Xi shows the annual SBPI score, $\bar{X}$ shows the SBPI score, and n represents the number of years (n = 10). This was calculated to assess the consistency of sustainable performance from 2014 to 2023.

Hindustan Unilever Ltd. (HUL) has the highest mean SBPI (14.68) and relatively low standard deviation (SD = 0.253), which shows sound and stable sustainability performance from 2014 to 2023. Colgate-Palmolive India Ltd. shows almost the same stability, with a mean = 14.56 and an SD = 0.241, reflecting consistent sustainability among the top two firms.

Procter & Gamble Hygiene & Health Care Ltd. maintained high performance with a mean SBPI of 13.66, but showed slightly higher variation with an SD of 0.288, indicating moderate fluctuations over the selected period.

Dabur and Britannia performed moderately, with relatively controlled dispersion (SD ≈ 0.210), indicating steady but lower sustainability trajectories. Firms like GlaxoSmith Kline Consumer Healthcare Ltd. and Jubilant Food Works

Table 4: Comparative Performance of Top 10 Companies in the NIFTY Consumer Index (2014 – 2023)

Company	Average Economic Performance	Average Environmental Performance	Average Social Performance	Average Sustainability Performance	Rank
Hindustan Unilever Ltd	33.5000	5.0750	5.5625	14.7	I
Colgate Palmolive (India) Ltd.	36.4000	3.5000	3.9500	14.6	II
Procter & Gamble Hygiene & Health Care Ltd.	33.1000	3.5250	4.3875	13.7	III
Dabur India Ltd	20.5000	3.6250	4.5042	9.5	IV
Britannia Industries Ltd.	21.5000	1.4750	3.0958	8.7	V
Tata Consumer Products Ltd	16.5000	2.6000	3.0000	7.4	VI
ITC Ltd	16.7000	2.1500	2.9583	7.3	VII
Emami Ltd	15.8000	2.8750	2.7792	7.2	VIII
GlaxoSmithKline Consumer Healthcare Ltd.	11.4000	4.4250	3.8208	6.5	IX
Jubilant Food Works Ltd	9.1000	1.9000	3.1333	4.7	X

Sources:
(1) Environmental and Social Performance -Based on ratings on SBPI
(2) Economic Performance - https://www.screener.in/

Table 5: Standard Deviation of Sustainable Business Performance Index (2014–2023)

Company	Mean SBPI	Standard Deviation
Hindustan Unilever Ltd (HUL)	14.68	0.253
Colgate Palmolive India Ltd	14.56	0.241
Procter & Gamble Hygiene & Health Care Ltd	13.66	0.288
Dabur India Ltd	9.52	0.210
Britannia Industries Ltd	8.72	0.210
Tata Consumer Products Ltd	7.43	0.189
ITC Ltd	7.33	0.189
Emami Ltd	7.23	0.189
GlaxoSmithKline Consumer Healthcare Ltd	6.52	0.210
Jubilant Food Works Ltd	4.72	0.210

Ltd. are low performers and exhibit similar variability (SD ≈ 0.210), showing consistent but modest sustainability outcomes.

The longitudinal trend analysis (Figure 2) shows that HUL maintained leadership from 2014 to 2023, with gradual, small improvements rather than abrupt spikes. The relatively low deviation values across firms show structured sustainability initiatives.

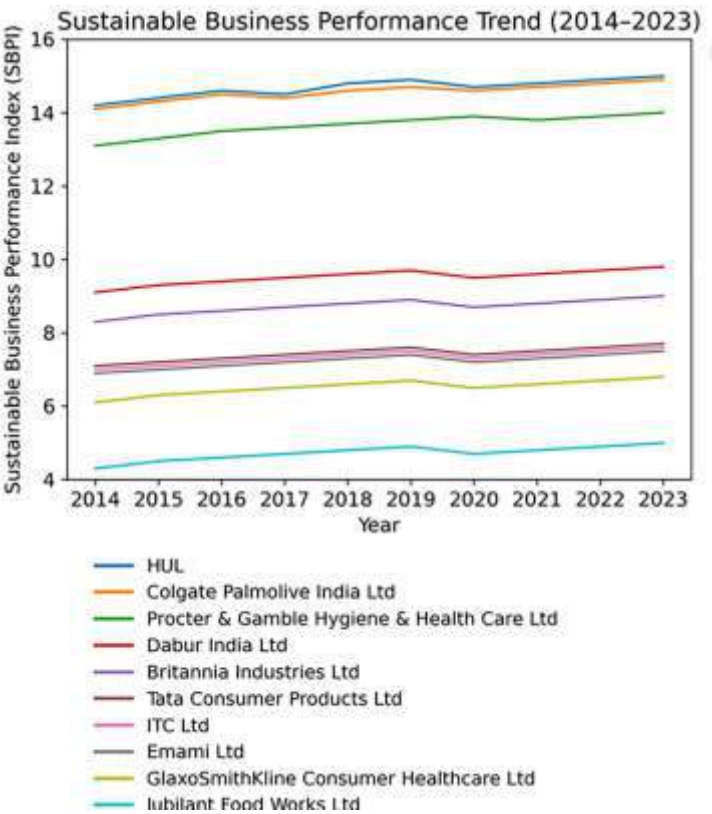
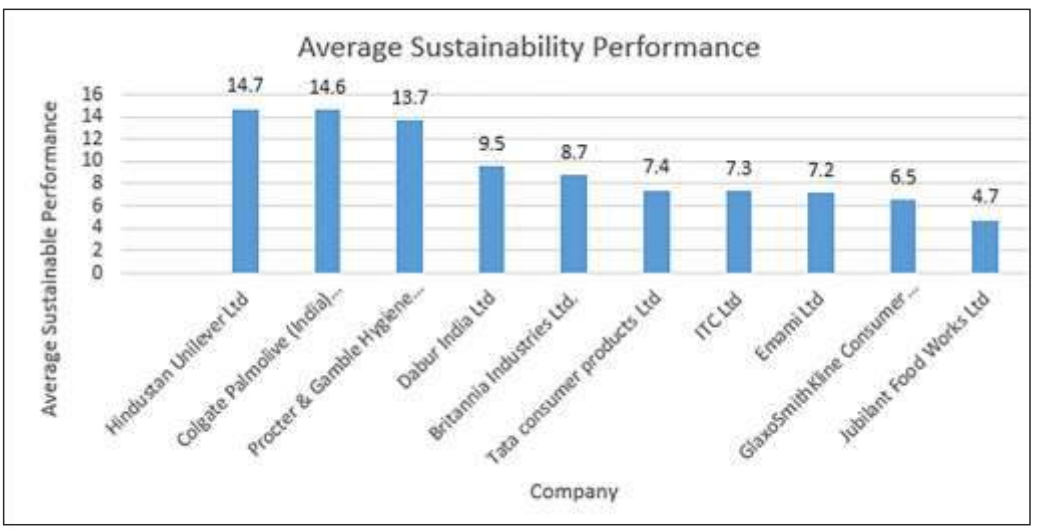


Figure 2: Sustainable Business Performance Trend Analysis



Source : Author's own

Figure 3: Comparative Sustainability Performance of the Indian FMCG Industry

The comparative findings in the study have become robust through mean comparisons, standard deviation analyses, and year-wise trend analyses. They also provide an empirical base for recognising HUL as the most sustainable company in the Indian FMCG sector.

Figure 3 shows the comparative sustainable business performance of the Indian FMCG industry (2014-2023). HUL emerges as the most outstanding company in the Indian FMCG industry.

Qualitative content analysis, as a text interpretation method, was used in the third phase (Kohlbacher, 2006) to explore HUL's dynamic capability by analysing publicly available secondary data.

We assessed publicly available information and asked whether using secondary qualitative data from credible sources would better achieve our study's objectives than collecting new data. After a thorough comparison, we determined that employing qualitative secondary data was the more effective choice for addressing our third research question.

In recent years, the respect, rigour, and credibility of qualitative secondary data have increased significantly, drawing more scholars to the secondary analysis of existing data. Secondary data can be numeric or non-numeric. Non-numeric, or qualitative secondary data, can include data retrieved second-hand from interviews, ethnographic accounts, documents, photographs, or conversations (Smith, 2008). There is a growing availability of resources and guidelines for utilising secondary qualitative data in research studies (e.g. Bishop, 2007; Largan and Morris, 2019; Beck, 2019; Hughes and Tarrant, 2020; Watkins, 2022).

Figure 4 summarises the flow and interlinkages of the multiphase, iterative, mixed-method approach discussed above.

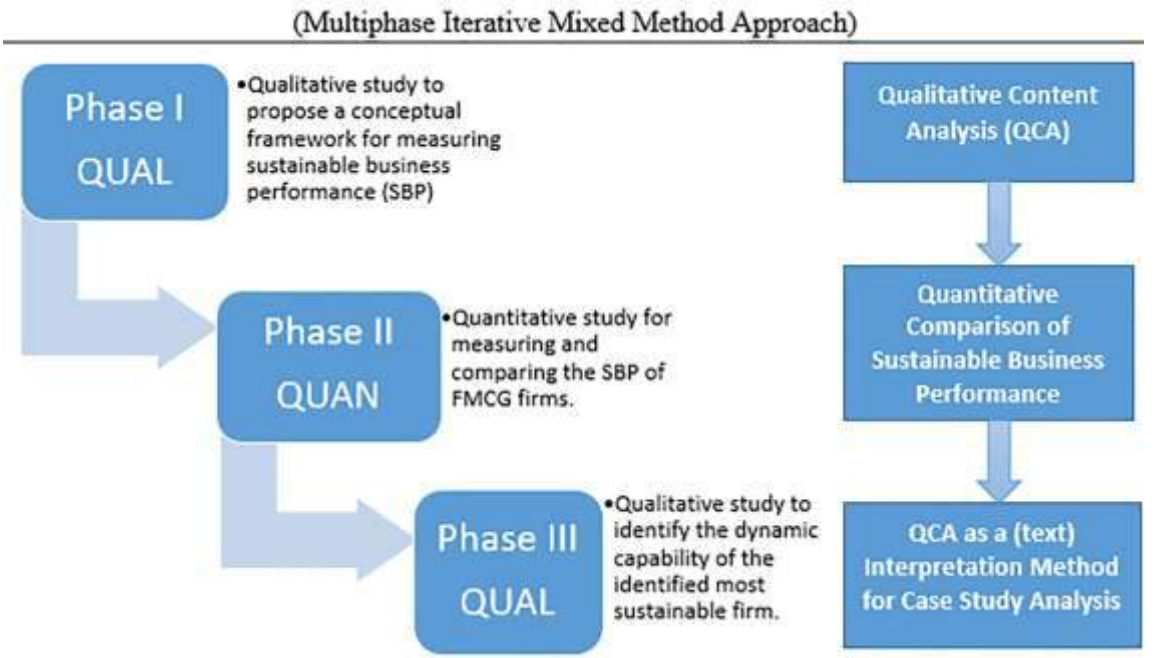


Figure 4: Multiphase Iterative Mixed Method Approach

As an outcome of the third phase, the next section presents a qualitative case study analysis of HUL, identifying Collaboration as a dynamic capability of the firm.

Collaboration at HUL: A Dynamic Capability for Sustainability

In the early 20th century, when many global companies hesitated to enter a complex and diverse country like India, **Unilever** made a bold move. It took root in India during the 1930s. Over time, three companies — Hindustan Vanaspati Manufacturing Company (for cooking oils), Lever Brothers India Ltd. (for soaps), and United Traders Ltd. (for personal care products) — came together and merged in 1956 to form Hindustan Lever Ltd. Decades later, in 2007, it became Hindustan Unilever Ltd. (HUL) (Shyle, 2012).

Seeing Opportunity in the Challenges of Rural India

India is a nation of villages, with more than 65 per cent of its population living in them. It's a risky affair to initiate business activities for corporates in rural areas (Kumar & Gogoi, 2013). HUL saw this problem as an opportunity. HUL did not avoid the rural areas and could see the demand for quality products there, but how could the company reach them effectively? Collaboration was the answer.

Collaboration: HUL's Secret Weapon

HUL made a smart decision by partnering with local communities. This helped to develop collaboration as a dynamic capability of HUL. Through collaboration, HUL built trust and adapted faster. To make its products, HUL needs raw materials like herbs, oils, and agricultural produce. The company surpasses vendors in raw material purchases and works directly with farmers and cooperatives, providing them with training in modern, sustainable farming methods. This helped farmers economically by increasing their crop yields (Large & Thomsen, 2011; Lio et al., 2017). This was a win-win partnership that helped in building long-term relationships and trust.

The Game-Changer: Project Shakti

An Idea that combined business with women's empowerment was launched by HUL as Project Shakti in 2001. HUL realised that many villages had no regular shops or reliable distribution channels. Women in these villages were often hardworking and seeking income opportunities. HUL decided to convert these women into its brand ambassadors and sales agents. The company began by identifying Self-Help Groups (SHGs) — small groups of rural women who saved money together and supported one another financially. Shakti Entrepreneurs or "Shakti Ammas" was the name given to these selected women.

Basic training was provided to these women in account keeping, product knowledge, and door-to-door selling. HUL gave them its products at a wholesale rate to sell in their own and nearby villages at a small profit (Raj & Aithal, 2018). The profit was small but made a big difference for rural households. It simply means reaching new customers without any extra expense.

Volunteers were trained for the Shakti Vani program. They raised awareness about health, hygiene, and women's empowerment. This built trust in HUL's other products, like soap and toothpaste. HUL provided Free samples, helping villagers try the products before purchasing. This built long-term loyalty towards HUL.

Technologies such as GPS mapping and density tracking were used to determine customer locations and improve efficiency. This is how HUL could easily determine the number of Shakti ammas needed, where to hire them, and how to make the supply chain effective. (Kolk, Rivera & Rufín, 2014). The company rewarded these Shakti ammas for their stellar performance. The company's digital plus human touch became a supply chain innovation supporting collaboration with the rural community.

The company faced several challenges, including villagers' backward, conservative thinking. But HUL worked to overcome these challenges (Shukla & Bairiganjan, 2014). Gradually, people in villages and rural areas changed their mindset as the company began to receive their support. The company could attract 45000 plus Shakti Ammas, and rural India is now contributing more than half of HUL's sales.

HUL also demonstrated its commitment to the environment by launching the Sustainable Packaging Program, thereby reducing plastic use, promoting recycling, and reducing waste. This approach, combined with its social impact, develops HUL as a model for sustainable business performance (Beske & Seuring, 2014).

HUL's journey is not just about its products. It reflects a collaborative approach to business. HUL showed what true collaboration and association with people is. The whole story has shown collaboration as a capability and a way forward.

4. Discussion

A multiphase, iterative, mixed-methods approach is used to explore the dynamic capability of the most sustainable company in the Indian FMCG industry. By combining primary and secondary qualitative and quantitative data sources (including sustainability reports, secondary qualitative data, top management interviews, independent ratings, and online information), the study introduces a novel approach to gaining a comprehensive understanding of sustainable business practices and performance in the field of business management.

HUL's success story in the Indian FMCG industry provides compelling evidence for collaboration as a dynamic sustainability capability. This study supports the existing literature on collaboration as a dynamic capability (e.g., Plattfaut, 2005; Ellonen *et al.*, 2011; Kindstrom *et al.,* 2013; Piening *et al.,* 2015; Ahn *et al.,* 2018; Bogers *et al.,* 2019; Hutton *et al.,* 2021; Dovbischuk, 2022; Farzaneh *et al.,* 2022). Collaboration as a dynamic capability enhances business performance and supports the organisation in overcoming business challenges (Plattfaut, 2005; Ahn *et al.,* 2018; Hutton *et al.,* 2021; Vanhaverbeke and Cloodt, 2014; Teece, 2014; Hutton *et al.,* 2021). Organisations that work collaboratively achieve higher profits than those that do not (Tidd *et al.*, 1997).

This study shows that collaboration is a dynamic capability developed by HUL, which has become key to sustaining its business effectively. The company not only responded to market changes but also sensed the needs and utilised its resources to develop partnerships with rural society specially women and farmers. All this could happen because of Project Shakti, which not only energised the distribution network but also generate employment opportunities at village level. This way, collaboration has supported both business growth and rural development.

In the context of dynamic capabilities, this process reveals the microfoundations of sensing, seizing, and reconfiguring (Teece, 2007). HUL identified rural market gaps and sustainability challenges, and seized the opportunity to develop structured partnerships with self-help groups and farmers. HUL launched Project Shakti to reconfigure its distribution. Thus, collaboration in HUL is not an incident but an embedded organisational capability supporting sustainable business performance.

Collaboration maintains balance amongst social, environmental, and financial aspects (Ponce et al., 2021). HUL has used collaboration as a tool for sorting social issues in unique ways. Social collaboration is important for solving community-level challenges (Ronning & Knutagard, 2015) and it improves sustainable business performance (Repo & Matschoss, 2019). HUL's *Project Shakti* approach demonstrates its sense of responsibility not only towards business but also towards society (Joshi et al., 2017).

Cooperation, teamwork, and knowledge sharing are forms of collaboration that lead to sustained financial performance (Leiponen, 2000). So we can say, collaboration also aids financial sustainability. In the case of HUL, it developed an inclusive business model to fulfil market demand and ensure sustained profitability. The achieved this by combining collaboration with social innovation. Thus, in the case of HUL, collaboration has not only shouldered social responsibility but also acted as a strategic capability that enhances financial soundness and competitive edge.

Implications

Better policies can be framed for organisations if collaboration is seen as an organisational strength; this will help policymakers and the government encourage a similar trend across the industry. The new norms, with collaboration as one of the essentials, will help build a sustainable market.

Managers can operationalise collaboration through effective stakeholder engagement, such as long-term supplier partnerships, rural entrepreneur networks, and cross-functional sustainability teams. Firms can integrate collaboration into their procurement strategies, product innovation processes, and distribution models. Sustainability achievements linked to employee performance assessment can further institutionalise collaborative practices.

The findings of the present study will ensure sustained success through collaboration. A collaborative approach will help the companies to fulfil customer demands and cope with environmental challenges. Measurable collaboration parameters, including community-based distribution metrics, should be developed by the firms. Including collaboration into value based governance ensures measurable sustainability in terms of financial and operational results. HUL sets an example that a firm can be profitable even being sustainable. Its profit can be increased by integrating social and environmental initiatives into its core business.

The study develops insight of how collaboration is not only

a practice or strategy but a dynamic capability in the FMCG industry. Supporting collaboration and sustainability will help professionals and researchers identify their strategic significance for long-term success.

5. Conclusion

HUL showed the function of collaboration as a dynamic capability in the FMCG sector. The company initiated Project Shakti to empower rural women and farmers; it was an effort for sustainable sourcing and green packaging. HUL aligned its daily activities with social, environmental and financial concerns. Collaboration was not just an operational alternative for HUL but also emerged as a strategic capability that helped the company achieve long-term success. The longitudinal trend observed in the study further shows that collaboration serves as a higher-order dynamic capability that sustains competitive advantage over a longer period.

HUL not only spanned its supply chain but also its organisational culture and community engagement, creating a benchmark in the industry. Collaboration strengthened HUL's market position and improved its social and environmental impact. HUL is the perfect example of balancing growth with responsibility.

This study contributes to the discussion of dynamic capabilities for sustainability (DCsS). Earlier work has focussed on the significance of dynamic capabilities with sustainable practices (Amui et al., 2017; Dangelico et al., 2017; Kabongo & Boiral, 2017; Yu et al., 2017; Kumar et al., 2018; Inigo et al., 2017; Bocken & Geradts, 2020; Buzzao & Rizzi, 2020; Bianchi et al., 2022), and the findings here add proof from the Indian FMCG sector. It may help Indian FMCG firms overcome present challenges and utilise collaboration for sustainable growth.

More empirical research is required in this field, as the present study relied solely on publicly available data and focused on a single industry. The significance of collaboration as a dynamic capability for sustainable business performance should be explored across industry studies. Recognising the different drivers of collaboration and assessing how it can be embedded in the business will be significant. The present study emphasises the FMCG industry, but its methodology, specifically the development of the Sustainable Business Performance Index (SBPI) and multiphase mixed-method, can be used for other industries. This would validate the generalizability of collaboration as a dynamic capability.

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Influence of Cultural Intelligence on Turnover Intention of Hotel Employees: Role of Emotional Labour as a Mediator

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Abstract

This study aims to investigate the role of emotional labour (EL) as a mediator in the relationship between cultural intelligence (CQ) and turnover intention (TI). A survey questionnaire was used to collect data from 280 employees in the hotel sector of Punjab, India. The data was then validated through frequency, reliability, confirmatory factor, and correlation analyses. The hypotheses were tested using structural equation modelling, and the mediation analysis results were further examined using the PROCESS macro with bootstrapping. According to this study, MetaCQ is significantly related to TI, whereas the other three dimensions are not. The results also show that MetaCQ is significantly related to SA, whereas the other three CQ dimensions (CogCQ, MotCQ, and BehCQ) are not. Conversely, CogCQ, MotCQ, and BehCQ are significantly related to DA, whereas MetaCQ is not.

Furthermore, SA is not significantly related to TI, whereas DA is. This study also reveals that SA mediates the relationship between MetaCQ and TI, whereas DA mediates the relationships between the other three CQ dimensions (CogCQ, MotCQ, and BehCQ) and TI. The study suggests that employees in the hotel industry must control their emotions at work; thus, the role of EL strategies (SA and DA) cannot be overlooked. With appropriate counselling, training, and other employee support initiatives, managers can help their staff members become more emotionally resilient. This study contributes to the body of literature by evaluating each of the four CQ dimensions separately in relation to the TI. The study highlights the mediating role of EL strategies in the relationship between the CQ's four dimensions and TI.

Keywords: *Cultural Intelligence, Emotional Labor, Deep Acting, Surface Acting, and Turnover Intention*

1. Introduction

Internationalisation is seeing a considerable increase in cultural diversity. This increasing cultural diversity or variety raises many issues, such as a more complex organization, cultural differentiation, intense competition, high turnover of employees, and difficulty in knowledge transfer within a global company (Koksal et al., 2023; Lam et al., 2022; Lo & Nguyen, 2023; Nazarian et al., 2024; Raithel et al., 2021). Given the key challenges in today's competitive market, providing superior hotel services and products to customers is important and strongly impacts customer satisfaction and loyalty (Bharwani & Jauhari, 2017). Furthermore, in a rapidly evolving hospitality environment, it is essential to ensure hotels' profitability and growth while providing high-quality customer service to guests. Therefore, hotels encourage "service with a smile" among employees to improve customer satisfaction and make every effort to ensure that employees provide excellent service to meet customer expectations (Narangajavana & Hu, 2008). To provide high-quality service, employees perform their roles in ways that align with customers' perceptions, often requiring extra emotional labour (EL) (Grandey & Sayre, 2019). Previous studies found two main forms of EL: deep acting (DA) and surface acting (SA) (Hulsheger & Schewe, 2011; Lam et al., 2022; Lam & Cheung, 2024; Wang, 2020). Repeated EL, especially SA, can lead to tension, discomfort, and dissatisfaction among staff, ultimately negatively affecting their physical and mental well-being (Hochschild, 1983) and increasing turnover rates (Ratasuk, 2022). By contrast, DA is frequently associated with greater job satisfaction and service quality (Diefendorff et al., 2005; Grandey et al., 2017). As such, employees must "express socially desirable emotions" and manage their emotional displays in cross-cultural interactions (Ashforth & Humphrey, 1993). Frontline hotel employees deploy cultural intelligence (CQ) and perform EL to deliver high-quality service to guests (Lam & Cheung, 2024). The most common antecedent of EL to be studied is emotional intelligence. However, in a cross-cultural hospitality environment, service personnel must use their CQ in demonstrating culturally appropriate EL. CQ is a strong predictor of EL, and studies have shown that people with higher CQ scores are more likely to engage in DA, while people with lower CQ scores are more likely to perform SA (Al Shaer et al., 2023; Brotheridge & Taylor, 2006; Devi & Randhawa, 2023; Rafiq et al., 2020; Salleh, 2014). CQ is the capacity of a person to function effectively in and deal with cultural differences. It is a multidimensional concept that aims to address problems arising from differences in racial, ethnic, and national backgrounds (Ang & Van Dyne, 2008). Existing studies primarily examine the direct impact of CQ on performance-related outcomes (Lee, 2023; Al Shaer et al., 2023), with little attention paid to the underlying emotional mechanisms through which its various aspects impact employees' intentions to leave. Furthermore, insufficient research has been conducted on the differentiated roles of SA and DA in linking specific CQ dimensions to turnover intention (TI). Accordingly, this study addresses the gap by integrating CQ and EL within a mediation framework to explain how and why culturally intelligent employees may exhibit lower TIs in the hotel industry.

Objectives

1. To examine the impact of cultural intelligence dimensions on turnover intention.
2. To investigate the impact of cultural intelligence dimensions on emotional labour strategies (surface acting and deep acting).
3. To examine the impact of emotional labour strategies on turnover intention.
4. To assess the mediating role of emotional labour strategies in the relationship between cultural intelligence dimensions and turnover intention.

2. Literature Review and Hypotheses

2.1 Concept of Cultural Intelligence

CQ is based on Gardner's theory of multiple intelligences (1983) and Sternberg's theory of successful intelligence (1985). In the original version of Gardner's theory, seven types of intelligence were described in terms of mental capacities: interpersonal, intrapersonal, bodily–kinesthetic, spatial–visual, logical–mathematical, verbal–linguistic, and musical intelligence (Gardner & Hatch, 1989). In addition, Sternberg's successful intelligence theory (1985) defines success in life as the ability to reach personal goals and function successfully within a given sociocultural context. It hypothesises four domains of intelligence: behaviour, biology, cognition, and motivation (Sternberg & Grigorenko, 2006). The concept of CQ was first proposed by Earley as an aspect of intelligence, as published in an article in 2003. The concept was popularised by the book by Earley and Ang (2003), titled *Cultural Intelligence: Individual Interactions Across Culture*s. They positioned

CQ as a new and important form of intelligence, linked to new conceptions of intelligence as a capacity to adapt to the environment. CQ is defined as the effective adaptation to new cultural situations, with the intention of capturing individual differences in adaptation to various cultural situations (Thomas et al., 2008). Thomas et al. (2008) divided CQ into three parts: meta-cognition, which refers to awareness and control of one's thinking and learning in the intercultural context; cultural knowledge, which pertains to how cultures differ and affect people's behaviour; and cultural skills, which refers to how a person adjusts one's behavior to the culture.

Furthermore, Ang and Van Dyne (2008) defined CQ as a four-factor construct comprising metacognitive, cognitive, motivational, and behavioural factors. Metacognitive CQ (MetaCQ) involves critical thinking, awareness of, and control over cognitive processes, and is concerned with broadening cultural knowledge and building on it. Cognitive CQ (CogCQ) encompasses both general cultural knowledge and culturally specific knowledge. Motivational CQ (MotCQ) includes self-efficacy of intercultural interactions as well as interest, motivation, and cognitive direction. Behavioural CQ (BehCQ) involves making decisions using thought processes and adapting behaviour in verbal and non-verbal situations. In 2012, Van Dyne et al. expanded the definition of CQ into three dimensions: biological loci of intelligence, including structural aspects such as brain hemispheres; process aspects, such as neuronal activities; and the interaction between structure and process, detailing how brain regions generate activities (Van Dyne et al., 2012). The diversity of cultures worldwide has increased the importance of CQ. This study explores the relationship between CQ and TI, emphasising EL as a potential mediator.

2.2 Relationship Between Cultural Intelligence and Turnover Intention

The term "conscious and deliberate willfulness to leave" refers to a person's decision to leave an organisation (Matz et al., 2014). Quite simply, it refers to a worker's psychological capacity to leave their current career, including their willingness to search for a new job, their intention to leave, and their dissatisfaction with their current job (Mobley et al., 1978). This leads to long-term productivity loss when qualified, skilled, and knowledgeable people leave the organisation (Rahim et al., 2015). Past studies of hotel employees' TIs found potential antecedents of employee intentions and key reasons for turnover, such as lack of job resources, EL, long working hours, underemployment, salary issues, and constant communication with the customers and team members (Lam & Chen, 2012; Park & Min, 2020; Ryu et al., 2020). Employees in the hotel industry are expected to attend to guests from diverse cultural backgrounds (Ratasuk, 2022). As the work environment becomes increasingly multicultural, employees' ability to engage in cross-cultural interactions can significantly influence their job satisfaction, organisational commitment, and intentions to stay or leave. Previous research has shown that many constructs (such as work–family conflict, supervisor support, job satisfaction, and organisational commitment) affect turnover and TI across different fields (Pu et al., 2022, 2024; Unguren et al., 2024). This research investigates how CQ relates to TI, both directly and indirectly, and emphasises the importance of EL.

H_{1a}: There is a negative relationship between metacognitive CQ and turnover intention.

H_{1b}: There is a negative relationship between cognitive CQ and turnover intention.

H_{1c}: There is a negative relationship between motivational CQ and turnover intention.

H_{1d}: There is a negative relationship between behavioural CQ and turnover intention.

2.3 Relationship Between Cultural Intelligence and Emotional labour Strategies (Mediator)

Employees perform two types of EL: SA and DA (Hochschild, 1983). SA is a prefabricated solution designed to reduce emotional effort and align with employer-stated norms. Employees who use this approach do not display their true emotions; they adopt a fake attitude to manage customers' emotions (Ashforth & Humphrey, 1993). Service workers who use DA influence customers' thoughts and perceptions by reflecting their genuine feelings (Rafiq et al., 2020). Therefore, improving employees' CQ is crucial in multicultural work environments to help them sustain positive client relationships. Highly culturally aware workers display positive emotions to customers and build strong relationships, benefiting their company (Al Shaer et al., 2023). Those who fake feelings under pressure to conform to organisational standards tend to provide lower service quality (Lawler & Thye, 1999). Within this framework, CQ and its four dimensions are conceptualised as a valuable personal resource that enables employees to navigate culturally diverse service interactions effectively.

First, MetaCQ enhances awareness and regulation of cultural assumptions during interactions. Employees with high MetaCQ are more likely to consciously monitor and adjust their emotional expressions in cross-cultural encounters. Therefore, drawing on COR theory, MetaCQ can be viewed as a cognitive regulatory resource that influences employees' emotional display strategies (Van Dyne et al., 2012).

H_{2a}: There is a negative relationship between metacognitive CQ and surface-acting.

H_{2b}: There is a positive relationship between metacognitive CQ and deep acting.

Second, CogCQ reflects knowledge of cultural norms and practices, enhances employees' ability to authentically understand customers from diverse backgrounds. This deeper cultural comprehension reduces emotional dissonance and promotes genuine emotional engagement, consistent with DA. From a conservation of resources (COR) perspective, cultural knowledge represents a resource that supports constructive emotional investment (Van Dyne et al., 2012).

H_{3a}: There is a negative relationship between cognitive CQ and surface-acting.

H_{3b}: There is a positive relationship between cognitive CQ and deep-acting.

Third, MotCQ reflects the intrinsic interest and drive to engage in cross-cultural interactions. Highly motivated employees are more willing to invest emotional effort in managing service encounters, making them more inclined toward DA rather than superficial emotional regulation (Van Dyne et al., 2012).

H_{4a}: There is a negative relationship between motivational CQ and surface-acting.

H_{4b}: There is a positive relationship between motivational CQ and deep-acting.

Fourth, BehCQ represents the capability to adapt verbal and non-verbal behavior across cultural contexts. Such adaptability reduces emotional strain and enhances authenticity in interactions, thereby supporting DA (Van Dyne et al., 2012).

H_{5a}: There is a negative relationship between behavioural CQ and surface-acting.

H_{5b}: There is a positive relationship between behavioural CQ and deep-acting.

However, research on intercultural service environments remains limited. To contribute to the existing literature, we developed and tested a model of EL in cross-cultural service interactions that links EL, performance, and CQ. By using previous studies (Al Shaer et al., 2023; Brotheridge & Taylor, 2006; Lam et al., 2022; Lam & Cheung, 2024; McCance, 2010; Rafiq et al., 2020; Salleh, 2014; Tasdemir et al., 2021) as basis, we anticipate a strong relationship between employees' CQ dimensions and EL.

2.4 Relationship Between Emotional labour and Turnover Intention

Only a few empirical studies examine the relationship between EL and individual outcomes. For example, Brotheridge and Lee (2002) and Glomb and Tews (2004) investigated the fundamental mechanisms that link service workers' emotional reactions to job burnout. Mahoney et al. (2011) investigated the relationship between EL and work outcomes among college professors, such as affective commitment, job satisfaction, and emotional fatigue. Grandey (2003) investigated the relationship between EL and the intention to leave one's job. He found a mechanism that indicates why team members who engage in SA are more likely to want to quit, whereas those who practice DA are not. Employees are expected to perform actions such as smiling during interactions to enhance service quality and customer satisfaction (Grandey, 2003). Employees performing high-intensity EL expend excessive emotional energy, leading to emotional fatigue. Emotionally stressed employees may stop working, take leave, or work late, and are more likely to leave their jobs (Côté & Morgan, 2002). Conversely, employees with a stronger emotional bond to their organisation are less likely to leave. Past research on the relationship between EL strategies and TI showed that SA is positively related to TI, whereas DA is negatively related to TI (Grandey, 2003; Kang & Jang, 2022; Kwon & Song, 2024).

H_6: There is a positive relationship between surface acting and turnover intention.

H_7: There is a negative relationship between deep acting and turnover intention.

2.5 Mediating Role of Emotional labour

Based on COR theory, this study examines how EL mediates the relationship between CQ and an employee's

likelihood of leaving their organisation (Hobfoll, 1989). According to COR, people experience stress when they are at risk of losing resources or when they do not gain resources after investing in them. When surface behaviour toward clients is combined with emotional depletion, this is a form of job stress that depletes regulatory resources. Higher emotional exhaustion in work groups arises from disparities in resource distribution and the potential benefits and drawbacks of EL strategies, both of which influence individual outcomes (Hu & Shi, 2015; Ozcelik, 2013). EL is an emotional resource that influences emotional fatigue and psychological job stress (Hobfoll, 2001).

Additionally, Lin and Lin (2011) argued that frontline employees who engage in SA experience higher levels of emotional exhaustion, which raises their likelihood of leaving their jobs. By contrast, DA, or the expression of positive emotions by highly culturally aware employees, supports the development and maintenance of positive customer relationships, which benefits the company (Al Shaer et al., 2023). CQ is a valuable, unique, and expensive resource. It helps employees better manage their emotions in multicultural work settings (Tay et al., 2008). In a 2014 study, Salleh found that employees with higher CQ are less likely to exhibit surface-level behaviours, resulting in higher job satisfaction and retention.

Drawing on COR theory, MetaCQ can be viewed as a cognitive regulatory resource that influences employees' emotional display strategies. CogCQ represents a resource that supports constructive emotional investment. MotCQ operates as an energetic resource that facilitates DA. Behavioural flexibility serves as a protective resource that minimises emotional dissonance. Studies have found that EL strategies mediate the relationship between CQ and these positive outcomes. For instance, Tasdemir et al. (2021) concluded that EL strategies partially mediated the relationship between CQ and job performance. In the hospitality sector, Lam and Cheung (2024) showed that CQ affected job satisfaction through the use of EL strategies in the workplace. The impact of EL strategies on the relationship between CQ and TI has rarely been examined in existing studies. Consequently, this study hypothesises that EL methods mediate the relationship between CQ and TI. The hypotheses are as follows:

H_{8a}: Surface acting mediates the relationship between metacognitive CQ and turnover intention.

H_{8b}: Deep acting mediates the relationship between metacognitive CQ and turnover intention.

H_{9a}: Surface acting mediates the relationship between cognitive CQ and turnover intention.

H_{9b}: Deep acting mediates the relationship between cognitive CQ and turnover intention.

H_{10a}: Surface acting mediates the relationship between motivational CQ and turnover intention.

H_{10b}: Deep acting mediates the relationship between motivational CQ and turnover intention.

H_{11a}: Surface acting mediates the relationship between behavioural CQ and turnover intention.

H_{11b}: Deep acting mediates the relationship between behavioural CQ and turnover intention.

Research Design

3. Sample of the Study

The study population included employees working in four- and five-star hotels in Punjab, a northern Indian state. Data were collected from three cities in Punjab—Amritsar, Ludhiana, and Chandigarh—based on total tourist arrivals (Department of Tourism and Cultural Affairs, Govt. of Punjab, accessed on June 25, 2025). Data were gathered from hotel staff across various service areas, including the food division, bell staff, front desk, and back-of-house/support staff, such as cashiers, hotel attendants, security officers, and managers. These staff members directly interact with or have first-hand experience with guests or customers from diverse backgrounds. Data were collected in these three cities using a cross-sectional research design and a purposive sampling survey. Respondents were surveyed via mail, social media (LinkedIn), or Google Forms. A total of 350 questionnaires were distributed, of which 280 were returned, yielding an 80% response rate.

3.1 Sample Characteristics

Male respondents accounted for 72.9%, and females for 27.1%. 53.2% of the sample were between the ages of 21 and 30. By educational qualification, 60.7% had a graduate degree, and 17.9% were postgraduates. Data were also collected from different roles, including 6.8% of managers, 10.7% of assistant managers, 32.1% of supervisors, 22.9% of stewards, and 27.5% from other roles. Most employees

Table 1: Profile of Respondent

Category	Frequency	Percentage
Hotel Star Rating		
4 Star	36	12.9%
5 Star	242	86.4%
5 Star Delux	2	0.7%
Gender		
Male	204	72.9%
Female	76	27.1%
Age		
18-21	36	12.9%
21-30	149	53.2%
31-40	83	29.6%
41-50	11	3.9%
50 & above	1	0.4%
Education		
12th	50	17.9%
Graduation	170	60.7%
Post Graduation	50	17.9%
Others	10	3.6%
Designation		
Manager	19	6.8%
Assistant Manager	30	10.7%
Supervisor	90	32.1%
Steward	64	22.9%
Other	77	27.5%
Experience		
Less than 1 Year	34	12.1%
1-2 Year	96	34.3%
3-5 Year	62	22.1%
More than 5 Year	88	31.4%
Local Language		
Yes	209	74.6%
No	71	25.4%
Home State		
Punjab	137	48.9%
Out of Punjab	143	51.1%
Note(s): N= 280		

had 1-2 years of experience (34.3%), followed by more than 5 years (31.4%). A total of 74.6% spoke the local language, while 25.4% did not. 48.9% were respondents from Punjab, and 51.1% were from other regions. Table 1 presents the profile of respondents, while Figure 1 shows the conceptual framework of the study.

Measurement of the Study

Cultural Intelligence Scale

According to Ang & Van Dyne (2008), cultural intelligence is a subset of intelligence that focuses on successfully recognising, interpreting, and responding to contexts marked by cultural diversity. The CQS (Cultural Quotient Scale) created by Ang *et al.* (2007) was used in this study. It is the most used and representative CQ measurement system. This scale consists of 20 items across four dimensions. Each item is scored on a 7-point Likert scale, with 1 representing "strongly disagree" and 7 representing "Strongly agree."

Emotional labour

The 13-item emotional labour scale used in this study was adapted by Diefendorff et al. (2005); seven questions were

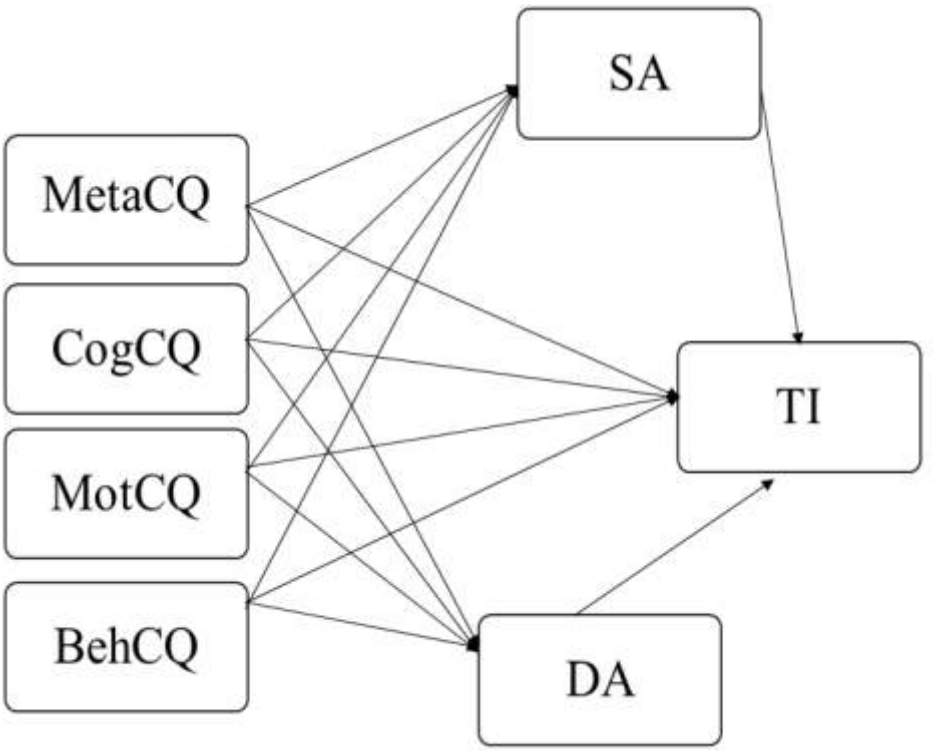

Figure 1: Conceptual Framework

created by Grandey (2003) and six by Krumal & Geddes (2000). Participants rated each item on a 5-point Likert scale from (1) "Strongly Disagree" to (5) "Strongly Agree."

Turnover Intention

The respondents' intention to leave the hotel was measured using the 3-item turnover intention scale developed by Akgunduz & Bardakoglu (2017). A five-point Likert scale, ranging from (1) "strongly disagree" to (5) "strongly agree," was used for rating.

Data Analysis

In this study, various statistical techniques have been used to analyse the data. Factor analysis, Pearson's correlation, and parallel multiple mediation analyses have been used to examine the study's hypotheses. Software used is Statistical Package for the Social Sciences (SPSS) version 21 and Analysis of Moment Structures (AMOS) version 24. In addition, the PROCESS macro is used to carry out the parallel multiple mediation analysis.

4. Analysis and Result

The data analysis comprised 3 steps: In the first step, we conducted an exploratory factor analysis in the software program of statistical packages (SPSS) using maximum likelihood and varimax rotation to explore the scale by conducting a preliminary analysis. The second step was to re-establish the factor structure by submitting the EFA to confirmatory factor analysis (CFA) using AMOS. The third step was to test the hypotheses by utilising AMOS to determine the structural model. Next, mediation effects were further examined using the PROCESS macro with 5000 bootstrap samples.

Exploratory Factor Analysis

An exploratory component analysis using the maximum likelihood approach with the varimax rotation is used to examine the factor structure and the relationships among the scale items. The results of the rotated factor matrix are shown in Table 2 below.

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Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.796
Bartlett's Test of Sphericity	Approx. Chi-Square	6565.796
	df	561
	Sig.	.000

The requirements for sampling adequacy are satisfied because the KMO value exceeds 0.50. Bartlett test of sphericity was found to be significant (($\chi^2 = 6565.796$, df = 561, $p < 0.001$), indicating that the correlation matrix differs significantly from the identity matrix ($p<.05$), and that factor analysis is suitable. Next, we examined the standardised factor loadings (SFLs). Aside from MetaCQ 3, Cog CQ 5, 6, 7, MotCQ 13, 14, BehCQ 14, and SA 2, 3, and DA9, all SFL values were above 0.5, which is a common cutoff. These items were deleted due to low factor loadings (<0.05). For further validation, we conducted the CFA.

Confirmatory Factor Analysis (CFA)

CFA was conducted with AMOS version 20 to evaluate the model's reliability, convergent validity, and discriminant validity. The analysis resulted in a reasonable CMIN/DF value of 2.592. The RMSEA was 0.076, CFI 0.920, GFI 0.874, TLI 0.901, and RMR 0.0491, suggesting that the baseline model offers the best fit for the data (Baumgartner & Homburg, 1996; Doll *et al.,* 1994). Based on the recommendations of Hu and Bentler (1999) and Browne and Cudeck (1992), the suggested values are given in the bracket (RMSEA < .08, RMR < .05, CFI > .90, TL I> .90). However, Baumgartner & Homburg (1996) and Doll *et al.* (1994) have also suggested a cut-off criterion of 0.80 for GFI. Table 3 shows that the standardised factor loadings for all items were greater than 0.60. All constructs demonstrated a Cronbach's alpha above 0.70. Additionally, all CR values ranged from 0.856 to 0.903, surpassing the standard threshold of 0.60, confirming internal consistency (Fornell & Larcker, 1981). Additionally, AVE is above 0.50, indicating strong and fit convergent validity (Hair *et al.,* 2016).

Table 3: Construct Reliability and Convergent Validity

Variables/ Constructs	Items	Standardised Factor Loadings	Cronbach Alpha	Composite Reliability	Average Variance Extracted
Metacognitive CQ	MetaCQ4	.83	0.806	0.820	0.604
	MetaCQ2	.77			
	MetaCQ1	.73			
Cognitive CQ	CogCQ9	.88	0.732	0.748	0.603
	CogCQ8	.66			
	MotCQ11	.82			
	MotCQ10	.79			
Behavioral CQ	BehCQ17	.85	0.781	0.894	0.741
	BehCQ16	.97			
	BehCQ15	.75			
Surface Acting	SA1	.68	0.919	0.921	0.701
	SA4	.87			
	SA5	.92			
	SA6	.87			
	SA7	.82			
Deep acting	DA8	.80	0.774	0.821	0.605
	DA10	.77			
	DA11	.750			
Turnover Intention	TI1	.90	0.886	0.887	0.723
	TI2	.82			
	TI3	.83			

We applied the criteria established by Fornell and Larcker (1981) to determine discriminant validity. The square root of AVE is indicated by the values on the diagonal in bold, whereas the other values denote the correlations between the variables. In Table 4, discriminant validity was evaluated using construct correlations. The bold diagonal figures in each row and column satisfy the criterion that they should exceed the other values. Consequently, we deduce that the discriminant validity of our variables is satisfactory.

Common Method Bias

Survey data is more susceptible to bias. Several studies (e.g., Bagozzi, 1984; Podsakoff et al., 2003, 2012) suggest using research design solutions to mitigate the risk of method biases in surveys. These solutions include collecting data at two different times using two different methods (e.g., online and offline), ensuring respondents' anonymity, minimising evaluation bias, and creating proximity, temporal, and psychological separation when answering different constructs (Podsakoff et al., 2003, 2012). In this study, both offline and online methods were used to collect responses. Offline information was collected through the hotel's channels, while online information was collected through social media platforms and personalised emails. To address possible common method bias (CMB), we conducted Harman's single-factor test with factor

Table 4: Discriminant Validity Coefficient

Construct	MetaCQ	CogCQ	MotCQ	BehCQ	SA	DA	TI
MetaCQ	*0.777*						
CogCQ	0.221	0.776					
MotCQ	0.225	0.353	0.802				
BehCQ	0.264	0.447	0.299	0.861			
SA	-0.276	0.057	-0.031	-0.075	*0.837*		
DA	0.046	0.390	0.248	0.314	0.113	*0.778*	
TI	- 0.115	-0.061	-0.138	0.045	0.407	-0.081	*0.850*

Note(s): CQ- cultural intelligence; SA- surface acting; DA- deep acting; TI- turnover intention. Diagonal elements (italics) are the square root of the variance shared between the constructs and their measures (average variance extracted – AVE). Off-diagonal elements are the correlations among constructs.

Table 5: Descriptive Statistics and Correlations

Construct	Mean	SD	MetaCQ	CogCQ	MotCQ	BehCQ	SA	DA	TI
MetaCQ	5.4095	1.38395	1						
CogCQ	5.5214	1.21205	.189**	1					
MotCQ	5.7946	1.26213	.165**	.266**	1				
BehCQ	5.1774	1.33687	.222**	.387**	.289**	1			
SA	3.2479	1.22008	-.252**	0.046	-0.034	-0.036	1		
DA	4.0845	0.80446	0.044	.293**	.188**	.288**	0.091	1	
TI	2.8619	1.12428	-0.110	-0.045	-.123*	0.019	.364**	-0.068	1

Source(s): Own Study
**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).
Note(s): CQ- cultural intelligence; SA- surface acting; DA- deep acting; TI- turnover intention.

analysis (Podsakoff et al., 2003). This test assesses whether most of the covariance among measures is explained by a single latent factor, indicating serious CMB problems (Podsakoff et al., 2003). Each item for every latent variable was constrained to load onto a single factor without rotation. The results indicated that a single factor accounted for 17.98% of the variance, which falls below the conventional threshold of 50%. Therefore, we conclude that there is no evidence of common method bias (CMB).

Mean, standard deviation, and correlation coefficients

Table 5 presents the means, standard deviations, and correlations among the variables. As expected, all four CQ dimensions are negatively related to SA (except CogCQ) and TI (except BehCQ), and positively related to DA. SA positively correlates with TI, whereas DA negatively correlates with TI.

Hypotheses Testing

To analyse the relationships among the four dimensions of CQ, EL, and TI, we used an analytical approach developed by Hayes (2013).

This approach was employed to determine all path coefficients through regression analysis using the PROCESS add-on in SPSS. Van Jaarsveld et al. (2010) explain that this method is beneficial because it allows for isolating the indirect effects of each mediator, SA and DA. Table 6 presents hypotheses derived from the regression analysis results. The findings indicate that all indirect effects have 95% confidence intervals that exclude zero, supporting the role of SA and DA as mediators between the four CQ dimensions and TI. Table 7 presents estimates of the indirect and direct effects, including standard errors and 95% bootstrapped confidence intervals for each path. The analysis of $H_{1a,}$ $H_{1b,}$ H_{1c}, and H_{1d} tested the total effects of MetaCQ, CogCQ, MotCQ, and BehCQ on TI. The regression results indicate that the hypothesized effects are positively significant with MetaCQ ($\beta = 0.2562$, SE = 0.393, $p < 0.001$); CogCQ ($\beta = 0.2279$, SE = 0.0467, $p < 0.001$); MotCQ ($\beta = 0.1674$, SE = 0.0444, $p < 0.001$); and BehCQ ($\beta = 0.2687$, SE = 0.0411, $p < 0.001$), but not supporting H_{1a}, $H_{1b,}H_{1c}$, and $H_{1d.}$

$H_{2a,}$ $H_{3a,}$ H_{4a}, and H_{5a} tested that among the four dimensions of CQ, only MetaCQ is negatively associated with SA (β = -0.2222, SE = 0.0512, p < 0.001), supporting H_{2a}; the other three dimensions CogCQ (β = 0.0461, p = .44), MotCQ (β = −0.0330, p > .05), and BehCQ (β = −0.0324, p = .55) are insignificant, not supporting $H_{3a,}$ $H_{4a,}$ and $H_{5a.}$

$H_{2b,}$ $H_{3b,}$ H_{4b}, and H_{5b} tested that, except for MetaCQ (β = 0.0257, p = .46), all three dimensions CogCQ (β = 0.1944, p < .001), MotCQ (β = 0.1201, p < .001), and BehCQ (β = 0.1734, p < .001) have a significant relation with DA.

H_6 and H_7 tested that SA is positively insignificantly related to TI (β = 0.0950, p = .034), which partially supports H_6. Though DA also positively but significantly influences TI (β = 0.4381, p < .001), it does not support $H_{7.}$

$H_{8a,}$ $H_{9a,}$ H_{10a}, and H_{11a} tested that surface acting mediates the relationship between the sequential MetaCQ, CogCQ, MotCQ, and BehCQ and TI. The analysis showed that MetaCQ impacts SA (β = -0.2222, SE = 0.0512, p < 0.001), and SA impacts TI (β = 0.0950, SE = 0.0447, p < 0.001). Next, the significance test for MetaCQ's indirect impact on TI through SA showed an effect size of 0.0211 (β = 0.2222 × 0.0950). The bootstrap confidence interval ranges from -0.0484 to -0.0360, which is above zero, indicating a significant impact. This supports H_{8a} but does not support $H_{9a,}$ $H_{10a,}$ and H_{11a}.

$H_{8b,}$ $H_{9b,}$ H_{10b}, and H_{11b} tested that deep acting serves as a mediator between the sequentially connected MetaCQ, CogCQ, MotCQ, and BehCQ and TI. The analysis showed

Table 6: Regression coefficients, standard error, and model summary information for the parallel multiple mediator model

Variable	M_1 (SA) Coefficient	SE	*p*	M_2 (DA) Coefficient	SE	*p*	Y (TI) Coefficient	SE	*p*
X (MetaCQ)	-0.2222	0.0512	.00	0.0257	0.0348	.46S	0.2562	0.0393	0.00
M_1 (SA)	-	-	-	-	-	-	0.0950	0.0447	0.34
M_2 (DA)	-	-	-	-	-	-	0.5395	0.0657	0.00
X (CogCQ)	0.0461	0.0603	0.44	0.1944	0.0381	0.00	0.2279	0.0467	0.00
M_1 (SA)	-	-	-	-	-	-	0.0156	0.0445	0.72
M_2 (DA)	-	-	-	-	-	-	0.4694	0.0706	0.00
X (MotCQ)	-0.0330	0.0579	-0.56	0.1201	0.0375	0.00	0.1674	0.0444	0.00
M_1 (SA)	-	-	-	-	-	-	0.0289	0.0453	0.52
M_2 (DA)	-	-	-	-	-	-	0.5186	0.0700	0.00
X (BehCQ)	-0.0324	0.0547	0.55	0.1734	0.0346	0.00	0.2687	0.0411	0.00
M_1 (SA)	-	-	-	-	-	-	0.0383	0.0433	0.37
M_2 (DA)	-	-	-	-	-	-	0.4381	0.0685	0.00

Source(s): Own Study
Note(s): X - independent variable; Y - dependent variable; M_1 and M_2 are mediators. CQ- cultural intelligence; SA - surface acting; DA - deep acting; LLCI–lower limit confidence interval; ULCI–upper limit confidence interval.

that CogCQ impacts DA (β = 0.1944, SE = 0.0381, p < 0.001), and DA impacts TI (β = 0.4694, p < .001); MotCQ impacts DA (β = 0.1201, SE = 0.0375, p < 0.001), and DA impacts TI (β ≈ 0.5186, p < .001); and BehCQ impacts DA (β = 0.1734, SE = 0.0346, p < 0.001), DA impacts TI (β = 0.4381, p < .001) significant. Additionally, the indirect effects of CogCQ (0.1944 × 0.4649 = 0.0912), MotCQ (0.1210 × 0.5186 = 0.0627), and BehCQ (0.1734 × 0.4381 = 0.0760) on TI through DA are valid (bootstrap confidence intervals above zero), except for MetaCQ. Therefore, $H_{9b,}$ $H_{10b,}$ and H_{11b} are supported, whereas $H_{8bisnot.}$

5. Discussion and Conclusion

Researchers have long studied the concept of CQ (Ang & Van Dyne, 2008), and its link to TIs has been particularly intriguing (AlMazrouei & Zacca, 2021). This study examines this relationship through the mediating role of EL and a four-construct CQ model. The current research focuses on how individuals with varying levels of CQ employ different EL strategies. Research on EL in cross-cultural settings and its effects on TI is scarce. Previous research hinted at some link between CQ and EL. People who have higher CQ are less likely to leave their jobs (AlMazrouei & Zacca, 2021). Past research has shown a negative correlation between employees' CQ and their intention to leave an organisation (Akhal & Liu, 2019; Froese et al., 2016). The present study demonstrates a positive association in the hotel industry, which may be due to CQ's higher mobility-enhancing nature in highly dynamic service industries (Ott & Iskhakova, 2019).

Table 7: Indirect and Direct Effects

Indirect effect	Effect	Boot SE	Boot LLCI	Boot ULCI
MetaCQ-> SA->TI	-0.0211	0.0107	-0.0484	-0.0360
MetaCQ-> DA->TI	0.0139	0.0189	-0.0217	0.0530
CogCQ-> SA->TI	0.0007	0.0029	-0.0044	0.0079
CogCQ-> DA->TI	0.0912	0.0281	0.0435	0.1512
MotCQ-> SA->TI	-0.0010	0.0027	-0.0071	0.0044
MotCQ-> DA->TI	0.0623	0.0251	0.0209	0.1184
BehCQ-> SA->TI	-0.0012	0.0031	-0.0088	0.0043
BehCQ-> DA->TI	0.0760	0.0224	0.0363	0.1240
Direct Effect				
MetaCQ->TI	0.2562	0.393	0.1789	0.3336
CogCQ->TI	0.2279	0.0467	0.1360	0.3199
MotCQ->TI	0.1674	0.0444	0.0800	0.2549
BehCQ->TI	0.2687	0.0411	0.1879	0.3496

Source(s): Own Study

Note(s): CQ- cultural intelligence; SA - surface acting; DA - deep acting; LLCI–lower limit confidence interval; ULCI–upper limit confidence interval

Employees with high CQ adapt easily to multicultural environments, feel confident seeking better opportunities, and have high employability (Arora et al., 2010). These findings align with human capital theory, which posits that employees with valuable competencies are more attractive to the external labour market (Becker, 1964). The results are also consistent with any previous studies showing that deep performers are more knowledgeable, diligent, and conscientious (Barrick & Mount, 1991). This helps them avoid superficial emotional acting and express real emotions more truthfully. In the case of SA, MetaCQ is significantly related to SA, while CogCQ, MotCQ, and BehCQ are significantly related to DA. To an extent, previous studies indicated that CQ has a significant impact on DA and a negligible impact on SA (McCance, 2010). This would lead one to believe that while cultural awareness and cognitive monitoring are important in regulating outward displays of emotion, they have less effect on internal changes in emotional state.

Additionally, results suggest that employees' emotional regulation will significantly affect employee retention in the hotel industry, given the prevalence of cross-cultural interactions. Moreover, the research shows that SA has a significant impact on TI, but not on DA. Previous studies also linked EL with the intention to quit (Rathi et al., 2013; Xu et al., 2017). This study aligns with emotional labor theory, which suggests that SA generates emotional dissonance and psychological strain. In hotels, continually faking and suppressing emotions may lead to TI (Hochschild, 1983). Interestingly, DA does not show a significant direct relationship with TI. However, mediation analysis using bootstrapping revealed that DA significantly mediates the relationship between CogCQ, MotCQ, and BehCQ and TI. In summary, employees with greater cultural understanding engage in SA and DA differently when interacting with clients from diverse cultural backgrounds (Salleh, 2014), which can help decrease or increase employee turnover in the hotel industry by increasing employees' perceived career mobility.

Theoretical Implication

Based on the results of this study, several theoretical implications are proposed. First, this work is significant because it expands the existing body of literature on human resource management and organisational behaviour by integrating CQ and EL into a single model. Second, it indicates that the effects of SA and DA on TIs may vary by the specific type of EL (SA and DA) used. Employees who practice DA are likely to genuinely modify their feelings, whereas those who use SA exhibit superficial and inauthentic feelings, which might lead to increased long-term turnover. Third, this research provides more detailed knowledge of CQ by analysing each dimension separately, yielding MetaCQ, CogCQ, MotCQ, and BehCQ, rather than treating CQ as a single concept. Fourth, the results indicate a negative relationship between CQ and TI, suggesting that individuals with higher CQ are less inclined to consider leaving the organisation; however, this study demonstrates a positive association in the hotel context due to CQ's higher mobility-enhancing nature. Finally, the results demonstrate that CQ influences TI through a parallel mediation process involving SA and DA, underscoring its importance in managing emotional interactions between employees and customers and mitigating TIs.

Practical Implications

This study highlights several practical implications for organisations to consider. First, as an emerging economy with a diverse population and distinct economic zones, India emphasises the development of employees' skills. Hotels should focus on grooming their employees through cultural and emotional training to enhance their cultural and emotional awareness. Employees with high CQ are better equipped to handle diverse interpersonal interactions with colleagues and clients, resulting in reduced emotional stress, fewer TIs, and greater organisational goodwill. Second, hotels should update their recruitment, training, and wellness policies to place greater emphasis on CQ and emotional intelligence. Incorporating the concept of CQ into hiring, offering ongoing emotional management seminars, and fostering genuine emotional connections with customers can help reduce staff turnover, improve service quality, and support staff wellness. Third, in the case of Punjab's hotel industry, which is becoming increasingly competitive, the combined impact of cultural diversity and heightened emotional demands necessitates managerial action. Investing in employees' cultural and emotional skills will ensure a more stable workforce and better guest experiences, which are important for the long-term success of four- and five-star hotels serving both domestic and international markets. Fourth, offering personalised career development plans that enable employees to leverage their cultural strengths and work in culturally diverse environments that play to their emotional capacities can be a great way to retain top talent and avoid the costs of hiring and training, particularly given the high turnover rates in the hotel sector. Finally, providing psychological support systems, such as emotional resilience workshops and seminars, may help mitigate the emotional costs associated with DA.

6. Limitations and Future Recommendations

Although this study has promising results, it has some limitations. First, the cross-sectional design limits our ability to conclude causality; future research should adopt a longitudinal design to establish causality. Second, the generalizability of the results is limited, as the study was conducted only with hotel employees in the state of Punjab, and different parts of India have distinct cultures that affect how individuals perceive and express emotions (Rafiq, 2020). Third, the study only examined TI as a result of CQ. Other outcomes, such as cultural adaptation, organisational commitment, and job performance, could be considered in future research to better understand CQ. Fourth, reliance on self-reported measures may have influenced the results, as Thomas et al. (2008) noted that self-report may not always be the ideal measure of CQ. However, self-reported data remain useful, particularly when studying personal perceptions, attitudes, feelings, or intentions that are difficult for external observers to measure, as only the respondent knows his or her internal state (Chen, 2019). Many theories in psychology and behaviour, such as the theory of planned behaviour and the social cognitive theory, rely on perceptions of the self and intentions (Myers & Horswill, 2006). Consequently, self-reporting can be the easiest way to test these theories. Furthermore, gathering data from multiple sources/dyads can be expensive, time-consuming, and prone to missing data problems (Holmbeck et al. 2002). Future research should incorporate multilevel designs and specialised methods to measure distinct aspects of CQ, rather than relying solely on a broad, multisource CQ measure.

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Barriers to AI Adoption in Singapore's Manufacturing Sector: An Integrated FDM–ISM–MICMAC Analysis

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Abstract

Manufacturing Industries are challenged for their survivability and sustainability in current disruptive market conditions. The disruption in the marketplace is caused by the availability of disruptive technologies, that have the potential to transform businesses in ways never possible in traditional ways. Industries must embrace these technologies to survive. Despite the potential of disruptive technologies to transform businesses, numerous barriers hinder their adoption within firms. The paper aims to examine the most prominent barriers and their interrelationships that hinder the successful adoption of disruptive technologies (Artificial Intelligence) in Singapore's manufacturing sector, using the FDM (Fuzzy Delphi Method), ISM (Interpretive Structural Modelling), and fuzzy MICMAC techniques. The study's results guide manufacturing firm managers in improving adoption by controlling the barriers to achieve desired outcomes and provide future research direction for researchers to evaluate the significance of these barriers through empirical studies.

Keywords: *Artificial Intelligence, Fuzzy Delphi Method, Interpretive Structural Modelling, MICMAC, Barriers*

1. Introduction

The current manufacturing industry market environment is characterised by deepened competition, rapid and dynamic market changes, mass customisation of products, and shorter product useful lives due to a continuous shift in demand. Fast, frequent changes in customer expectations, the competitive environment, lower entry barriers, and innovative technologies are causing major uncertainty about the future of manufacturing firms. Agility in manufacturing firms is a key to survival in a turbulent market environment. To achieve this agility in these turbulent times, firms must effectively use the resources available within the firm (Bianchini et al., 2025; Costa et al., 2006; Oberoi et al., 2008; Ramaul et al., 2024). To be agile and lean, organisations are automating business processes using computers. Disruptive innovation has a major influence on manufacturing industry operations, from mass production to mass customisation. Organisations must transform their processes to remain relevant to changing market requirements (Battistella et al., 2025; Winkelhaus & Grosse, 2020). By applying data-sharing platforms like Tradelens among European firms, data on supply chain facilities, innovations, and minimised trade barriers can be improved, thereby boosting global trade. Professionals believe that blockchain can deliver noteworthy results (Hughes et al., 2019). Manufacturing and Logistics firms favour using simpler over advanced technologies (Hirata et al., 2025; Janjevic et al., 2019). Multinational companies are expected to increase their adoption of disruptive technologies, e.g., Artificial Intelligence (AI), to meet their growing needs. Traditional manufacturing firms depend on human labour and traditional technologies for their manufacturing processes. The adoption of disruptive technologies like AI & IoT will enhance operational efficiency and reduce costs. In a highly dynamic marketplace, data and intelligence around data will provide an edge for firms to survive and outperform. The operating environment in the marketplace makes it clear that survivability and sustainability require firms to embark on a journey to adopt disruptive technologies such as AI. The organisation must find barriers that potentially cause impediments to the success of the journey to embrace disruptive technologies like AI (Battistella et al., 2025; Christensen, 2008; Hirata et al., 2025; Hofmann & Rüsch, 2017; Hopkins & Hawking, 2018; S. J. Kim et al., 2017; Rogers et al., 2016; Sah et al., 2021; Zhong et al., 2016).

Multiple studies have examined barriers to technology adoption in firms. However, there is a gap in identifying barriers and their interrelationships from a Singapore manufacturing industry perspective. The study aims to find the barriers to the adoption of disruptive technology (AI) in manufacturing firms, develop relationships among those barriers using Interpretive Structural Modelling (ISM), and group them as per their power to drive or be dependent on the application of MIMAC methodology ('Matrics d'Impacts Croises-Multiplication Applique a Classement').

Therefore, the study addresses the following research gaps in the knowledge body:

Rq1. What are the important barriers to a successful adoption of Artificial Intelligence?

Rq2. What are the most and least important barriers from the list of barriers?

Rq3. How are the prominent barriers related and interact with each other?

The remaining section in the study is as follows. Part 2 covers a literature review on barriers to the adoption of artificial intelligence (AI), followed by theoretical frameworks. Part 3 covers the research method adopted for this study. Part 4 covers data collection, followed by data analysis. Part 5 covers the analysis results. Part 6 covers the study's implications. Part 7 covers the future research direction and limitations.

2. Literature Review

Disruptive technologies differ from incumbent technologies because they introduce a new performance dimension for products and services where previously there was no competition or no business model was possible (Bower & Christensen, 1995; Danneels, 2004; N. Singh et al., 2025; Walsh, 2004). Disruptive technologies have the potential to create a new wave of technological cycles in the development of production systems and to disrupt the traditional marketplace. With the application of these disruptive technologies, firms will build new capabilities in their products and services that were not possible with traditional methods and technologies.

Some prominent disruptive technologies found are Blockchains, IoT, 'UAV/Drone', AI, Big Data, Auto Driving cars/AVs, and 3D printing in various industries (Ajili Ben Youssef et al., 2025; Hopkins & Hawking, 2018; Hughes et al., 2019; N. Singh et al., 2025). Each of them has a different level of applicability in its respective industry. In the manufacturing sector, these disruptive technologies have been widely applied and have the potential for

significant adoption (Ajili Ben Youssef et al., 2025; Golovianko et al., 2023; Hofmann & Rüsch, 2017; Kellermann et al., 2020; S. J. Kim et al., 2017; Rogers et al., 2016; Zhong et al., 2016).

The paper aims to further examine the barriers to the adoption of Artificial Intelligence for Singapore's manufacturing industries. The purpose of artificial intelligence is not just to improve manufacturing industries and the products they produce, but also to enable firms to disrupt the marketplace through radical changes in their products and services, transforming entire business models. This disruption will create a new wave of innovations and improve economic value for firms and their customers. These technologies will enhance the organisation's capabilities to sustain and survive in the marketplace of the future. These technologies have the potential to create new opportunities, business models, and to scale and future-proof firms' existence.

2.1 Definition & Application of Artificial Intelligence

The research adopts the definition of Artificial Intelligence provided by Marvin Minsky, which is widely accepted among researchers (Duarte & Baptista, 2025; Minsky, 1968): "the science of the creation of a machine to perform tasks which would require intelligence if performed by a human resource."

Computers use algorithms to analyse datasets, patterns, and trends, as the human brain can, and to make decisions (N. Singh et al., 2025; Syam & Sharma, 2018). The various applications of Artificial Intelligence techniques in the manufacturing sector include, e.g., Genetic Algorithms, ANN, CNN, and fuzzy logic, used in applications such as Supply Chain Planning, Manufacturing, Quality control, Product development, and Distribution Resource Optimisations.

2.2 Identification of Barriers to Adoption of Artificial Intelligence

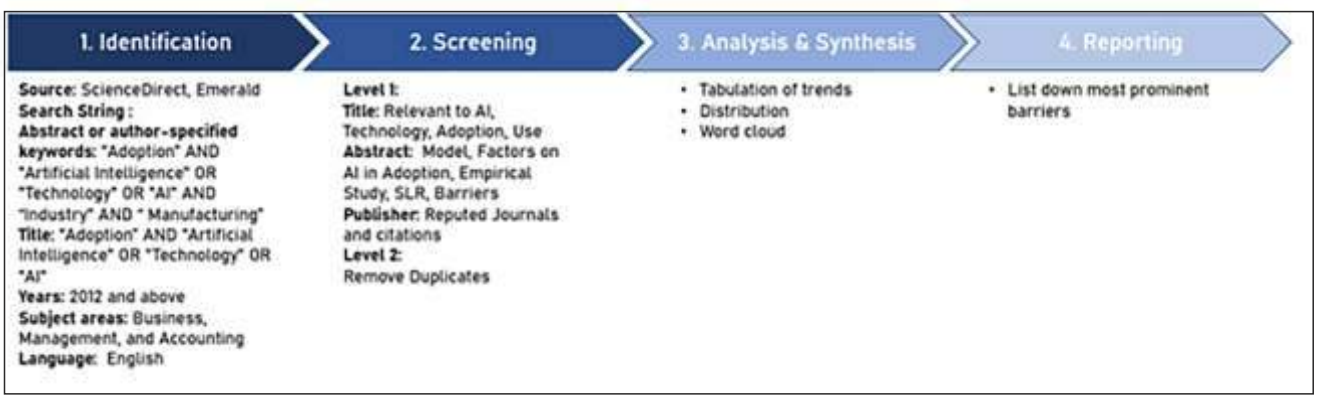
A systematic literature review has been conducted to find the barriers to the adoption of artificial intelligence in manufacturing industries. A 4-step approach has been applied in a systematic literature review to drill down the target outcome from the existing literature (1. Identification, 2. Screening, 3. Analysis and synthesis, and 4. Reporting).

1. Identification: At this stage, a search string has been used with relevant keywords and found 180 research papers.

2. Screening: At this stage, added filters and review criteria are applied to sort out the relevant research papers, manually review all abstracts, and remove duplicates. A total of 107 papers have been finally selected for the next stage.

3. Analysis and Synthesis: At this stage, various analysis techniques are used to drive inferences from the selected research articles which are relevant to the area of study. A word cloud has been prepared for better visualisation using NVivo (Version 15) software.

4. Reporting: This stage is to list the most prominent barriers to the adoption of AI in the setting of manufacturing industries. These will be used in further parts of the research.



Source: Authors' compilation

Figure 1: Literature Review

Source: Authors' analysis using NVivo (Version 15)

Figure 2: Word Cloud

Table 1: Prominent Barriers

Barriers	Literature Sources
Legal and regulatory framework	(Bianchini et al., 2025; R. K. Gupta & Kumari, 2017; Wirtz et al., 2019)
Resistance to change	(Golgeci et al., 2025; Wirtz & Müller, 2019)
Lack of infrastructure	(Abduljabbar et al., 2019; Golgeci et al., 2025; Golovianko et al., 2023)
Data management	(Abduljabbar et al., 2019; Ali & Thakkar, 2023; Sun & Medaglia, 2019; Tizhoosh & Pantanowitz, 2018)
Lack of trust	(Abduljabbar et al., 2019; Brown et al., 2025)
Lack of top management support	(B.-J. Kim et al., 2025a; Wirtz et al., 2019)
Lack of adequate resources	(Abduljabbar et al., 2019; Golovianko et al., 2023; B.-J. Kim et al., 2025a)
Lack of reliability	(Cheung et al., 2024; Wirtz et al., 2019)
Privacy and security	(Abduljabbar et al., 2019; Ajili Ben Youssef et al., 2025; Balthazar et al., 2018; Fast & Jago, 2020; Luxton, 2014)
Technical issues	(Baldassarre et al., 2017; Basnayake et al., 2015; Battistella et al., 2025; Edwards et al., 2018; Sun & Medaglia, 2019; Tizhoosh & Pantanowitz, 2018; Villaronga et al., 2018)
Lack of communication	(Birkel et al., 2019; B.-J. Kim et al., 2025b; Lawrence et al., 2006)
Lack of advanced analytics skills	(Bianchini et al., 2025; Golovianko et al., 2023; Gunasekaran et al., 2001; Waldeck & Leffakis, 2007)

Source: Authors' compilation based on literature review

The 1st research question of this study is to identify the most important barriers to the adoption of Artificial Intelligence in manufacturing firms in Singapore. The following is a list of the most prominent barriers identified in the literature review, along with the answers to the 1st research question of the study [Table 1].

B1: Legal and regulatory frameworks.

Governments play a vital role in anticipating unforeseen issues arising from the implementation of disruptive technologies in the areas of monetary policy, health, and people's safety and security (GAO, 2015). Some disruptive technologies, such as blockchain, do not depend on regulator-provided frameworks because of their distributed architecture (Ajili Ben Youssef et al., 2025; Biswas & Gupta, 2019). For driverless cars, a framework is required to establish accountability for vehicle licensing and liability in the event of malfunction (Bianchini et al., 2025; Fagnant & Kockelman, 2015). The regulatory framework will provide guidance and an ethical framework for the application of artificial intelligence, thereby improving user trust in its use. In summary, a comprehensive legal and regulatory framework will speed up the adoption of disruptive technologies (Hughes et al., 2019; Valtonen et al., 2025). Recent regulations like the EU AI Act - 2024 and Singapore's National AI Strategy 2.0 – 2023, directly strengthen the relevance of the legal and regulatory framework as an evolving and contemporary barrier (Cihon et al., 2023)

B2: Resistance to change.

Adoption of DTs in any organisation evolves around issues such as acceptance of change, scepticism, organisational socio-dynamics, and participants' beliefs towards technology (Kostoff et al., 2004). Fear of losing jobs due to the application of artificial intelligence is also a resistance to adopting technology in a firm (Kwon et al., 2017). Anxiety due to perceived security risks and the complexity of using technology also results in adoption confrontation (Ali & Thakkar, 2023; Dickson, 2025; Mani & Chouk, 2018). Bean & Davenport (2019) found that, after technology implementation, if organisational change management is not properly implemented, users may become even more resistant to adopting it.

B3: Lack of Infrastructure.

Organisations must have invested in the infrastructure components needed for the successful implementation of innovative technologies like Artificial Intelligence. Due to the lack of organisational infrastructure or flexibility, implementing and adopting technologies is difficult and a blocker to adoption. The current infrastructure of multiple organisations is not ready for artificial Intelligence implementation; they must enhance their IT infrastructure (Alharthi et al., 2017; Golovianko et al., 2023). IoT implementation requires efficient use of OT and IT networks, with segregation, connectivity, and associated processing power (Golovianko et al., 2023; Luthra et al., 2018). Kaur & Rampersad, (2018) found tht security & connectivity inandrastructure are key for successful adoptithe on of artificial intelligence in an organisation.

B4: Data management.

The current organisational majority of the data centres will not be able to manage the large amount of data and heterogeneous formats (Philip Chen & Zhang, 2014). Organisations must bring agility and scalability in data centre design to embrace artificial intelligence. An effective, agile data management practice must be implemented to address issues arising from a firm's data centre (Ali & Thakkar, 2023; Alwateer et al., 2019; R. L. Finn & Wright, 2016). The use of 3D Printing technology, which often generates large volumes of data in multiple formats, poses challenges for the data management framework (Ali & Thakkar, 2023; Liu et al., 2022). Data is key to implementing Artificial Intelligence technology, so organisations with a capability in large-scale data management will have an advantage.

B5: Lack of trust.

An organisation is a collection or group of individuals who oversee and act within their roles. Trust in technology plays a greater role in adopting it (Hsiao, 2003). In the adoption of IoT and Blockchain trust and reliability are the key (Ajili Ben Youssef et al., 2025; Heiskanen, 2017). For artificial intelligence, trust in recommendations and results is important for enabling automated discussion. Lack of trust in the technology decision-making process leads to safety issues within the organisation and its consumers, hindering implementation and adoption (Bianchini et al., 2025; R. Finn & Donovan, 2016).

B6: Lack of top management support.

A lack of futuristic organisational policies and vision leads to improper resource allocation, which, in turn, creates problems with effective adoption (Bianchini et al., 2025; Mendling et al., 2018; N. Singh et al., 2025). Several times, top management's lack of priority in budget allocation to

innovative technology projects hinders their implementation and use (LaValle et al., 2010). Missing top management commitment and support restrain additive manufacturing adoption (G. Dwivedi et al., 2017; Golovianko et al., 2023).

B7: Lack of adequate resources.

The organisation's ability to provide adequate resources for the implementation program is a key driver of the program's success and also gives the organisation a competitive advantage (Bianchini et al., 2025; Danneels, 2004; Sah et al., 2021). These technological adoptions require significant investment, which organisations must be willing to make to achieve competitive advantage. Adoption of these is an expensive affair in organisations and their partner's networks (Mougayar, 2016). Organisational skills are a collection of skills held by employees. Due to a lack of skilled employees who can manage and implement these programs within the organisation, the adoption of these technologies will be hindered. Organisational infrastructure capability to manage and process data at a large scale also slows adoption and requires high costs to upgrade underlying infrastructure and technology (Bianchini et al., 2025; LaValle et al., 2010). Similarly, in the study of IoT-based platform adoption, Janssen et al. (2019) confirm that the lack of the right resources and skills significantly hinders its development.

B8: Lack of reliability.

The absence of reliability directly causes various issues in manufacturing quality (Colefax et al., 2019; G.-H. Kim et al., 2014). The manufacturing process refers to the consistency in its output. Variability is low, and the outcome is highly predictable. Trust in digital technologies is low when they are unable to maintain their reliability (Bianchini et al., 2025; Biswas & Gupta, 2019; G. Dwivedi et al., 2017). Colefax et al. (2019) found in their study on drones that reliability issues directly affect critical functions, i.e., monitoring and surveillance. If reliability is low, the application is also low, as this poses a business concern.

B9: Privacy and security.

Digital technologies are data-hungry for better results; as a result, there are concerns about data privacy, security, and ethical use. Manufacturing and supply chain partners must share data to achieve common goals. Still, concerns about data privacy, security, and ethical use create a barrier to fully realising the potential of these technologies. Janssen et al. (2019) concluded that IoT applications collect confidential data, raising concerns about data privacy and security. The adoption of big data analytics is severely affected by poor data management and protection (Attié & Meyer-Waarden, 2022; Dickson, 2025; Philip Chen & Zhang, 2014).

B10: Technical issues.

Technical issues refer to the lack of standardisation of data formats, technical infrastructure to process the data, and software or applications to collect the right data set. The technical issue is not only limited to data aggregation and processing but also to Digital technologies' technical capabilities. In the context of drone adoption, technical issues, i.e., the payload, harsh weather, battery life, and range coverage, directly influence it (Ajili Ben Youssef et al., 2025; Sah et al., 2021; N. Singh et al., 2025). Similarly, for IoT, technical issues such as networking, sensing, poor standardisation, and edge-level processing capabilities drive adoption (Golovianko et al., 2023; Janssen et al., 2019).

B11: Lack of communication.

Implementing technology in an organisation that can challenge the status quo. In these programs, organisational change management is a critical part. In the change management process, communication plays a critical role in avoiding confusion among human resources in the use and application of technology. Business users who consume these technologies should adopt the new practices and capabilities provided by the tools. This seamless integration between Digital technologies and human resources will give the organisation a competitive advantage. Lack of training is identified as a barrier to the adoption of Industry 4.0 technologies in a firm (Dickson, 2025; Golovianko et al., 2023; Ingaldi & Ulewicz, 2019; Tiwari & Khan, 2020)

B12: Lack of advanced analytics skills.

Digital technologies are advanced and complex technologies; the availability of the right analytical skills plays a crucial role in the success of such programs. In the context of Industry 4.0, it was found that the lack of skilled specialists is a critical barrier to its adoption (S. Ahmad et al., 2020; Golovianko et al., 2023). Similarly, earlier studies also found that the availability of specialist knowledge is crucial for the adoption for complex technologies like artificial intelligence (Bianchini et al., 2025; Ingaldi & Ulewicz, 2019; Ivascu, 2020).

2.3 Theoretical frameworks

The study adopted the central foundation from Behavioural Reasoning Theory (BRT) (Westaby, 2005). BRT expands the previous behavioural intention model like Theory of Planned Behaviour (TPB) (Ajzen, 1991) and Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975) by clearly defining two groups among reason to shape behavioural intentions: "reason for (enablers) " and " reason against (barriers)". The dual viewpoint explains how organisations or individuals weigh motivation and constraints when deciding whether to adopt disruptive technologies like Artificial Intelligence.

Perceived operational efficiency, cost reduction, innovation capability, and strategic competitiveness are examples of motivations for adoption (enablers) in the context of industrial transformation (Ali & Thakkar, 2023; Y. K. Dwivedi et al., 2021; Kamble et al., 2018). On the other hand, impediments to adoption include things like insufficient infrastructure, resistance to change, lack of support from upper management, and data security issues (Biswas & Gupta, 2019; Cihon et al., 2023; R. Singh & Bhanot, 2020). According to BRT, these explanations function as underlying cognitive justifications that affect attitudes and, eventually, adoptive behaviour (Westaby, 2005).

This study's interpretation of the hierarchical structure of obstacles (identified through ISM) as expressions of more profound behavioural reasoning processes within companies is enabled by using BRT as a guiding framework. Organisational concerns regarding risk, accountability, or competency are reflected in barriers at the lower levels of the ISM model, such as "lack of top management support" or "regulatory uncertainty," which serve as fundamental "reasons against" implementation. On the other hand, regulatory clarity, supportive leadership, and management commitment serve as "reasons for" adoption, serving as opposing facilitators that can turn opposition into proactive involvement (Claudy et al., 2013; Cui et al., 2022; Sheppard et al., 1988)

As a result, incorporating BRT provides a behavioural complement to the structural analysis conducted using FDM-ISM-MICMAC techniques. It puts the interrelationships between obstacles in the context of dynamic conflicts between opposing forces—inhibitors and motivators—that influence organisations' adoption choices. By showing how managers can use strategic reasoning and change interventions to transform identified barriers into actionable enablers, this dual reasoning framework not only deepens theoretical understanding but also enhances the study's practical applicability.

Decision-making in the context of complex problems, such as the adoption of Artificial Intelligence, is influenced by multiple criteria. The use of the MCDM (Multi-Criteria Decision Making) technique is quite prominent among

Table 2: ISM Technique Applied

Authors	Objectives
Yadav et al., (2020)	Adoption Barriers for Blockchain in the Indian Agriculture Supply Chain
Singh & Bhanot (2020)	IoT Implementation barriers to Indian manufacturers
Gardas et al. (2018)	Reverse logistics barriers in developing economies
Kamble et al., (2018)	I4.0–Industry 4.0 Adoption barriers to Indian manufacturers
Rana et al., (2019)	Barrier to M-commerce application in SMEs in UK market
Movahedipour et al., (2017)	Barriers in respect of sustainable supply-chain implementations
Shukla et al., (2018)	Barrier to mass customisation with the application of 3D printing
Vasanthakumar et al. (2016)	Influencing factors in the Indian automotive industry for the adoption of lean manufacturing.
Kumar et al., (2022)	Barrier for sustainability & Industry 4.0 implementation in SMEs

Source: Authors' compilation

decision makers. The MCDM technique is even useful in cases where decision-makers have different experiences, characteristics, and knowledge of the complex problems. It provides a systematic approach to solving complex problems (Ali & Thakkar, 2023; Aoun et al., 2021; Ramaul et al., 2024). Researchers find the most prominent barriers in the adoption of artificial intelligence in manufacturing from the literature review and filter based on their relevance and importance to the context of this research. Qualitative techniques, such as expert opinions and the Delphi method, are applied to the collected opinions. It is a time-consuming technique and is more likely to be found in exploratory-type studies.

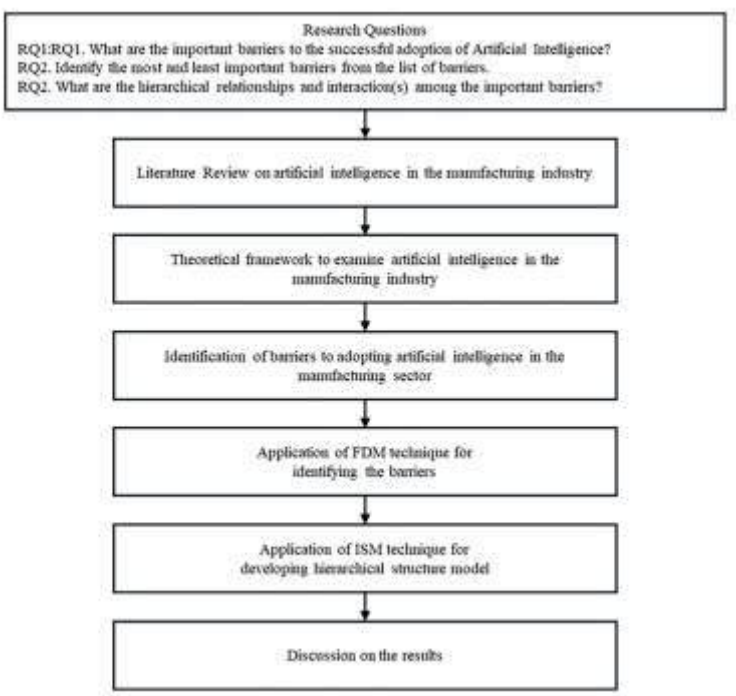
In comparison, the Fuzzy-Delhi-Method technique addresses issues related to grey shades and the uncertainty of experts' opinions (R. Gupta et al., 2022). Similarly, solves problems where a human cannot decide accurately (Jharkharia & Shankar, 2004; Rathore, 2021; Rathore & Gupta, 2022). DEMATEL (Decision-making trial & evaluation) and ISM have been used in earlier research to understand the barrier relations (Biswas & Gupta, 2019; G. Dwivedi et al., 2017; Hirata et al., 2025). Singh & Bhanot (2020) concluded that ISM has an advantage over the DEMATEL technique, as it provides a structured, ranked model that is easy to explain. Some recent studies that used the ISM technique to analyse adoption barriers in the technology domain (Duarte & Baptista, 2025; Rana et al., 2019; Yadav et al., 2020).

3. Research Methodology

A two-step research approach was used in this study. The first step is to identify the key barriers to the adoption of technology or artificial intelligence in manufacturing industries, based on earlier research articles. The second step is to prepare an FDM questionnaire and conduct surveys with experts in the domain of Artificial Intelligence,, including technology implementation partners and manufacturing managers. Perform various analyses using techniques FDM (Fuzzy Delphi Method), ISM (Interpretive Structural Modelling). As part of the research, each expert has been asked about the importance of each barrier to the adoption of artificial intelligence in the context of the Singapore manufacturing firms. Expert opinions are transformed into Fuzzy Numbers using the linguistic scale in Table A1.

Once the relevant barriers list is completed. In the next stage, develop a tiered model based on ISM techniques. The ISM technique has the ability to examine barriers within groups and the relationships among them '(Kamble et al., 2018).

Below Figure 3 explains the Proposed Methodology.



Source: Authors' compilation

Figure 3: Methodology used

3.1 Fuzzy Delphi Method (FDM)

The current study applies the FDM analysis method and steps proposed by Ishikawa et al. (1993).

1. Using a literature review, find a list of barriers to the adoption of artificial intelligence in manufacturing industries.
2. Design a questionnaire and engage experts (n) to rate the importance of the barriers (m) using linguistic scale (Refer to Table A1).
3. Calculate fuzzy numbers from collected expert opinions, and use the geometric mean to assess the group's opinions.

If Fuzzy Number = X_{ij} then it represents X_{the} J th barrier and by the X_i th expert

$$X_{ij} = (a_{ij}; b_{ij}; c_{ij})$$

Where value of i & j is from 1 to n, and 1 to m

n = count of experts, and m = count of barriers.

4. Calculated fuzzy weight using the formula below for each barrier.

The study uses the geometric method for calculating the fuzzy weight as proposed by Buckley et al. (1985). The geometric mean for the X_j th barrier is as follows.

Fuzzy weight for X_{the} J th barrier is as follows.

$$a_j = \frac{(a_{1j} * a_{2j} * a_{3j} \ldots\ldots * a_{nj})^{1/n}}{\sum_{j=1}^{m} c_j}$$

$$b_j = \frac{(b_{1j} * b_{2j} * b_{3j} \ldots\ldots * b_{nj})^{1/n}}{\sum_{j=1}^{m} b_j}$$

$$c_j = \frac{(c_{1j} * c_{2j} * c_{3j} \ldots\ldots * c_{nj})^{1/n}}{\sum_{j=1}^{m} a_j}$$

5. Calculate the COA value of the X_j th barrier to arise defuzzification number.

$$COA_j = \frac{(a_j + b_j + c_j)}{3}$$

6. Compare the defuzzification values for each barrier to evaluate the importance of each barrier in the context of the adoption of artificial intelligence in manufacturing firms, and proceed to the next-level analysis.

3.2 Interpretive structural modelling (ISM)

ISM (Interpretive Structural Modelling) is one of the interactive techniques commonly used to represent complex systems in a simplified way (Warfield, 1974). ISM is one of the most popular techniques among researchers for developing a map of the multiple factors that have multifaceted relationships and complex circumstances. This technique was initially developed in 1970 and is still quite popular among researchers for studying interrelationships among factors.

Some previous research has used the ISM method, e.g. Jharkharia & Shankar (2004) applied the ISM technique on IT enablers technology for supply-chain, Singh & Kant (2008) examined the relationships between knowledge management factors, Singh et al. (2007) SMEs competitiveness factors, Thakkar et al. (2008) IT enablers implementation in Indian SMEs. The ISM technique is applied to study the association between barriers and derive concepts in any case (Golgeci et al., 2025; Kumar et al., 2021). Raj et al. (2008) use ISM to show the interaction among enablers that support the implementation of flexible manufacturing systems.

Key features of the ISM technique are:

- This expert verdict & endorsement shape their interaction.
- Building a ranked model of the barriers under study.
- Identify basic interactions between barriers and in complete structure.
- Enables ranking & directional complexities in barrier relationships.

Detailed ISM methodology steps are listed in Table A2. The study uses the software (http://smartism.sgetm.com/) published by N. Ahmad & Qahmash (2021).

3.3 MICMAC analysis

A MICMAC analysis was performed by classifying the barriers in four categories grounded on dependency & driving values. These groups are 'Autonomous', 'Dependent', 'Linkage' & 'Independent' (Ravi & Shankar, 2017). The total value in row (x) & column (y) represents coordinates (x, y) in a two-dimensional graph, which is further divided into four quadrants. Each quadrant stands for a group.

1. Quadrant 1 (Autonomous): This quadrant barriers will have low driving and dependence power. Hence these will not yield major influence.

2. Quadrant 2 (Dependent): This quadrant barrier will have weak driving power but strong dependence power. Hence, these barriers are influenced by the others at a lower level of the ISM Model. They generally appear at the top of the ISM model.

3. Quadrant 3 (Linkage): This quadrant barriers will have strong driving power and strong dependence power. Hence, these barriers are unstable; any action on them will affect them and other barriers. These should be managed with care.

4. Quadrant 4 (Interdependent or Driver): This quadrant barrier will have strong driving power and weak dependence power. Hence, these barriers have greater capacity to influence other barriers. These need immediate attention to control desired outcomes. These constitute the foundation of ISM and are found in the bottom tier.

4. Data Collection & Analysis

A list of 24 experts working in the domain of complex technology implementation in manufacturing industries in Singapore with more than 10 years of experience has been contacted to take part in the survey. One expert declined to participate in the survey, and the remaining 23 expressed willingness to do so. Several earlier studies have collected 15 experts inputs and applied MCDM (Nassereddine & Eskandari, 2017; P. K. Singh & Sarkar, 2020). Hence, 23 expert opinions are sufficient to proceed. Demographic details of the experts involved are in Table 3.

4.1 FDM

The expert opinions on the importance of each barrier are converted into fuzzy numbers using a linguistic scale [Table

Table 3: Expert's Demographics

Category	Values	N	%
Industry	ICT	13	56.5%
	Manufacturing	10	43.5%
Management Level	Associate Director	5	21.7%
	Director	2	8.7%
	Manager	3	13.0%
	Managing Director	1	4.3%
	Senior Manager	12	52.2%
Experienece	More than 10 years but less than 20 years	20	87.0%
	More than 20 years	*3*	*13.0%*

Source: Primary data collected by Authors

Table 4: FDM Result

Barriers	TFN Fuzzy Weight			Defuzzification Normalised Weight
B1. Legal and regulatory framework	0.03	0.08	0.21	0.080
B2. Resistance to change	0.04	0.10	0.24	0.094
B3. Lack of Infrastructure	0.03	0.10	0.23	0.091
B4. Data Management	0.03	0.09	0.22	0.088
B5. Lack of trust	0.03	0.08	0.21	0.080
B6. Lack of top management support	0.05	0.10	0.24	0.099
B7. Lack of adequate resources	0.03	0.09	0.22	0.086
B8. Lack of reliability	0.03	0.08	0.21	0.079
B9. Privacy and security	0.03	0.09	0.22	0.086
B10. Technical issues	0.03	0.08	0.21	0.082
B11. Lack-of-communication	0.02	0.04	0.14	0.051
B12. Lack-of advanced analytics skills	0.04	0.09	0.22	0.088

Source: Authors' analysis.

A1], and the geometric mean model is applied to assess the combined opinions of the experts. The analysis found that "Resistance to change" has the highest weight, while "Lack of communication" has the lowest weight for the adoption of Artificial Intelligence in manufacturing industries in Singapore [Table 4].

The second research question of the current study is to identify the most and least important barriers to the adoption of artificial intelligence in Singapore manufacturing firms. Table 4 FDM results answer the question: the barrier with the lowest Defuzzification Normalised Weight is the least important, and the barrier with the highest Defuzzification Normalised Weight is the most important.

4.2 ISM & MICMAC

After evaluating the importance of each barrier to the adoption of artificial intelligence in manufacturing firms, we built a comprehensive, structured model with a hierarchical view and assessed the interrelationships among the barriers using the ISM technique described in section 3.2 of this report. We built a structural self-interaction matrix (SSIM) for all the barriers found though literature review. Using the expert opinions collected via questionnaires, we next develop the SSIM table [Table A3]. Once the SSIM table is developed, we next develop the initial reachability matrix (IRM) [Table A4]. And A final reachability matrix (FRM) [Table 5] is prepared after validating IRM for transitivity.

Once FRM was developed, for each barrier we extracted 'reachability' & 'antecedent' sets. 'Reachability set' ('R-S') includes barrier & others which are impacted by it. 'Antecedent set' ('A-S') includes barriers and others which can influence it. An 'intersection set' ('I-S') is developed for each barrier which has the common elements of 'reachability set' ('R-S') and 'antecedent set' ('A-S'). The barriers where the elements of the reachability set, and intersection set are equal will be assigned as partition level 1. After assigning the partition, remove them and repeat the same steps until all barriers have a partition value assigned. A total of 6 iterations are needed to fully assign a partition-level value to each barrier under study [Table 6]. Finally, develop an ISM hierarchical model [Figure 4] based on the partition level value assigned to each barrier (place partition 1 at the top of the model). Figure 4 also provides an answer to the third research question: how these barriers interact with one another in the context of artificial intelligence adoption in Singapore manufacturing firms.

In the end, we analysed the barriers using the MICMAC technique, which is based on driving and dependence powers calculated from the FRM. Driving power for any barrier is the sum of the row for the barrier in the FRM table, and dependence power is the sum of the column for the barrier in the FRM table.

Plot barriers based on the dependence & driving power values in a two-dimensional graph. All twelve barriers are categorised into four quadrants (Autonomous, Dependent, Linkage, and Independent) [Figure 5].

Table 5: FRM Table

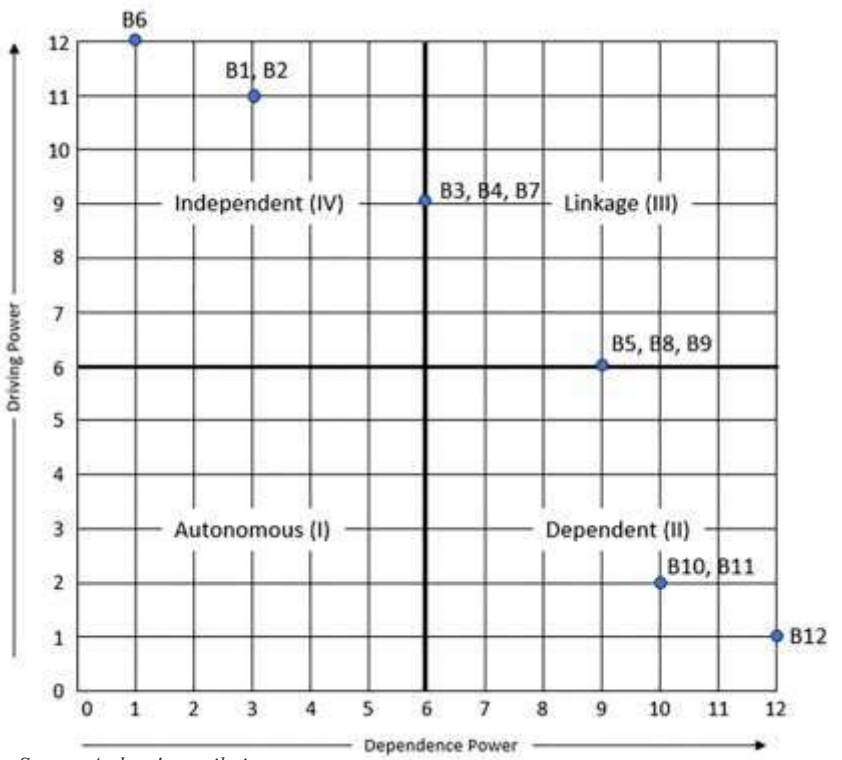
Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	Driving Power
B1	1	1	1	1	1	0	1	1*	1*	1	1*	1	**11**
B2	1	1	1	1	1	0	1	1	1	1	1*	1	**11**
B3	0	0	1	1	1	0	1	1	1*	1	1*	1	**9**
B4	0	0	1	1	1	0	1	1	1	1	1*	1	**9**
B5	0	0	0	0	1	0	0	1	1	1	1*	1	**6**
B6	1	1	1*	1	1	1	1	1	1	1	1*	1	**12**
B7	0	0	1	1	1	0	1	1	1*	1	1*	1	**9**
B8	0	0	0	0	1	0	0	1	1*	1	1	1	**6**
B9	0	0	0	0	1*	0	0	1	1	1	1*	1	**6**
B10	0	0	0	0	0	0	0	0	0	1	0	1	**2**
B11	0	0	0	0	0	0	0	0	0	0	1	1	**2**
B12	0	0	0	0	0	0	0	0	0	0	0	1	**1**
Dependence Power	**3**	**3**	**6**	**6**	**9**	**1**	**6**	**9**	**9**	**10**	**10**	**12**	

Source: Authors' analysis using SmartISM '"(N. Ahmad & Qahmash, 2021)

Table 6. Level Partition

Elements(Mi)	Reachability Set R(Mi)	Antecedent Set A(Ni)	Intersection Set R(Mi)∩A(Ni)	Level
1	1, 2,	1, 2, 6,	1, 2,	5
2	1, 2,	1, 2, 6,	1, 2,	5
3	3, 4, 7,	1, 2, 3, 4, 6, 7,	3, 4, 7,	4
4	3, 4, 7,	1, 2, 3, 4, 6, 7,	3, 4, 7,	4
5	5, 8, 9,	1, 2, 3, 4, 5, 6, 7, 8, 9,	5, 8, 9,	3
6	6,	6,	6,	6
7	3, 4, 7,	1, 2, 3, 4, 6, 7,	3, 4, 7,	4
8	5, 8, 9,	1, 2, 3, 4, 5, 6, 7, 8, 9,	5, 8, 9,	3
9	5, 8, 9,	1, 2, 3, 4, 5, 6, 7, 8, 9,	5, 8, 9,	3
10	10,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10,	10,	2
11	11,	1, 2, 3, 4, 5, 6, 7, 8, 9, 11,	11,	2
12	12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	12,	1

Source: Authors' analysis



Source: Authors' compilation

Figure 5: MICMAC Analysis

5. Discussion

One of the research questions for the study is to identify the list of relevant barriers that are hindering the adoption of artificial intelligence in manufacturing firms in Singapore. A literature review identified 12 prominent barriers to the adoption of artificial intelligence in manufacturing firms [Table 1]. We apply the Fuzzy Delphi method (FDM) to evaluate the importance of these barriers based on the experts' opinions. Based on the result of analysis, it is found that "Resistance to change" is the maximum weight barrier while "Lack of communication" has the smallest weight in the adoption of artificial intelligence in manufacturing firms in Singapore [Table 4]. Another research question is: what are the hierarchical relationships and interactions among the barriers? We apply the ISM technique to the barriers to evaluate internal relationships and build an ordered framework.

A six-level structured hierarchical model was developed and shown in Figure 4. The model aided in explaining the relationship between the barriers and how they support the implementation of artificial intelligence in manufacturing firms in Singapore [Figure 4].

Based on the research findings, "Lack of top management support" (B6) is at level 6 and at the bottom of the hierarchical model. In summary, this means that "Lack of top management support" is the most critical barrier and serves as a foundation for the other barriers to the adoption of Artificial Intelligence. This also acts as a single pillar behind the level 5 barriers [“Resistance to change” (B2), “Legal and regulatory framework” (B1)] in the ISM model. This means that the implied risk associated with the application of artificial intelligence and resistance within the workforce are the reasons for slow adoption. These barriers act as strong inhibitors of adoption because manufacturing leaders are trying to avoid the risks associated with technology and workforce concerns.

If there is no proper adoption framework and policies are not in place, it will slow the adoption of complex technologies in manufacturing firms. Biswas & Gupta (2019) found that blockchain technology adoption is significantly affected by its decentralised nature and limited scope for regulators and policymakers to frame policies and frameworks. Similarly, in manufacturing industries, obsolete regulations can create bottlenecks to the adoption of artificial intelligence. Therefore, it is clear that top management in companies and associations should come together to implement appropriate, flexible regulations and policies to scale the adoption of artificial intelligence in their industries and drive sustainable growth and value. Earlier studies found that top management is the main driver of technology adoption ——(Ali & Thakkar, 2023; G. Dwivedi et al., 2017; Govindan & Hasanagic, 2018; LaValle et al., 2010). Top management backing is not counted as a single pillar of support, but employees see this backing across multiple dimensions, including hidden factors (Golovianko et al., 2023; Govindan & Hasanagic, 2018).

The study also concluded that "Lack of top management support" is the most prominent blockade and has a wider impact on the linking barriers. High driving and low dependence power of 'Lack of top management support' (B6) positioned in the quadrant 'IV' [Independent Variables] along with 'Legal and regulatory framework' [B1] and 'Resistance to Change' [B2]. Barriers in quadrant IV will influence the other barriers and drive them, given their greater driving power.

'Lack of infrastructure' [B3], 'Data Management' [B4] & 'Lack of adequate resources' [B7] are having higher driving and dependence power. Due to these power combinations, these are in quadrant 'III' at level 4. This means that these are influenced by the other barriers in lower levels in quadrant IV but can influence the barriers in lower levels. Kaur & Rampersad (2018) found that organisations lack in IT infrastructure, Data Management and adequate IT resources will be affected by the adoption of complex technologies. These infrastructure gaps are occurring due to 'lack of top management support' [B6], 'Legal and Regulatory frameworks' [B1] & 'Resistance to change' [B2]. 'Lack of trust' [B5], 'Lack of reliability' [B8], and 'Privacy and Security' [B9] are also placed in quadrant 'III' but at level 3 in hierarchical ISM model due to their medium driving power and higher dependence power. This means that that these are influenced by the quadrant IV barriers 'top management support' [B6], 'Legal and Regulatory frameworks' [B1] & 'Resistance to change' [B2]. Lack of legal regulation and resistance to change will have driven up the trust, reliability, privacy and security concerns and ownership of risk is not clear.Mellor et al. (2014) concluded that changing tasks and related procedures with the implementation of technology results in resistance to use by the workforce. Traditional manufacturing firms are not agile enough to adopt these innovative technologies due to the in-built process and procedures that are causing resistance to change. The barriers found their place in quadrant 'III' will function as a linkages variable which

provides a linkage between Independent and dependent variables.

'Barriers Lack of communication' [B11] and 'technical issue' [B10] are at level 2, and 'Lack of advanced analytics skills' [B12] in the ISM model and position in quadrant 'II' [Dependent] due to low driving & high dependency powers. Previous research found that if security and privacy concerns are managed with care, then this will improve consumer confidence "(G. Dwivedi et al., 2017; Golgeci et al., 2025; Golovianko et al., 2023). Hence, this study confirms the prominent barriers that need to be addressed at the industry level to improve the adoption of artificial intelligence.

There are no barriers found in quadrant 'I' [Autonomous], which concludes that barriers selected from earlier studies for these studies are relevant and have greater interrelation in the setting of artificial intelligence adoption in manufacturing industries.

6. Implications

6.1 Theoretical implications

Beyond the structural identification of barriers, this study's theoretical contribution is enhanced by the use of Behavioural Reasoning Theory (BRT) (Westaby, 2005) as the guiding framework. A more thorough knowledge of how cognitive and motivational reasoning processes influence the choice to implement artificial intelligence (AI) in manufacturing enterprises is made possible by BRT. This study creates a behavioral basis for understanding the hierarchical structure produced from the ISM model by differentiating between "reasons for" (enablers) and "reasons against" (barriers) adoption.

It is now possible to understand obstacles like regulatory ambiguity, aversion to change, and a lack of support from top management as the main "reasons against" the adoption of AI, which represent the underlying justifications that prevent organisational action. On the other hand, the presence of "reasons for"—like data-driven value creation, regulatory clarity, and leadership commitment—represents motivating factors that can overcome these obstacles. Compared to simply structural or technical models, this dual reasoning approach offers a more comprehensive conceptual explanation of adoption dynamics.

Therefore, by connecting structural interdependencies (from ISM–MICMAC analysis) with behavioral justifications impacting managerial decisions, the incorporation of BRT advances the theoretical discourse on technology adoption. It provides a more comprehensive framework for upcoming research on AI and other disruptive technology adoptions by bridging the gap between organisational behavior theory and multi-criteria decision analysis "(Ajili Ben Youssef et al., 2025; Y. K. Dwivedi et al., 2021). It finds each barrier's relevance and how they interact. A hierarchical model shows the influence of these barriers on AI adoption. The ISM model from this study serves as a foundation for future research where researchers can expand and evaluate these barriers using an empirical study.

6.2 Managerial implications

From a managerial perspective, using BRT to frame the results provides practical insights into how businesses may proactively turn obstacles into facilitators by addressing the underlying logic that motivates leadership and employee behavior. For instance, creating internal "reasons for" adoption through organised change management, upskilling programs, and showcasing observable advantages of AI-driven efficiency can help reduce resistance to change. In the same vein, developing a forward-thinking strategy that synchronises AI adoption with strategic competitiveness and innovation objectives might counteract a major "reason against," namely, the absence of support from senior management.

Therefore, managers should understand that barriers are manifestations of underlying organisational values and reasoning rather than discrete operational limits. By altering perceptions of risk, trust, and value related to AI implementation, interventions should focus on these reasoning tendencies. Using this reasoning-based paradigm, policymakers can also create incentive mechanisms that increase "reasons for" adoption, including financing assistance, regulatory clarity, and capability-building initiatives, while decreasing "reasons against," such unclear regulations or insufficient resources.

This study offers practitioners a revolutionary approach by integrating behavioral reasoning with structural analysis, moving the emphasis from just finding obstacles to strategically reframing them into motivators for Artificial Intelligence adoption. The study did not find any autonomous barriers which implies that all barriers used in the study are self-interacting with each other's. Practicing manger should not treat these as isolated barriers, but each

one has a cascading implication of other may be positive or negative on overall behaviour. Based on ISM model analysis lower-level barriers influences the higher-level barriers. This means that managers should carefully apply their resources to manage lower levels to achieve the desired outcome and give a quick win for adoption of AI. Barriers found in quadrant 'III' [Linkages] should be managed carefully as any action on them will have a positive and negative impact on others. If these apply appropriately then will create a positive situation which will improve adoption of artificial intelligence. Barriers in the quadrant 'II' [Independent] are the most critical barriers in adoption of AI in manufacturing industry where practicing managers should exert maximum attention to alter behaviour of adoption.

7. Conclusion & Future Research Directions

This study used an integrated FDM–ISM–MICMAC methodological approach to identify and assess the major obstacles preventing the adoption of artificial intelligence (AI) in Singapore's manufacturing industry. A thorough assessment of the literature and expert validation led to the identification of twelve major obstacles, including a lack of infrastructure, legislative uncertainty, opposition to change, lack of top management support, and privacy and security issues. The address the first research question of the current study. Using FDM method we had found the most and least important barriers to the artificial intelligence adoption in Singapore manufacturing firms. This addresses the second research question. While the MICMAC analysis categorised these obstacles according to their driving and reliance power, the ISM model created a six-level hierarchical structure that showed the interactions between these barriers. This addresses the third research question of the current study.

These barriers are 'B1. Legal and regulatory framework', 'B2. Resistance to change', 'B3. Lack of Infrastructure', 'B4. Data Management', 'B5. Lack of trust', 'B6. Lack of top management support', 'B7. Lack of adequate resources', 'B8. Lack of reliability', 'B9. Privacy and security', 'B10. Technical issues', 'B11. Lack of communication', and 'B12. Lack of advanced analytics skills.

Among these barriers, the three barriers at the bottom of the ISM model (B6. 'Lack of top management support', B1. 'Legal and regulatory framework', and B2. 'Resistance to change') needs immediate attention from for a successful adoption of artificial intelligence.

Barriers (B10. 'Technical issues', B11. 'Lack of communication', and B12. 'Lack of advanced analytics skills') are having higher dependence power, therefore these are not having major influence in adoption and least concern for the management. If advanced analytics skills are not available in-house it can easily be outsourced and technical issue will resolved with application of right skills.

The contributions from the study are in multiples. First, Identification of the relevant barriers in adoption using literature review. Second, critically assess the importance of each barrier using Fuzzy Delphi Method (FDM) and find the most & least relevant to the adoption of artificial intelligence in manufacturing industries. Third, find and evaluate barriers to adopting artificial intelligence by applying ISM technique. Fourth, build the inter-relationships model for the prominent barriers using ISM Method.

A deeper comprehension of AI adoption behavior is made possible by combining BRT with the ISM-based structural approach. It shows that obstacles' structural dependencies are molded by cognitive and motivational reasoning at both the human and institutional levels, rather than just being technical or organisational. This dual reasoning approach provides a more thorough framework for researching technology adoption in intricate organisational contexts by bridging the gap between behavioral theory and systems-based analytical modeling. By applying BRT to the subject of industrial technology adoption—an area where behavioral reasoning has gotten little attention—the study advances theory. By connecting the macro-level structural dynamics (barrier interdependencies) that affect adoption results with the micro-level reasoning processes (beliefs, motivations, resistance), it advances the conversation. Practically speaking, the study offers managers and legislators useful advice, highlighting the necessity of turning "reasons against" into "reasons for" through focused interventions including staff empowerment, regulatory change, and leadership alignment.

While the study provides multiple contributions, it has few limitations also. Firstly, the nature of the study is exploratory due to the application of the Delphi Approach. Second, this study is limited to 12 relevant barriers whereas future researchers could extend the list. Third is study limited to Singapore & manufacturing firms only.

There is multiple scope for future researchers, First- the BRT-ISM Framework's Empirical Validation: In order to verify the impact of "reasons for" and "reasons against" on

AI adoption intents and outcomes, future research could empirically examine the dual reasoning structure put out here using quantitative methods like structural equation modeling (SEM). Second- Cross-Industry and Cross-Cultural Applications: Extending this study to different industries or countries may highlight contextual differences in the ways that institutional forces and organisational structures interact with behavioral reasoning in the adoption of AI. Third- Integration with Other Behavioral Theories: By combining BRT with complementary models like the Unified Theory of Acceptance and Use of Technology (UTAUT) or the Technology–Organisation–Environment (TOE) framework, future

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Beyond Marketing: Organisational Justice, Meaning, and Engagement as Pathways to Employer Branding in Indonesian Higher Education – A Variance-Based SEM Approach

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Abstract

Private universities in Indonesia face intense competition for talent and reputation, not only against each other but also against public universities that enjoy greater state support. This study reframes employer branding as an internal behavioural outcome rather than an external marketing tool, emphasising how organisational resources shape employees' identification and advocacy. Drawing on the Job Demands-Resources, Social Exchange, and Signalling frameworks, we investigate how person-organisation fit, psychological safety, and organisational justice influence employer branding. Specifically, we examine the sequential mediation through meaningful work, affective commitment, and employee engagement. Responses from 432 lecturers and staff across five Indonesian regions were analysed using variance-based structural equation modelling (WarpPLS 8.0).

The findings demonstrate that fairness, fit, and safety foster meaningful work, which strengthens commitment and engagement – the psychological mechanisms that transform internal well-being into external reputation. Notably, perceived external prestige emerged as a negative moderator, indicating that high institutional reputation can dilute the impact of engagement on branding by creating a reputational ceiling. The study extends employer-branding research beyond marketing discourse to organisational behaviour, offering a culturally grounded explanation of how internal justice and meaning generate authentic branding in higher education. Practical implications emphasise the importance of leadership attention to fairness, inclusion, and meaningfulness as sustainable sources of institutional identity and employee-driven reputation.

Keywords: *Employer branding; meaningful work; engagement; organisational justice; psychological safety; person-organisation fit; higher education.*

1. Introduction

Employer branding has evolved far beyond its original marketing roots. Once perceived as a tool for attracting external talent, it is increasingly recognised as a behavioural and organisational phenomenon shaped by employees' internal experiences (Theurer et al., 2018; Kaur et al., 2020). Within universities – particularly private institutions in Indonesia – this shift is critical. Unlike public universities that enjoy greater state support, private universities must rely heavily on their internal culture, fairness, and meaning-driven engagement to sustain reputation and talent retention. In Indonesia and across Southeast Asia, private universities face increasing pressure to attract and retain qualified lecturers in a landscape dominated by state-funded institutions (Nguyen et al., 2024). Employer branding thus becomes not merely a marketing effort but a mechanism of organisational identity and commitment building.

In this context, employer branding becomes less about outward promotion and more about the internal sense of belonging, justice, and purpose that employees collectively embody. When lecturers and staff feel respected and valued, their work acquires meaning that transcends mere employment, reflecting the institution's values to students and the broader society. Yet, while employer branding research has advanced in corporate contexts, its exploration within higher education – especially in non-Western, resource-constrained settings – remains limited (Tanwar & Prasad, 2016; Kaur et al., 2020; Meng & Berger, 2019).

Theoretical integration is therefore required to illuminate the mechanisms through which internal organisational factors translate into branding identity. Drawing upon Job Demands-Resources (JD-R) theory, Social Exchange Theory (SET), and Signalling Theory, this study conceptualises a sequential process: organisational justice, person–organisation fit, and psychological safety act as *resources*; these resources foster *meaningful work* and *affective commitment* as inner psychological energies; and these, in turn, lead to *employee engagement,* which manifests as externalised identity signals – employer branding. This progression links internal morality, human meaning, and institutional identity within one coherent model.

The study thus addresses several key gaps. First, it extends employer branding theory into the higher education domain, emphasising employee-centred psychological mechanisms rather than marketing practises. Second, it integrates moral (justice), existential (meaning), and motivational (engagement) dimensions, constructs rarely combined in a single framework. Third, it employs a variance-based SEM approach (WarpPLS 8.0), which aligns with the study's epistemological aim: *to develop rather than merely confirm theory,* emphasising prediction and explanation over fit optimisation.

By situating this inquiry in the Indonesian private university context, the study provides both empirical insight and theoretical depth. It demonstrates that in collectivist and resource-limited environments, justice and meaning are not peripheral luxuries but central forces that construct institutional identity from within. The relationships among these constructs are elaborated in the conceptual framework (*see Figure 1, presented in the following section*), which integrates internal fairness, meaning, and engagement as pathways leading to employer branding.

The subsequent section elaborates the theoretical underpinnings of each construct, synthesises empirical evidence, and formulates hypotheses that articulate how organisational resources shape psychological and institutional outcomes within the proposed framework.

2. Theoretical Foundation and Literature Review

2.1 Theoretical Integration: From Resources to Meaning and Identity

This study integrates three major theoretical foundations – Job Demands-Resources (JD-R) theory, Social Exchange Theory (SET), and Signalling Theory – to explain how organisational resources cultivate psychological mechanisms that translate into institutional outcomes.

The JD-R theory (Bakker & Demerouti, 2007) serves as the ontological anchor, positing that work environments characterised by sufficient resources (such as justice, fit, and safety) enable motivation and personal growth. In this perspective, resources are not merely variables but conditions of existence that enable meaningful and energised work. When employees perceive fairness, congruence, and safety, they experience not only satisfaction but coherence between self and organisation.

The Social Exchange Theory (Blau, 1964; Cropanzano & Mitchell, 2005) frames these experiences within a relational logic. Fair treatment and trust cultivate a moral reciprocity, where employees respond to organisational care with loyalty, effort, and advocacy. Engagement and commitment

thus represent the epistemological realisation of reciprocity – a knowledge structure built on trust and mutual respect.

Finally, Signalling Theory (Spence, 1973; Connelly et al., 2011) bridges internal psychological states and external reputation. When employees display enthusiasm, dedication, and purpose, their behaviour becomes a signal of institutional quality. Thus, employer branding is not only an externally constructed image but an emergent semiotic process, in which internal meaning manifests in public identity.

Together, these theories articulate how organisational resources (fit, safety, justice) activate personal and relational mechanisms (meaning, commitment, engagement) that culminate in institutional identity (employer branding). This integrative logic establishes the conceptual pathway illustrated in Figure 1.

2.2 Bridging Epistemology and Empiricism

Having outlined the theoretical and philosophical logic underlying this study, it is essential to situate the model within the broader empirical literature. The following section synthesises prior research findings that validate each hypothesised path, ensuring that the conceptual structure is not only theoretically integrative but also empirically grounded.

This dual-layer design – conceptual integration and empirical substantiation – reflects the study's epistemological commitment: to extend theory while remaining accountable to data.

2.3 Empirical Literature Review and Hypotheses Development

Person–Organisation Fit and Meaningful Work

Person-organisation fit (P-O Fit) represents the degree of compatibility between an employee's personal values and the organisation's culture and mission (Cable & DeRue, 2002). When employees experience alignment between their beliefs and institutional values, they perceive greater purpose and coherence in their work (Kristof-Brown et al., 2005). Empirical research supports that value congruence enhances psychological well-being, intrinsic motivation, and perceptions of meaningfulness (Zhang et al., 2019).

H1: Person-Organisation Fit positively influences Meaningful Work.

Psychological Safety and Meaningful Work

Psychological safety refers to shared beliefs that the work environment is safe for interpersonal risk-taking and voice (Edmondson, 1999). When individuals feel safe to express ideas and admit mistakes, they experience authenticity – a central component of meaningful work (May, Gilson, & Harter, 2004; Carmeli & Gittell, 2009). Studies across educational and service contexts indicate that psychological safety enhances both engagement and meaningfulness by reducing fear and promoting learning orientation (Frazier et al., 2017).

H2: Psychological Safety positively influences Meaningful Work.

Organisational Justice and Meaningful Work

Organisational justice reflects employees' perceptions of fairness across distributive, procedural, and interactional dimensions (Colquitt, 2001). Recent meta-analytic findings reaffirm that organisational justice – particularly procedural and interactional dimensions –serves as a powerful job resource that enhances employees' affective states and work engagement (Colquitt & Zipay, 2022). Fairness communicates moral respect and trustworthiness, which shape employees' sense of dignity and purpose in work (DeConinck, 2010). Empirical evidence shows that justice strongly predicts organisational identification and job satisfaction (Greenberg, 2011; Loi, Yang, & Diefendorff, 2009). In education settings, procedural and interactional justice are critical in maintaining a meaningful academic environment (Meng & Berger, 2019).

H3: Organisational Justice positively influences Meaningful Work.

Meaningful Work and Affective Commitment

Meaningful work is a psychological state in which employees perceive their work as significant and purposeful (Steger et al., 2012). It fosters identity alignment between the individual and the organisation, leading to emotional attachment and loyalty (Meyer & Allen, 1991). Numerous studies confirm the strong association between work meaning and affective commitment (Allan et al., 2019; Lips-Wiersma & Wright, 2012). In higher education, purpose-driven work is a primary determinant of academic commitment and institutional identification (Rosso, Dekas, & Wrzesniewski, 2010). Beyond its motivational value, meaningful work has been found to sustain long-term engagement, particularly in academia where intrinsic purpose and autonomy define professional identity (Schnell

& Hoffmann, 2020; Lips-Wiersma & Wright, 2019).

H4: Meaningful Work positively influences Affective Commitment.

Affective Commitment and Employee Engagement

Affective commitment denotes an employee's emotional attachment and identification with the organisation (Meyer & Allen, 1991). Committed employees tend to show greater enthusiasm and persistence, which are central to engagement (Saks, 2006). Research by Schaufeli et al. (2002) and Christian et al. (2011) confirms that emotional attachment fosters vigour, dedication, and absorption – the three components of engagement.

H5: Affective Commitment positively influences Employee Engagement.

Employee Engagement and Employer Branding

Employee engagement represents the extent to which individuals invest cognitive, emotional, and physical energy into their work roles (Kahn, 1990). Engaged employees become the most credible ambassadors of their organisations (Theurer et al., 2018; Tanwar & Prasad, 2016). Prior research shows that internal engagement directly enhances external reputation and employer attractiveness (Kaur et al., 2020). Employer branding effectiveness increasingly depends on employee-based signals of engagement and identification (Aggerholm & Andersen, 2022; Kaur et al., 2020). Recent HRM studies show that branding rooted in internal experiences fosters authentic and sustainable attractiveness.

H6: Employee Engagement positively influences Employer Branding.

Sequential Mediation

The proposed model assumes a serial mediation process where organisational resources promote meaning, which fosters commitment, leading to engagement and finally to employer branding. Studies by Bailey et al. (2017) and van Wingerden et al. (2018) show that meaningful work predicts engagement through affective commitment, supporting this sequential pathway.

H7: Meaningful Work, Affective Commitment, and Employee Engagement sequentially mediate the relationship between organisational resources and Employer Branding.

Moderating Role of Perceived External Prestige

Perceived External Prestige (PEP) is the extent to which employees believe outsiders hold their organisation in high regard (Mael & Ashforth, 1992). When employees feel that their institution is respected, they are more likely to engage in behaviours that reinforce this image (Carmeli, 2005). PEP therefore strengthens the positive effect of engagement on employer branding by amplifying identity pride.

H8: Perceived External Prestige strengthens the positive relationship between Employee Engagement and Employer Branding.

To consolidate these theoretical linkages, Table 1 summarises the foundations and empirical support for each hypothesis.

Table 1: Summary of Theoretical Foundations and Empirical Support for Hypotheses

Constructs / Relationships	Theoretical Basis	Key References	Empirical Evidence	Related Hypothesis
Person–Organisation Fit → Meaningful Work	Job Demands–Resources Theory: value congruence as a resource fostering intrinsic motivation and purpose.	Cable & DeRue (2002); Demerouti et al. (2001)	Fit enhances purpose and job significance (Park & Hai, 2024).	H1
Psychological Safety → Meaningful Work	JD-R and Social Exchange Theory: safety enables learning, openness, and shared meaning.	Edmondson (1999); Frazier et al. (2017)	Safety promotes creativity and perceived meaningfulness (Newman et al., 2020).	H2

Constructs / Relationships	Theoretical Basis	Key References	Empirical Evidence	Related Hypothesis
Organisational Justice (formative) → Meaningful Work	JD-R and Equity Theory: fairness as a resource enhancing cognitive engagement.	Colquitt (2001); Colquitt & Zipay (2022)	Justice predicts engagement and moral meaning (Peng et al., 2024).	H3
Meaningful Work → Affective Commitment	Self-Determination and Meaningful Work Theories: sense of purpose builds emotional attachment.	Meyer & Allen (1991); Steger et al. (2012)	Meaningful work strengthens organisational commitment (Schnell & Hoffmann, 2020).	H4
Affective Commitment → Employee Engagement	Social Exchange Theory: emotional bond drives effort and energy.	Saks (2006); Schaufeli et al. (2006)	Commitment predicts vigour and dedication (Bakker & Albrecht, 2018).	H5
Employee Engagement → Employer Branding	Signalling Theory: engagement signals credibility and authenticity to external stakeholders.	Backhaus & Tikoo (2004); Aggerholm & Andersen (2022)	Engaged employees act as brand ambassadors (Kaur et al., 2020).	H6
Sequential Mediation: MW → AC → EE → EB	JD-R and Social Exchange: internal meaning and emotion channel resources into visible branding behaviour.	Demerouti et al. (2001); Cropanzano & Mitchell (2005)	Indirect pathway validated in academic settings (Kim & Park, 2024).	H7
Moderation of PEP on EE → EB	Signalling and Reputation Theories: prestige as a boundary condition for	Spence (1973); Bitektine & Haack (2015); Leung et al. (2022)	Prestige moderates engagement-branding link (Allen & Shanock, 2022).	H8

Note: Table 1 integrates major theoretical frameworks and recent empirical studies (2017–2024) that inform the conceptual model. The relationships are positioned within JD-R, Social Exchange, and Signalling perspectives to explain how internal organisational resources translate into behavioural expressions of employer branding.

Building upon the theoretical linkages and hypotheses summarised in Table 1, the conceptual framework illustrated in Figure 1 visually represents the proposed relationships among constructs. The model integrates organisational resources – Person-Organisation Fit (POF), Psychological Safety (PS), and Organisational Justice (OJ) - as antecedents of Meaningful Work (MW), which subsequently fosters Affective Commitment (AC) and Employee Engagement (EE), ultimately leading to Employer Branding (EB). The moderating role of Perceived External Prestige (PEP) is also depicted, highlighting its potential to influence the strength of the engagement-branding link.

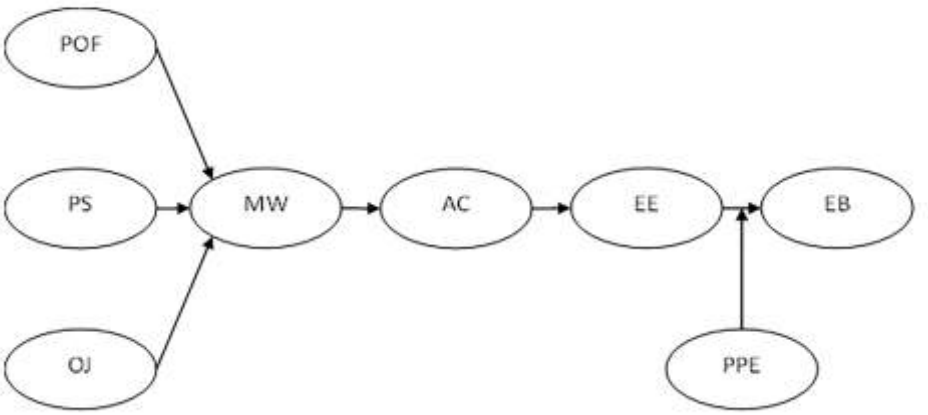

Figure 1: Conceptual Framework

Note: The model synthesises Job Demands-Resources, Social Exchange, and Signalling theory perspectives to explain how internal organisational resources translate into behavioural expressions of employer branding within higher-education institutions.

The next section elaborates the research logic, data collection procedures, and analytical techniques. It also explains the rationale for adopting a variance-based PLS-SEM approach and the specific two-step process used for validating the second-order formative construct of Organisational Justice.

3. Methodological Orientation and Analytical Logic

3.1 Research Design and Epistemological Stance

This study adopts a quantitative cross-sectional design grounded in the philosophical orientation of variance-based reasoning. Rather than seeking to confirm an existing model through covariance reproduction, the present research aims to develop and extend theory by identifying the most influential pathways linking organisational resources, psychological mechanisms, and employer branding outcomes. Accordingly, the analytical logic follows a variance-based Structural Equation Modelling (PLS-SEM) framework using WarpPLS 8.0 (Kock, 2013), which aligns with the study's developmental and predictive orientation.

The epistemological stance underpinning this choice is abductive and pragmatic. It acknowledges that theory and data interact iteratively to generate new explanations that are both theoretically meaningful and empirically grounded. While covariance-based SEM (e.g., AMOS, LISREL) emphasises theory confirmation and model fit, PLS-SEM emphasises prediction, exploration, and explanation of variance (Hair et al., 2022). This makes it particularly appropriate for emerging theoretical extensions, such as contextualising Western-based frameworks (JD-R, SET, Signalling) within Indonesian higher education - a setting where meaning, justice, and relational belonging operate differently. The choice of variance-based SEM (WarpPLS 8.0) aligns with recent methodological recommendations emphasising prediction-oriented analysis and hierarchical modelling in HR and higher-education research (Ringle et al., 2020; Sarstedt et al., 2020).

3.2 Population, Sampling, and Data Collection

The population comprised lecturers and administrative staff from private universities across five major Indonesian regions: Sumatra, Java, Kalimantan, Sulawesi, and Bali-Nusa Tenggara. A purposive sampling approach was applied to ensure representation from diverse institutional contexts, academic disciplines, and administrative roles. Data were gathered through a structured online questionnaire distributed in October 2025. Participation was voluntary and anonymous. A total of 432 valid responses were obtained after data screening.

This sample size exceeds the minimum threshold suggested for PLS-SEM, satisfying both the 10-times rule (Hair et al., 2022) and power-based sample estimation for complex models with multiple mediations and moderations. The large sample ensures stable estimates and generalizability across Indonesia's diverse educational landscape.

3.3 Measures and Instrumentation

All measurement items were adapted from validated scales and rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The instruments reflect a combination of reflective and formative measurement models. To operationalise the constructs shown in Figure 1, validated measurement scales were adopted from established studies. Each construct was measured using reflective or formative indicators consistent with theoretical definitions and prior validation. Table 2 summarises the construct names, scale sources, number of items, and measurement types employed in this study.

Table 2: Summary of Constructs, Scale Sources, and Measurement Types

Construct	Source	No. of Items	Measurement Type
Person-Organisation Fit (P-O Fit)	Cable & DeRue (2002)	4	Reflective
Psychological Safety (PS)	Edmondson (1999)	5	Reflective
Organisational Justice (OJ)	Colquitt (2001)	20 (3 subdimensions)	Second-order formative (first-order reflective)
Meaningful Work (MW)	Steger et al. (2012)	10	Reflective
Affective Commitment (AC)	Meyer & Allen (1991)	6	Reflective
Employee Engagement (EE)	Schaufeli et al. (2002)	9	Reflective
Employer Branding (EB)	Tanwar & Prasad (2016)	6	Reflective
Perceived External Prestige (PEP)	Mael & Ashforth (1992)	5	Reflective (Moderator)

All items were translated into Bahasa Indonesia using a back-translation procedure (Brislin, 1980) to maintain linguistic and conceptual equivalence. A pilot test involving 30 lecturers confirmed the clarity and reliability of the adapted scales before full deployment.

3.4 Higher-Order Construct Validation: Organisational Justice

Organisational Justice (OJ) was modelled as a second-order formative construct comprising three reflective first-order dimensions: (1) Distributive Justice, (2) Procedural Justice, and (3) Interactional Justice.

Following the two-step approach recommended by Hair et al. (2022) and Kock (2013):

1. In the first stage, the three first-order constructs were validated as reflective latent variables.
   - Outer loadings and reliability were assessed for each dimension.
   - All indicators met the loading threshold (≥0.70), confirming strong convergent validity.
2. In the second stage, the latent variable scores (LVS) of the three dimensions were used as formative indicators for the second-order construct.
   - Outer weights and significance ($p < 0.05$) confirmed their unique contribution to the overall construct.
   - Multicollinearity diagnostics (VIF < 3.3) indicated absence of redundancy.

This approach allows OJ to be treated as a multidimensional formative construct capturing holistic perceptions of fairness across distributive, procedural, and interpersonal domains. Prior to incorporating Organisational Justice (OJ) into the full structural model, a preliminary validation model (OJ → MW) will be examined separately to ensure that the formative construct functions effectively in predicting its theoretically related outcome – *Meaningful Work* – as recommended for second-order formative assessments (Hair et al., 2022; Kock, 2013).

3.5 Data Analysis Procedure

Data were analysed in WarpPLS 8.0 through the following steps:1. Preliminary Screening:

2. Missing values (<2%) were handled by mean substitution. No extreme outliers were detected through Mahalanobis distance tests.
3. Data distribution showed mild non-normality (skewness ±1.2; kurtosis ±1.5), justifying the use of PLS-SEM.
4. Measurement Model Evaluation:
   - Reflective Constructs:
   - Indicator loadings ≥0.70, composite reliability (CR) ≥0.70, and AVE ≥0.50 confirmed internal consistency and convergent validity.
   - Discriminant validity was verified via Fornell–Larcker criterion and HTMT ratios <0.85.
   - Formative Constructs (OJ):
   - Outer weights, VIF, and significance ($p < 0.05$) assessed as per two-step method.
5. Structural Model Evaluation:
   - Path coefficients (β), p-values, and effect sizes (f^2) were examined.
   - Coefficient of determination (R^2) and predictive relevance (Q^2) were reported for endogenous constructs.
   - Multicollinearity and model fit indices (APC, ARS, AVIF, GoF) were checked, with acceptable thresholds:
     - APC, ARS ($p < 0.05$); AVIF < 3.3; GoF > 0.36 (large).
     - Bootstrapping with 5,000 resamples ensured robust significance testing.
6. Mediation and Moderation Tests:
   - Mediation effects (MW → AC → EE → EB) examined using indirect effects with bootstrapped confidence intervals.
   - Moderation by PEP tested via interaction term (PEP × EE → EB), following Kock's (2015) nonlinear moderation approach.

4. Results and Discussion

4.1 Model Fit and Measurement Quality

The structural model demonstrated excellent fit and predictive adequacy. Global indices indicated robust model quality:

APC = 0.371 ($p < 0.001$), ARS = 0.375 ($p < 0.001$), AARS = 0.373 ($p < 0.001$), AVIF = 1.692, AFVIF = 2.949, all below the 3.3 threshold. The GoF = 0.524 exceeded the 0.36 benchmark, signifying a large overall fit (Kock, 2013; Hair et al., 2022). All model quality criteria (SPR, RSCR, SSR = 1.0; NLBCDR = 0.857) confirmed the absence of Simpson's paradox and suppression effects.

The measurement model also met reliability and validity criteria. Most indicators exhibited loadings ≥ 0.70, while a

Table 3: Reliability and Convergent Validity of Reflective Constructs

Construct	No. of Items	Loading Range	CR	AVE	Decision
Person-Organisation Fit (POF)	4	0.74–0.85	0.88	0.60	Accepted
Psychological Safety (PS)	5	0.69–0.82	0.87	0.57	Accepted
Organisational Justice (OJ)*	3 (DJ, PJ, IJ)	0.86–0.92	—	—	Valid
Meaningful Work (MW)	10	0.71–0.85	0.94	0.63	Accepted
Affective Commitment (AC)	6	0.75–0.88	0.91	0.63	Accepted
Employee Engagement (EE)**	8	0.54–0.86	0.90	0.52	Accepted
Employer Branding (EB)	6	0.73–0.89	0.92	0.63	Accepted
Perceived External Prestige (PEP)	5	0.76–0.88	0.90	0.61	Accepted

** OJ validated as a second-order formative construct (distributive, procedural, interactional).*

*** EE7 removed; EE8 and EE9 retained to preserve theoretical dimensionality*

.4.2 Structural Model Results

All hypothesised paths were positive and significant ($p < 0.01$), except the moderating effect of PEP, which was negative yet meaningful. The model explained substantial variance across endogenous constructs (**R^2 MW = 0.37; AC = 0.29; EE = 0.48; EB = 0.36**), confirming strong explanatory power. Table 4 presents the detailed structural model results, including standardised path coefficients, significance levels, and hypothesis decisions derived from the bootstrapping procedure.

o visualise the relationships and path strengths among constructs, Figure 2 presents the final structural model estimated using WarpPLS 8.0. All significant paths ($p < 0.05$) are highlighted, while non-significant links were omitted for clarity. The model depicts the positive influence of organisational resources (person-organisation fit, psychological safety, and justice) on meaningful work and subsequent outcomes – affective commitment, employee engagement, and employer branding – along with the moderating effect of perceived external prestige.

Table 4: Structural Model Results and Hypothesis Testing

Hypothesis	Path	β	p-value	Decision
H1	P-O Fit → Meaningful Work	0.325	<0.001	Supported
H2	Psychological Safety → Meaningful Work	0.159	<0.001	Supported
H3	Organisational Justice → Meaningful Work	0.225	<0.001	Supported
H4	Meaningful Work → Affective Commitment	0.539	<0.001	Supported
H5	Affective Commitment → Employee Engagement	0.704	<0.001	Supported
H6	Employee Engagement → Employer Branding	0.521	<0.001	Supported
H7	Sequential Mediation (MW → AC → EE → EB)	—	<0.001	Supported
H8	PEP × EE → Employer Branding	−0.150	<0.001	Supported (Negative Moderation)

Note: Bootstrapping was performed with 5,000 subsamples using WarpPLS 8.0. All paths were significant at $p < 0.01$. The negative moderating effect of Perceived External Prestige (PEP) indicates a boundary condition in the engagement-branding link, suggesting that high external prestige may attenuate the behavioural signalling role of engagement.

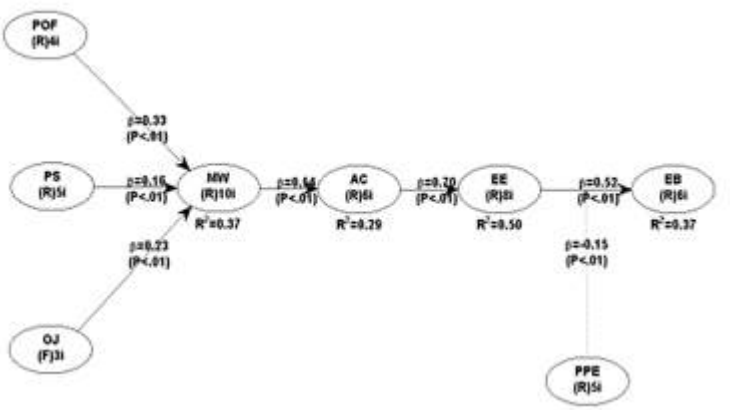

Figure 2: Final Structural Model

4.3 Mediation Effects

Bootstrapping with 5,000 resamples confirmed the sequential mediation through MW → AC → EE. The indirect effects of POF ($\beta = 0.063$, $p < 0.01$), OJ ($\beta = 0.043$, $p < 0.05$), and PS ($\beta = 0.031$, $p < 0.10$) on EB were significant, validating the integrated mechanism linking organisational resources to external branding outcomes. This finding supports the JD-R principle that workplace resources stimulate psychological energy – manifested as meaning, commitment, and engagement – which subsequently translates into organisational advocacy and brand signalling. Collectively, these results reinforce that employer branding originates internally, grounded in fairness and psychological resources, rather than through externally driven campaigns.

4.4 Moderation and the Paradox of Prestige

The moderation test revealed a negative interaction between perceived external prestige (PEP) and the engagement–branding link ($\beta = -0.15$, $p = 0.009$). Rather than amplifying the effect of engagement on employer branding, high institutional prestige appears to attenuate it – a theoretically coherent but rarely documented outcome within higher-education contexts. This paradoxical pattern can be interpreted through four complementary mechanisms grounded in signalling and resource theories.

First, signalling substitution occurs when institutional prestige serves as an overarching reputation signal, thereby reducing the incremental signalling value of employee engagement. In highly prestigious universities, external audiences already associate the institution with quality, leaving little room for additional behavioural cues to alter perceptions. This dynamic resembles the *law of diminishing returns* in signalling theory.

Second, an attributional discounting mechanism may unfold: stakeholders attribute institutional success primarily to its established brand name rather than to individual employee efforts. As a result, the visibility and symbolic weight of engagement behaviours diminish, even when such behaviours remain robust internally.

Third, identity saturation and role conservatism can emerge as employees internalize the belief that "the brand speaks for itself." Prestige creates a sense of security and institutional pride that redirects engagement inward – toward academic excellence and task performance –rather than outward advocacy. Engagement thus persists but becomes less performative in its branding expression.

Finally, the reputational ceiling effect suggests that prestigious universities may already occupy an upper boundary in perceived attractiveness, where further engagement yields marginal branding gains. This aligns with the Job Demands-Resources (JD-R) principle of *resource substitution*, in which abundant macro-level resources (prestige) overshadow micro-level motivational ones (engagement). The phenomenon resonates with the concept of *reputational ambivalence* (Bitektine & Haack, 2015; Leung et al., 2022), wherein prestige simultaneously legitimises and constrains employee behaviour. Under such conditions, employees may rely on institutional reputation as a substitute for individual advocacy, resulting in reputational saturation rather than amplification.

4.5 Integrative Discussion

Beyond the specific moderating dynamics, the overall findings converge toward a unified theoretical interpretation that situates employer branding within the broader nexus of organisational resources, psychological mechanisms, and contextual prestige.

Taken together, the findings reaffirm that employer branding within higher-education institutions is not a marketing artifact but a behavioural outcome of internal organisational vitality. Fairness (OJ), safety (PS), and fit (POF) operate as foundational psychological resources that cultivate meaningful work, nurture affective commitment, and energise engagement – the motivational engines of branding-by-behaviour. This internal pathway underscores that branding is enacted through lived employee experiences rather than orchestrated through external campaigns.

The moderating role of perceived external prestige (PEP) adds a critical layer of nuance to this mechanism. Rather than amplifying engagement's branding impact, prestige attenuates it, suggesting that institutional reputation both legitimises and constrains the behavioural visibility of individual contributions. This finding reframes employer branding as a dynamic equilibrium between internal meaning systems and external symbolic capital.

Consequently, the negative moderation by PEP should not be interpreted as a statistical anomaly but as an epistemic refinement. It exposes a boundary condition within the JD-R and signalling frameworks, where macro-level prestige may substitute for micro-level behavioural signalling. In essence, prestige functions as both a blessing and a constraint – enhancing legitimacy while diminishing the incremental signalling power of individual engagement.

The integrative pattern aligns with the model's satisfactory global fit indices reported earlier, confirming that the proposed framework captures a theoretically coherent and empirically supported structure of relationships. Together, these results illuminate how organisational justice, safety, and fit collectively anchor a psychological infrastructure that sustains employer branding from within, moderated by the subtle paradox of institutional prestige.

4.6 Theoretical Implications

Building upon the integrative interpretation of the results, several theoretical implications emerge that extend the current understanding of employer branding within organisational behaviour and resource-based frameworks.

First, the study **expands the integration of the Job Demands-Resources (JD-R) and Signalling frameworks** by identifying external prestige as a contextual moderator that substitutes, rather than strengthens, the motivational pathway from engagement to branding. This finding refines the JD-R theory's assumption of additive resource interaction and introduces the notion of *reputation saturation* as a boundary condition. By doing so, the study bridges signalling theory with organisational psychology, showing how macro-level reputation can regulate micro-level motivational outcomes.

Second, the findings **reconceptualize employer branding as a *behavioural identity process*** emerging from internal psychological conditions – namely justice, meaning, and engagement – moderated by contextual reputation cues. Employer branding, therefore, is not merely a product of communication or HR marketing initiatives but a manifestation of employees' internalised values and lived experiences. This shifts the conceptual focus of EB from message management to identity enactment, situating branding within the broader discourse of meaningful and value-driven work.

Finally, the study defines boundary conditions for engagement effectiveness. The impact of engagement on branding is contingent on the level of perceived external prestige: in less-prestigious institutions, engagement acts as a strong differentiator that enhances the employer brand, while in highly prestigious universities, its effect tends to plateau due to reputational inertia. This nuanced view challenges the universalist assumption of engagement as an unconditionally positive force and underscores the importance of contextual prestige in shaping behavioural branding outcomes.

4.7 Practical Implications

For high-prestige universities, the challenge is *visibility of authentic engagement*. Administrators should design mechanisms that make engagement **personally attributable** –such as lecturer-led projects, faculty storytelling, and co-branded student initiatives – so engagement is not absorbed by institutional prestige.

For emerging or lower-prestige universities, investment in **justice, psychological safety, and meaningful work** remains the most effective route to strengthening employer brand identity, as engagement's marginal value is higher when reputation is still developing.

5. Conclusion

This study demonstrates that employer branding in higher education is primarily an internal behavioural process rather than a marketing artifact. Integrating the Job Demands-Resources, Social Exchange, and Signalling frameworks, it establishes that fairness, psychological safety, and person-organisation fit foster meaningful work, which subsequently enhances affective commitment and engagement – the psychological engines of branding-by-behaviour. Through this mechanism, organisational vitality becomes visible externally as a credible and sustainable employer brand.

The findings also reveal that external prestige, often assumed to strengthen branding, can paradoxically weaken the engagement–branding link. High-prestige institutions may experience a reputational ceiling effect, where macro-level reputation substitutes for micro-level behavioural signalling. This discovery extends existing theory by positioning prestige as both a resource and a boundary condition in employer-brand development.

5.1 Limitations and Future Research

While the study offers theoretical and methodological advancements, several limitations suggest avenues for future inquiry. *First,* its cross-sectional design restricts causal interpretation; longitudinal studies could trace how psychological and reputational resources interact over time. *Second,* the data were collected from Indonesian private universities, which may differ from public or Western institutions in cultural and governance contexts; comparative or multi-country designs would enrich generalizability. *Third,* future research could explore additional moderators such as leadership style, organisational culture, or digital transformation, which may

amplify or buffer the pathways linking engagement to employer branding. *Finally,* qualitative or mixed-method approaches could further uncover how employees narrate and embody their institutional identities, providing a richer understanding of branding as a lived, everyday process rather than a survey construct.

5.2 Closing Reflection

Ultimately, the study reinforces a simple but powerful insight: *a university's most authentic brand is expressed through the daily meaning, commitment, and engagement of its people*.

When institutions nurture fairness, safety, and fit, branding ceases to be an external performance and becomes a natural reflection of internal well-being – the lived identity that speaks louder than any campaign.

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The Role of Artificial Intelligence in Transforming Marketing Strategies and Its Impact on Consumer Buying Behaviour and Brand Engagement in the Indian Retail Sector

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Abstract

The present research explores retail consumer behaviour in the Indian marketing context, focusing on AI-based marketing principles such as AI-driven personalisation, chatbot effectiveness, and predictive analytics, and their effects on consumer trust, purchase intention, brand engagement, and customer loyalty. The study adopts a quantitative research approach with a descriptive research design. Data were collected through structured online questionnaires administered to approximately 450 respondents across selected locations in India. The collected data were analysed using descriptive statistics, exploratory factor analysis (EFA), structural equation modeling (SEM), and hierarchical regression to examine the relationships among variables. The findings reveal that AI-driven personalisation has a significant positive impact on purchase intentions, while chatbot efficiency, consumer trust, and predictive analytics positively influence brand engagement. The results further indicate that consumer trust plays a crucial role in shaping purchasing decisions and strengthening brand engagement, ultimately leading to customer loyalty. Overall, the study highlights that AI technologies significantly influence the customer decision-making process by delivering customised advertising and efficient customer service, thereby enhancing long-term brand relationships.

Keywords: *AI-driven marketing strategies, Personalisation, Consumer Buying behaviour, Brand engagement, Purchase intention, Digital literacy, Indian Retail Sector*

1. Introduction

The rapid progress in artificial intelligence (AI) has revolutionised several industries, and the retail sector is no exception. AI-driven marketing is transforming how businesses approach consumers, customise customer experiences, and optimise marketing programmes**.** As the Indian retail sector becomes more digitised, businesses are using AI to enhance consumer insights through predictive analysis, recommendation engines, chatbots, and automated content. The use of AI in marketing makes operations more efficient; however, it can also significantly influence consumer behaviour, perceptions, and Brand engagement. The Indian retail industry is undergoing a paradigm shift, with AI-driven solutions redefining customer interactions. AI applications such as machine learning (ML), natural language processing (NLP), predictive analytics, and automated decision-making enable companies to deliver highly personalised marketing campaigns, dynamic pricing, and AI-powered customer service interactions.

In India, online and omnichannel retailing have brought AI to the forefront, enhancing customer loyalty, engagement, and purchasing behaviour. Conventional marketing approaches relied primarily on historical consumer data, demographic analysis, and managerial intuition. Marketers can now target, segment, and optimise campaigns more efficiently by predicting consumer preferences in real time through big data and AI. Tools such as chatbots, recommendation engines, programmatic advertising, and voice search optimisation have redefined how brands communicate with customers. AI-controlled mood analysis helps brands understand consumer emotions and adapt marketing messages accordingly. Computer Vision Technologies enable brands to analyse visual content and consumer behaviour in physical retail stores, thereby improving inventory management and customer engagement. In the Indian retail sector, AI-driven marketing helps reduce cart abandonment, improve conversion rates, deliver personalised product recommendations, and promote business growth. Consumer behaviour in the digital age is dynamic and increasingly influenced by AI-controlled personalisation, recommendations, and automated interactions. With AI, brands can create microsegmented audience clusters based on behavioural data to deliver targeted, tailored advertising campaigns. Language assistants (e.g., Amazon Alexa, Google Assistant) and AI-operated virtual shopping assistants have further improved brand engagement by providing seamless consumer experiences. Brand engagement, a critical component of customer loyalty, is strengthened through AI-driven marketing automation. With AI, brands can track customer interactions, predict purchase intentions, and create real-time engagement opportunities. Additionally, AI enables consistent and relevant communication across multiple touchpoints (social media, email marketing, personalised notifications), thereby promoting stronger brand–customer relationships.

The Indian retail industry is one of the world's fastest-growing markets, driven by rising e-commerce penetration, smartphone adoption, affordable internet access, and digital payments. AI is helping both online and brick-and-mortar retailers adapt to emerging consumer trends, improve supply chain management, and enhance user experience. Leading Indian retailers such as Reliance Retail, Flipkart, Amazon India, Tata Cliq, and Myntra are deploying AI to manage inventory, improve demand forecasting, and strengthen customer service. Virtual assistants and AI-enabled chatbots are widely used to handle customer queries, assist with shopping, and provide post-purchase support. Furthermore, AI-driven recommendation engines drive sales by suggesting products based on search history and prior purchases. While AI-driven marketing models are prevalent in developed markets, research examining their impact within emerging markets such as India remains limited**.** Given India's diverse consumer demographics, varying levels of digital exposure, and evolving retail environment, a systematic examination of how AI influences consumer behaviour and brand engagement is necessary. This study aims to address this research gap by providing empirical evidence on how AI-controlled marketing strategies influence consumer decision-making, brand perception, and engagement in the Indian retail sector. AI redefines marketing by enabling real-time personalisation, predictive analysis, and automated consumer interactions. As the Indian retail sector increasingly adopts AI-controlled marketing strategies, understanding their effects on consumer behaviour and brand engagement becomes essential. The study seeks to provide insights for retailers, marketers, and policymakers regarding the strategic potential of AI while addressing ethical and technological considerations. Furthermore, the research explores the moderating role of digital competence in the relationship between AI-driven personalisation and brand engagement. The findings aim to offer insights into how AI can strategically drive consumer and brand engagement, and overall marketing effectiveness in the retail sector.

2. Literature Review and Hypothesis Development

Artificial intelligence (AI) has changed the game for marketing, and now it can change how we market to our audiences. The practices for how companies interact with end users to modify their shopping behaviour and loyalty are changing with the arrival of AI-based tools, chatbots, recommendation engines, and mood analysis. This section reviews the existing scholarly literature on AI-driven marketing strategies and systematically examines how these strategies influence consumer behaviour and brand engagement, particularly in the Indian retail context. While several studies have examined AI applications in marketing, limited research has integrated these variables within a single comprehensive framework in emerging markets such as India.

2.1 AI-Driven Marketing Strategies and Consumer Purchase Intentions

The use of Artificial Intelligence (AI) has become a key tool for enhancing digital marketing, notably for influencing consumer sentiment. According to Chintalapati & Pandey (2022), AI innovations, such as predictions and personalised recommendations used for marketing purposes, enhance retailers' ability to obtain practical insights into consumer behaviour and market trends by processing vast volumes of information from multiple sources. Discoveries of this kind help marketers craft relevant marketing messages that engage individual consumers and thus increase their likelihood of purchase. Similarly, Bhagat et al. (2022) note that AI-driven personalisation significantly amplifies consumer intention and satisfaction. The research outlines that individual recommendations, behavioural objectives, chatbots, and virtual assistants play a determining role in making online advertising strategies more productive, resulting in stronger consumer engagement and increased conversions. The study by Kumar and Ramesh (2023) examines the variables that influence online buying decisions through AI-controlled digital marketing. The findings show that the practical applicability of AI, such as personalised marketing messages and predictive analytics, positively influences consumers' online purchase intentions. However, most prior studies have examined these AI tools independently rather than analysing their combined influence on consumer purchase behaviour in the Indian retail sector. Therefore, a contextualised investigation is required. Resting on the light of the above arguments, one may move to the following hypothesis:

Hypothesis 1: *AI-driven marketing strategies positively influence consumer purchase intentions in the Indian retail sector.*

2.2 AI-Powered Predictive Analytics in Inventory Management and Operational Efficiency

AI-driven predictive analytics has transformed inventory management, enabling real-time visualisation of stock levels and accurate demand forecasting. Businesses that forecast inventory purchases avoid retailers, surplus parts, or congestion, and as such enhance operations and customer experiences. Kumar and Ramesh (2024) also emphasise that AI technology eliminates human errors by automating real-time inventory perception and management. Automation leads to more efficient inventory management and contributes to overall operating efficiency—minimising situations outside of existence. AI analyses historical sales data to predict demand patterns and manage stock levels more effectively, leading to improved operational efficiency and customer satisfaction. Although prior studies recognise the operational benefits of predictive analytics, limited research connects these efficiencies directly with broader retail performance outcomes in the Indian context. Based on the light of the above arguments, the following hypothesis can be advanced:

Hypothesis 2: *AI-powered predictive analytics in inventory management lead to increased operational efficiency in Indian retail businesses.*

2.3 AI Chatbots and Virtual Assistants Enhancing Customer Satisfaction

AI chatbots and virtual assistants have become integral components of customer service in the retail sector and offer immediate support and personalised interactions. Bhagat et al. (2022) identify chatbots and virtual assistants as essential factors for improving the effectiveness of online advertising strategies. These AI-controlled tools offer personalised recommendations and support, leading to increased consumer commitment and satisfaction. (2021) supports these results and shows that high-quality Chabot interactions significantly improve customer satisfaction. The studies show that effective KS-controlled customer service tools can efficiently address a wide range of customer inquiries and provide timely, precise answers that improve the overall customer experience. In the Indian retail context, Kumar and Ramesh (2023) found that AI-driven personalisation, including chatbots and virtual assistants,

significantly improves consumer intentions and satisfaction. The paper states that these Artificial Intelligence tools have the final say in shaping customers' purchasing attitudes at online individual trading points. Despite these findings, empirical evidence examining chatbot efficiency and its behavioural consequences within the structured Indian retail ecosystem remains limited and requires further validation. It is in light of the above arguments that the following hypothesis may be advanced:

Hypothesis 3: *The use of AI Chatbots and virtual assistants enhances customer satisfaction in the Indian retail context.*

2.4 AI-Enabled Personalised Marketing Strategies and Brand Engagement

It is demonstrated that an I-enabled tailored marketing approach to brand engagement can be enhanced by offering customised content and offers to consumers. Hintalapati and Pandey (2022) explain how AI applications in marketing, such as personalised suggestions and customer insights, enable retailers to create marketing campaigns that are well received by individual consumers and thus improve brand commitment. Bhagat et al. (2022) also underline the role of personalised recommendations in the influence of consumer behaviour. The analysis reveals that personalised marketing strategies, behavioural goals, and predictive analyses powered by AI will lead to greater consumer commitment and more conversions. The actual use of personalised marketing subsequently positively influences human beings' online purchasing intentions. Studies have indicated that customised marketing communications and forecasting surveys enhance consumers' dedication to the brands and result in a positive brand image and loyalty. However, fewer studies have specifically examined how AI-enabled personalisation contributes to sustained brand engagement in emerging markets such as India, creating a clear empirical gap. Resting on the light of the above arguments, one can make the following hypothesis:

Hypothesis 4*: Personalisation strategies that are enabled by I enhance the engagement of brands among consumers within the Indian retail industry***.**

2.5 Mediation Analysis: Consumer Trust as a Mediator

Trust among consumers has been known to be a very important element in the design of consumer behaviour, particularly in online and digital contexts. Trust influences various aspects of consumer decision-making, including intentions to buy (GEFS, 2000). The role of trust in the context of AI-controlled technologies, such as chatbots, is equally important. Studies have shown that effective chatbots can increase consumer trust by providing timely, relevant, and consistent information (Hussain et al., 2021). When consumers trust technology, they are more likely to develop positive feelings toward the brand, which, in turn, increases their intentions to buy (Chen et al., 2018).

The consumer's trust is crucial, as the chatbot's efficiency not only affects the consumer's intention to buy but also, indirectly, builds trust. Therefore, several studies have emphasised that efficient chatbots enhance the overall customer experience, thereby promoting trust and increasing consumers' willingness to engage with brands (Pereira et al., 2022). Nevertheless, limited research has empirically tested consumer trust as a mediator between chatbot efficiency and purchase intentions in the Indian retail sector (Sashi, 2012). In light of the aforementioned arguments, the following hypothesis can be suggested:

H5*: Consumer trust mediates the relationship between Chatbot efficiency and purchase intentions.*

2.6 Moderation Analysis: Digital Literacy as a Moderator

Digital literacy is becoming a crucial concept as technology becomes increasingly relevant to consumers' lives. Definition: Digital literacy is the ability to use, understand and access digital technology. Research has also found that highly digitally-literate individuals are more likely to comprehend and trust AI-optimised systems (Venkatesh & Bala, 2008). Further, regarding AI-based personalisation, digital literacy is likely to enhance the effectiveness of personalised marketing strategies as digitally enabled consumers engage with and understand the benefits of these technologies (Liu et al., 2019). It has been suggested that digital literacy may serve as a moderator in the relationship between use of technology and consumers' commitment (Van Deursen et al., 2014). It could be one of the factors suggesting that the higher a consumer's level of digitalisation, the greater the likelihood they encounter personalised information from AI systems. In addition, digital competence enables consumers to make more well-founded decisions, which reinforces the relationship between AI-controlled personalisation and brand engagement (Shankar et al., 2020). If AI-controlled personalisation develops, the moderating role of digital literacy will become increasingly important, as it enhances consumers' ability to fully benefit from a personalised experience (Fulgoni, 2018). However, empirical research examining digital literacy as a moderating variable in AI-driven personalisation models within emerging retail

markets remains insufficient. This hypothesis posits that chatbot effectiveness directly influences consumer trust and, in turn, consumer intentions to purchase. Thus, the following hypothesis is proposed:

H6*: Digital literacy moderates the relationship between AI-driven personalisation and brand engagement.*

3. Theoretical Framework

The proposed research has a solid theoretical basis, combining the Technology Acceptance Model (TAM), the Stimulus-Organism-Response (S-O-R) framework, the Commitment-Trust Theory of Relationship Marketing, and Digital Literacy Theory. By combining these theoretical approaches, it is possible to provide a detailed description of the effects of AI-based marketing strategies on consumer confidence, purchase intentions, brand involvement, and customer loyalty in the Indian retail market. Given the technological sophistication and behavioural consequences of AI implementation in the retail sector, a multi-theoretical framework is required to elaborate on technology acceptance and the relational marketing implications in the emerging world.

This study draws on the Technology Acceptance Model (Davis, 1989) as its main theoretical background. According to TAM, perceived usefulness and perceived ease of use are the determinants of users' behavioural intentions towards a technological system. Consumer behaviour intentions are more likely to develop when a consumer sees a system as helpful in improving their decision-making efficiency and finds it easy to interact with. When it comes to AI-based marketing, perceived usefulness is boosted by personalisation algorithms, predictive analytics, chatbot interfaces that provide relevant recommendations, real-time assistance, and increased shopping efficiency. These AR technologies also make interaction processes easier, thereby enhancing perceived ease of use. Using the TAM framework, one can say that AI-based marketing strategies positively impact consumer purchase intentions and brand engagement. Moreover, effective chatbot systems make digital interactions more trustworthy by minimising uncertainty and increasing the perceived reliability of the system.

Although TAM describes the process of technology adoption, the Stimulus-Organism-Response (S-O-R) model (Mehrabian and Russell, 1974) provides insight into the psychological processes underlying consumer behaviour. S-O-R paradigm postulates that the environmental stimuli have effects on the internal cognitive and emotional conditions (organism), which in turn affect behavioural responses. The AI-based marketing strategies serve as technological stimuli in this study. Such new stimuli affect internal psychological factors such as consumer trust, perceived reliability, and confidence in systems built with AI capabilities. Such in-house assessments subsequently lead to behavioural outcomes, such as brand participation and loyalty, and purchase intentions. The S-O-R model then justifies the mediating role of consumer trust in the relationship between chatbot efficacy and buy intention, as well as in the transformation of technological encounters into behavioural reactions.

The relational aspect of this study is further asserted by the Commitment-Trust Theory of Relationship Marketing (Morgan and Hunt, 1994). According to the theory, trust and commitment are the key factors in successful long-term relationships between firms and customers. Personalised interactions and effective chatbot systems in AI-enabled retail businesses increase perceived reliability, leading to perceived transparency and responsiveness and fostering trust. By gaining trust in AI-created systems, consumers will be more willing to interact with the brand and have a higher purchase intention. Customer loyalty develops over time through brand engagement. In this way, trust can be considered a direct predictor of purchase intention and a mediating variable between the efficiency of AI-based chatbots and consumers' behavioural outcomes.

Moreover, Digital Literacy Theory provides the theoretical background for the study's moderator role in digital literacy. Digital literacy is the set of skills a person needs to access, comprehend, and use digital technologies effectively. Customers who are more digitally literate are better positioned to make sense of algorithm-based recommendations, scrutinise AI-generated content, and communicate with chatbots. This will also mean that digitally literate consumers are more likely to be influenced by AI-based personalisation in brand engagement. Digital literacy thus mediates the success of AI-driven personalisation in improving brand engagement, especially in emerging markets like India, where digital capabilities across consumer groups vary widely.

Using TAM, S-O-R, Commitment-Trust Theory, and Digital Literacy Theory, this study introduces a multidimensional conceptual model in which AI-based marketing tools, as technological stimuli, affect internal psychological processes (consumer trust), which in turn

mediate behavioural changes (purchase intention, brand engagement, and customer loyalty). Moreover, the quality of these relations depends on consumers' digital literacy. This conceptually based model offers a systematic explication of AI-inspired consumer behaviour and serves as the foundation for the formulation and empirical analysis of the study's hypotheses through Structural Equation Modelling (SEM).

4. Research Methodology

This study applies a quantitative approach to explore the impact of AI on marketing strategy changes and focuses directly on consumer behaviour and brand engagement in the Indian retail industry. A structured questionnaire serves as the main data-collection instrument to obtain standardised responses, enabling statistical analysis. This study seeks to investigate how consumers interact with AI-driven marketing tools during their purchase journeys, such as personalised recommendations, AI chatbots, and predictive analytics.

Research Design and Approach

A descriptive and causal study design is used to measure the relationship between AI-based marketing decisions and consumer response. Descriptive research is useful for understanding the broad patterns of AI adoption, and causal research can be employed to discern cause-and-effect relationships among AI use, shifts in purchase intentions, branding participation, and customer satisfaction. This dual strategy enhances the informativeness and generalizability of study findings.

Sample Selection and Size

The research uses non-probability purposive sampling and focuses on the group previously exposed to an AI advertising strategy in retail. The sample size for the study is 450 participants, calculated using the Yamane (1967) formula, with sufficient statistical power to conduct meaningful analysis**.** The sample is drawn from specific metro cities in India (Mumbai, Delhi, Bengaluru, and Hyderabad), where AI-based marketing strategies are frequently used.

Data Collection Methods

Primary data is obtained through structured online surveys, which are followed up via social media, email invitations, and collaboration with online retail brands. Key aspects to capture in the questionnaire include AI-controlled personalisation, predictive analysis, Chatbot dialogues, consumer reliability, and intent to purchase products related to the brand. The survey uses a Likert scale (1 = strongly disagree to 5 = strongly agree) to measure consumers' perceptions and experiences with AI-based marketing strategies.

Measurement of Variables

The variables to be measured using existing scales that will provide reliability and consistency of the research data. AI-controlled marketing strategies are measured using a scale developed by Chintalapati and Pandey (2022) that focuses on the various AI tools and techniques used in personalised marketing, e.g., chatbots, predictive analytics, and personalised recommendations. This scale measures how strongly consumers feel that the application of AI in marketing is applicable, successful, appropriate, and effective. The intention-to-buy consumer behaviour scale is used by Bhagat et al. (2022) to assess the likelihood that a consumer will purchase following exposure to AI-controlled marketing strategies. The scale assesses the perceived relevance of marketing messages, the impact of personalised recommendations, and the overall persuasiveness of marketing driven by AI.

The commitment of the brands is measured using a scale developed by Kumar and Ramesh (2023), which focuses on the emotional connection and the commitment a consumer feels toward a brand resulting from AI-controlled marketing strategies. The scale encompasses factors such as consumer interaction, attention, and emotional proximity to the brand, and all of these are related to how AI can be used to improve relations between consumers and brands. Customer satisfaction, another key variable in this study, is measured using the scale developed by Nichifor et al. (2021). The scale measures consumers' satisfaction with their overall experiences involving AI-controlled marketing interactions. It captures various aspects, including user-friendliness, usefulness, and perceived value of AI-based tools, with the emphasis on how far they contribute to the brand's overall satisfaction.

In this study, we assume that consumer trust will mediate the relationship between AI-controlled marketing strategies (such as chatbots and personalised recommendations) and consumer intentions. Consumer trust is crucial, as it underpins consumer decisions about whether to contact the brand through AI-controlled interactions. As shown in previous research (Gefen, 2000; Hussain et al., 2021), when consumers trust AI systems, they are more likely to engage with the brand and complete a purchase. Additionally, we

expect digital competence to moderate the association between AI-controlled personalisation and brand engagement. Audience selections with greater digital literacy should be more positively influenced by AI-enhanced experiences because they can communicate with these technologies and comprehend them. And this hypothesis of moderation assumes that digital competence equips individuals to surf the web wisely and enhances their capability to cope with personalised content (Liu et al., 2019; Deursen et al., 2014).

Data Analysis Techniques

Advanced statistical analyses were conducted for the current study. Descriptive statistics were applied to all demographic characteristics and overall respondent patterns. Exploratory factor analysis (EFA) was used to examine the extent of influence of factors affecting AI-based marketing strategy and its effects on consumer behaviour. Structural Equation Modelling (SEM) was applied, together with mediation and moderated mediation analyses, to verify this study's theoretical model through mechanism analysis and causal inference. The hierarchical regression test was also applied to support moderating and mediating effects and provide elaborate interpretations on other variables, including consumer trust and digital skills.

5. Results

Descriptive Statistics

The descriptive statistics section summarises respondents' demographic information and provides an overview of their interactions with AI-controlled marketing strategies. The sample comprised 450 respondents from large metropolitan areas in India, including Mumbai, Delhi, Bengaluru, and Hyderabad. The graphical demographic breakdown of the respondents is depicted in Table 1 below. The demographic results show that the majority of respondents were male (56%), while 44% were female, indicating a rather balanced gender distribution in the sample. Regarding age, 43.3% of the participants were aged 25-34, the largest group. The second category was 18-24-year-olds, who accounted for 25.6 per cent of the individuals surveyed.

The remaining respondents were evenly distributed across the 35 to 44-year and 45-year age groups. Concerning education, an essential part of the sample (54%) had a postgraduate degree, while 26.9% graduated in basic studies and 19.1% had professional qualifications. These results indicate a highly educated pool of respondents.

Table 1: Descriptive Statistics

Variable	Category	Frequency (N=450)	Percentage (%)
Gender	Male	252	56.0%
	Female	198	44.0%
Age Group	18-24 years	115	25.6%
	25-34 years	195	43.3%
	35-44 years	98	21.8%
	45 and above	42	9.3%
Education	Undergraduate	121	26.9%
	Postgraduate	243	54.0%
	Professional Degree	86	19.1%
Role in Marketing	Marketing Manager	110	24.4%
	Digital Marketer	100	22.2%
	Brand Strategist	90	20.0%
	General Consumer	150	33.3%
Work Experience	Less than 5 years	160	35.6%
	5-10 years	180	40.0%
	More than 10 years	110	24.4%
AI Exposure	High Exposure	140	31.1%
	Moderate Exposure	180	40.0%
	Low Exposure	130	28.9%

The distribution of professional experience shows that 40% of respondents had 5-10 years of experience, followed by 35.6% with less than 5 years and 24.4% with over 10 years. These figures show that a considerable number of respondents were professionally involved in the marketing industry, which made their findings valuable for the study. Regarding AI exposure, 31.1 per cent were highly exposed, 40 per cent were moderately exposed, and 28.9 per cent were less exposed. This indicates that a large proportion of respondents had knowledge of AI-mediated targeted marketing techniques and confirms the research's aim of learning more about AI's contribution to consumer behaviour and brand dedication. These demographic results show that a good sample of professionally experienced, technologically astute, and well-trained respondents has been incorporated in the study. This provides a good foundation for examining how AI-controlled personalisation, predictive analytics, and chatbot efficiency would affect consumer trust, brand commitment, and customer loyalty in the retail sector.

Reliability and Validity

The reliability of the constructs was assessed using Cronbach's alpha, a measure of internal consistency. The results of reliability and validity are presented in Table 2 below. Every argument in the study had high reliability, with the coefficient well above the acceptable range of 0.70. The reliability coefficients for each construct were as follows: AI-controlled personalisation ($\alpha = 0.88$), chatbot efficiency ($\alpha = 0.85$), predictive analyses ($\alpha = 0.87$), consumer trust ($\alpha = 0.90$), and brand engagement ($\alpha = 0.86$). The findings indicate that the scales of measurement employed in this research exhibit excellent internal consistency.

Validity Analysis: For construct validity, both refer to exploratory factor analysis (EFA), and the other is confirmatory factor analysis (CFA). The results of EFA indicated that the data file was appropriate for factor analysis, with a Kaiser-Meyer-Olkin (KMO) value of 0.876 and a Bartlett's Test of Sphericity significant ($\chi^2 = 3142.56$, $p < 0.001$). In addition, the extracted AVE for all factors was higher than 0.50, and therefore, it confirmed the convergent validity of the measurement model. The CFA results also showed a good fit for the model, with all adaptation indices (CFI = 0.935, TLI = 0.921, RMSEA = 0.046, SRMR = 0.039) within the recommended threshold values. These results confirm the validity of the constructs used to measure marketing strategies, AI-controlled consumer behaviour, and brand involvement.

To identify the key factors influencing consumer behaviour and brand commitment, an exploratory factor analysis (EFA) was conducted. Principal component analysis (PCA) with Varimax rotation was used to extract meaningful factors. The Kaiser-Meyer-Olkin (KMO) value for the appropriateness of the samples was 0.876, indicating that the sample size was suitable for the factor analysis. In addition, Bartlett's Sphericity Test was significant ($\chi^2 = 3142.56$, $p < 0.001$), confirming that the data were suitable for factor analysis by indicating the presence of correlations among variables.

Factor Extraction

The factor-extraction process identified five key factors, with more than 1, which together explained 72.5% of the total variance, indicating strong explanatory performance. The extracted factors were: AI-controlled personalisation, chatbot efficiency, predictive analysis, consumer trust and brand engagement. Among these, AI-controlled personalisation was the most dominant factor, with an eigenvalue of 3.85, accounting for 21.2% of the variance. This underscores the importance of personalised AI-based marketing efforts in shaping consumers' intentions. The detailed results are shown in Table 3 below.

Table 2: Reliability and Validity

Factor	Cronbach's Alpha (α)	KMO Measure	Bartlett's Test	AVE
AI-driven Personalization	0.88	0.876	$p < 0.001$	0.57
Chatbot Efficiency	0.85	0.876	$p < 0.001$	0.55
Predictive Analytics	0.87	0.876	$p < 0.001$	0.52
Consumer Trust	0.90	0.876	$p < 0.001$	0.59
Brand Engagement	0.86	0.876	$p < 0.001$	0.54

Exploratory Factor Analysis (EFA)

Table 3: Factor Extraction

Factor	Eigenvalue	Variance Explained (%)
AI-driven Personalisation	3.85	21.2%
Chatbot Efficiency	2.96	17.4%
Predictive Analytics	2.53	14.6%
Consumer Trust	2.21	12.5%
Brand Engagement	1.89	9.8%

The second factor, chatbot efficiency, had an equal value of 2.96 and explained 17.4% of the variance. This increases the role of AI-controlled chatbots in improving the customer service experience and, in turn, consumer trust and satisfaction. The predictive analysis with an Eigenvalue of 2.53 accounted for 14.6% of the variance, underscoring the growing impact of AI-driven predictive tools on consumer expectations and the branding process.

The fourth extracted factor, Consumer trust, had a value of 2.21, accounting for 12.5% of the variance. This underscores the fundamental role of trust in AI-driven marketing strategies, especially amid growing concerns about data protection and consumer security. Lastly, the fifth factor, with an equal score of 1.89, was commitment to the brands, and this factor accounted for 9.8 per cent of the variance. This implies that customer relations amongst customers who have received AI reinforcement have immensely impacted long-term consumer relations and brand engagement. On the whole, these findings demonstrate that trust in the consumer and brand operations can be defined by the relevance of AI-controlled personalisation, chatbot performance, and predictive analytics. The findings highlight the transformative aspects of AI in contemporary promotional plans and offer businesses a reflection on the rationalisation of AI-driven technologies to enhance customer experiences and stimulate organisational development.

Confirmatory Factor Analysis (CFA)

In order to validate the measurement model derived from the EFA, a confirmatory factor analysis (CFA) was carried out. Adaptation indices of the CFA model indicated that the measurement model was well-fit. The χ^2/df ratio of 2.45 was also lower than the acceptable level of 3.0, and the RMSEA of 0.046 indicates that the model fits well. The CFI (0.935) and TLI (0.921) were above the recommended threshold of 0.90, indicating that the model fits the data adequately. It also yielded an SRMR value of 0.039, which is much lower than the recommended value of 0.08, further supporting the model's relevance. These findings indicate that the measurement model adopted in the research is valid and, therefore, the relationships between AI-controlled marketing strategies, consumer behaviour, and brand engagement are accurately captured. The detailed results are shown in Table 4 below.

Structural Equation Modeling (SEM) and Hypothesis Testing

The structural equation model (SEM) was used to examine the relationships between AI-controlled marketing strategies, consumer behaviour, and brand engagement. The results of the path analysis are summarised in the following table 5, which provides the standardised regression weights (β), T-values , and P-values for each hypothesis. The detailed results of the structural equation model are shown in Table 5 below.

Table 4: Confirmatory Factor Analysis

Fit Index	Threshold	Observed Value
χ^2/df (CMIN/DF)	< 3.0	2.45
RMSEA	< 0.08	0.046
CFI	> 0.90	0.935
TLI	> 0.90	0.921
SRMR	< 0.08	0.039

Table 5: Structural Equation Modelling

Hypothesis	Path	Standardised β	t-value	p-value	Result
H1	AI- driven personalisation → Purchase Intentions	0.472	4.85	<0.001	Supported
H2	Chatbot efficiency → Consumer Trust	0.396	3.92	<0.001	Supported
H3	Predictive Analytics → Brand Engagement	0.431	4.12	<0.001	Supported
H4	Consumer Trust → Purchase Intentions	0.521	5.23	<0.001	Supported
H5	Brand Engagement → Customer Loyalty	0.489	4.87	<0.001	Supported

The results of the SEM analysis support all five hypotheses. The paths between AI-controlled personalisation and intentions (β = 0.472, p <0.001), chatbot efficiency and trust of the consumer (β = 0.396, p <0.001), predictive analysis and brand engagement (β = 0.431, p <0.001), trust - and intentions of the consumer (β = 0.521, p <0.001), the commitment of the brands and customer loyalty (β = 0.489, p <0.001) were statistically significant. These results show that AI-controlled marketing strategies significantly influence consumer behaviour and brand commitment in the Indian retail sector, ultimately leading to increased customer loyalty.

Mediation Analysis: Consumer Trust as a Mediator

The mediation analysis aimed to examine whether consumer trust mediates the relationship between chatbot efficiency and intentions. Boat trapping with 5000 Resamples was used for the analysis. The results showed significant findings on all paths. The detailed results of the mediation analysis are shown in Table 6 below.

The first path examined the relationship between chatbot efficiency and consumer trust(Path A). This relationship was positive and significant (β = 0.396, p <0.001), which indicates that an increase in chatbot efficiency leads to an increase in the trust of consumers in the brand. The second way (path B) examined the relationship between consumer trust and intentions. The impact of the trust of the consumer on purchase intentions was also significant (β = 0.521, p <0.001), which indicates that a higher level of trust in the intentions of consumers positively influences a purchase. The third path (path C) showed that Chatbot efficiency significantly influenced intentions to buy (β = 0.472, p < 0.001), indicating that efficient chatbots positively influence purchase decisions.

Table 6: Mediation Analysis (Consumer Trust as Mediator)

Path	Effect	Standard Error (SE)	t-value	p-value	Result
Chatbot Efficiency → Consumer Trust (a)	0.396	0.041	3.92	<0.001	Significant
Consumer Trust → Purchase Intentions (b)	0.521	0.039	5.23	<0.001	Significant
Chatbot Efficiency → Purchase Intentions (c)	0.472	0.046	4.85	<0.001	Significant
Indirect Effect (a × b)	0.215	0.027	-	<0.001	Significant
Direct Effect (c') (After Mediation)	0.257	0.045	3.28	0.001	Partial Mediation

In addition, the indirect effect of chatbot efficiency on purchase intentions due to the trust of the consumer (a × b) was significant (β = 0.215, p <0.001), which confirms that the consumer trust partially mediates the relationship between chatbot efficiency and intentions conveyed. Even after controlling for the mediation effect of consumer trust, the direct effect of chatbot efficiency on purchase intentions remained significant (β = 0.257, p = 0.001), indicating that chatbot efficiency continues to influence purchase intentions, albeit partly through consumer trust. These results support the hypothesis that the trust of the consumer conveys the relationship between chatbot efficiency and intentions and demonstrates both direct and indirect effects. The mediation analysis shows a partial mediation in which the trust of the consumer plays an important role in strengthening the effects of chatbot efficiency on the purchase decisions of consumers.

Moderation Analysis: Digital Literacy as Moderator

The moderation analysis tested whether digital competence moderates the relationship between AI-controlled personalisation and brand engagement. A hierarchical regression analysis was used to evaluate the interaction effects. The detailed results of the moderation analysis are shown in Table 7 below.

The first model tested the direct relationship between AI-controlled personalisation and brand engagement. The results showed a significant positive effect (β = 0.431, p <0.001), which points out that AI-controlled personalisation significantly improves the commitment of consumer brands. In the second model, it was found that digital literacy has a positive and significant influence on brand engagement (β = 0.289, p <0.001), which indicates that higher digital literacy values lead to increased engagement of consumers with brands. The third model comprised the interaction between AI-controlled personalisation and digital literacy, which was found to be significant (β = 0.274, p = 0.002).

This result shows that digital literacy moderates the relationship between AI-controlled personalisation and brand engagement. Consumers with a higher level of digital literacy have a stronger positive relationship between AI-controlled personalisation and brand engagement compared to people with lower digital literacy levels. The inclusion of the interaction term explained an additional variance of 6.3% in brand engagement (R^2 Change = 0.063), which emphasises the significant moderating effect of digital competence. The moderation analysis confirms that digital competence increases the effect of AI-controlled personalisation on the commitment of the brands. Consumers who are digitally triggered experience a stronger influence of AI-controlled personalisation on their occupation with brands and emphasise the importance of digital competence to maximise the effectiveness of AI-controlled marketing strategies.

6. Discussion and Conclusion

This study will contribute to the few studies in the literature that have been developed around the influence of AI-controlled marketing strategies on consumers. The findings collectively support the integrated theoretical framework combining the Technology Acceptance Model (TAM), the Stimulus–Organism–Response (S-O-R) paradigm, and Commitment–Trust Theory, thereby offering a unified explanation of AI-driven consumer behaviour in the Indian retail context. The positive association between AI-mandated personalisation and intentions (β = 0.472) is directed towards, based on previous research which revealed that custom-made marketing initiatives build consumer commitment and would result in purchase intention (Arora et al., 2020). Personalisation has been found to significantly enhance consumer satisfaction because consumers feel more understood and cared for

Table 7: Moderation Analysis (Digital Literacy as Moderator)

Model	β (Coefficient)	SE	t-value	p-value	R^2 Change
AI-driven Personalization → Brand Engagement	0.431	0.038	4.12	<0.001	-
Digital Literacy → Brand Engagement	0.289	0.041	3.75	<0.001	-
Interaction Term (AI-driven Personalization × Digital Literacy)	0.274	0.045	3.14	0.002	0.063

when they are presented with personalised recommendations and offers (Luo et al., 2021). This result is consistent with that of de Haan et al. (2020), who show that consumers tend to respond more favourably to marketing actions tailored to their personal tastes and needs. From a TAM perspective, this finding reflects the role of perceived usefulness and ease of use in strengthening behavioural intentions. The effect of conversational AI efficiency on consumers' trust (β = 0.396) further emphasises the significant power of Convers -AI as a means for determining the brand's legitimacy. Earlier studies by Van der Heijden (2021) suggest that efficient, intelligent chatbots improve the general customer service experience and lead to higher trust of consumers and satisfaction. When chatbots have the chance to answer consumer questions with a perfect response immediately, it will create the illusion of reliability that will impart specific orientation to the current age, since customers are getting more demanding and are becoming sensitive regarding fast transactions. This knowledge reflects the work of Kim and Lee (2022), who found that customer service tools from AI-powered customers improve customer satisfaction and trust by offering quick, consistent and precise answers. Consistent with the S-O-R framework, chatbot efficiency acts as a technological stimulus that enhances internal psychological states, particularly trust, which subsequently shapes behavioural responses.

Furthermore, the dimension of predictive analysis plays a significant role in brand engagement (β = 0.431), as they emphasise the importance of anticipation of consumer preferences and desires. Retailers are using predictive analytics to gain insights from customer data and predict future shopping habits in order to develop more precise marketing campaigns (Chaffey, 2020). The findings in this study are consistent with those of Sahu and Shucla (2021), where the predictive analysis provides a better brand performance by delivering the right message to the right customers at the right time. The application of AI, such as machine learning and predictive models, to better comprehend and influence consumers is increasingly pervasive with increased adoption of AI by leading global retailers (Brynjolfson & McAfee, 2017). The findings of the study are also consistent with previous literature on the effects of trust on purchase intentions (β=0.521). Trust has been acknowledged as the keystone in successful customer relations (Morgan & Hunt, 1994). Now that customers are increasingly aware of data privacy and cybersecurity, cultivating trust among companies that apply AI in marketing becomes even more important. This finding confirms the work of Lu et al. (2020), who argue that trust in AI-controlled systems, especially in areas that affect data protection, significantly influences the behaviour of the consumer. These results further reinforce the Commitment–Trust Theory by demonstrating that trust functions as a central mechanism linking AI-enabled interactions to long-term relational outcomes.

Finally, the study underlines the relationship between brand engagement and customer loyalty (β = 0.489), emphasising that committed customers of a brand remain loyal. This result supports the results of Kumar and Shah (2020), who argue that the commitment of brands that were promoted by personalised experiences and AI-controlled knowledge leads to higher customer loyalty. The product brands which constantly may engage their consumers and, thus, establish mutual, meaningful interactions diversify long-term commitment and reduce the rate of emigration. In addition, the use of predictive analyses to improve brand engagement, with the research of Sahu and Shucla (2021) is well received, which demonstrated that predictive modeling and AI technologies increase customer loyalty by providing consumers with more relevant content. In addition, the determination of the study that the trust of the consumer has a significant impact on the intentions of the purchase, the work of Morgan and Hunt (1994), who have identified trust as a fundamental factor for the design of customer relationships. The paper also adds the existing body of knowledge on the topic of brand engagement on customer loyalty. Earlier studies such as those of Kumar and Shah (2020) have emphasised the direct connection between consumer loyalty and brand engagement. The findings of this paper still confirm the notion that a high level of a commitment prompted by interactions operated by AI can garner a long-run consumer loyalty. Collectively, these findings validate the integrated conceptual framework proposed in this study, where AI-driven strategies influence behavioural outcomes through trust-building and engagement mechanisms.

The results of mediation and moderation analysis conducted in the present research offer important information about the mechanisms through which AI-controlled marketing strategies/strategy change the consumer behaviour and commitment of the brands. The mediation analysis demonstrates that consumer trust is a major mediator in the relationship between such AI-controlled marketing strategies as chatbots and personalised recommendations and the intentions of the consumer. In particular, the results

show that AI-controlled marketing strategies increase consumers' trust, which in turn increases the likelihood that consumers make a purchase. The important role identified in this finding, which occurs during the process of designing consumer decisions in the co-relationship with the AI-driven marketing tools, is what establishes the fact that consumer trust is neither a mere outcome of the co-relationship process but also a key-driving force in the buying behaviour. Also, to a certain extent, the analysis illustrates mediation, i.e., one can see that direct and indirect effect contribute to the overall relation, and the trust increases the effects of AI on the purchase intentions. This mediating mechanism is theoretically grounded in the S-O-R paradigm, where trust represents the organismic state translating technological stimuli into behavioural responses.

Conversely, moderation analysis indicates that the digital literacy changes the interaction between the AI controlled personalisation and brand engagement. The findings indicate the higher positive correlation between the AI-controlled personalised marketing and the brand commitment of consumers who possess a higher rate of digital literacy. This explains the necessity of digital competence in the enhancement of the performance of AI-based marketing strategies. It has been shown that consumers who are more conversant with the digital products and technologies will be in a better place to comprehend, as well as value, personalised marketing initiatives, and this will determine greater emotional attachment, as well as brand commitment. The noticeable moderating influence of digital literacy also reveals the necessity that marketers should consider various digital literacy among whom they are targeting in the formation of AI-managed personalised marketing campaigns. This moderation effect strengthens the theoretical contribution of the study by demonstrating that the effectiveness of AI-driven personalisation is contingent upon consumers' digital capabilities, thereby consolidating the proposed integrated framework.

7. Practical and Social Implications

Application implications of the research also matter to the companies interested in introducing AI-controlled marketing tools to their business. First and foremost, the results emphasise how important it is to invest in AI-operated personalisation instruments to improve consumers' commitment and increase the intention of purchase. The retail stores and companies must leverage the power of AI to understand consumer interests and deliver personalised marketing messages, as well as offers and recommendations. This way, they will be able to create wider and richer consumer experiences, something critical for improving customer satisfaction and loyalty in a fiercely competitive environment. Moreover, this paper also points out that the extent to which users trust a chatbot is an influential factor in how efficient it is. For businesses, they should start paying attention to creating AI-backed virtual agents capable of answering audience questions quickly and accurately**.** A frictionless and quick-response customer service experience does more than just elevate satisfaction among customers; it enhances the relationship with them. There should be investment in the learning of relevant AI systems to facilitate handling more challenging questions while retaining a human touch that enhances confidence and accountability. It also focuses on predictive measurement as a key driver of brand engagement. Note this. Again, it is important to consider the fact that the retailers are strategic or rational agents over consumers and use predictive modeling techniques too, not only before but also the actors of marketing on consumers also count static. And by this process of prediction, companies are encouraged to shrink-wrap their marketing up to that higher level, which generates ever more brand exposure and wealth in return. minutes remaining. Integrating AI technologies across the company will allow it to better adapt to shifting customer expectations in the future and function as a driver of long-term growth.

The social relevance of this study is related to the growing importance of AI in shaping consumer behaviour and how it influences society in general. AI control over different aspects of the marketing mix has both positive and negative social consequences. Because of AI, such personalised services and products will become accessible to all, creating fairer and more inclusive consumer experiences. By analysing consumer data and preferences, personalised, topical and real-time offering of consumer goods/services with the capacity to enrich everybody's total individual experiences can be exposed. However, becoming increasingly dependent on AI brings concerns of data privacy and security, too. As AI systems can gather huge volumes of consumer data and analyse it, there is increasing pressure that there should be transparency with regard to using such data. The lack of trust in AI-driven marketing systems may be caused by the apprehension of consumers regarding the possible use of their personal information in an abusive manner. Therefore, businesses should take

precautionary measures to safeguard the information of the consumers and ensure that their AI applications are ethical. Companies should be very forthcoming in informing consumers about how their data is acquired, maintained, and utilised, thereby making them feel secure. Moreover, the diffusion of the use of AI in marketing might also strengthen pre-existing social injustices. In case some consumer groups are under-represented because of the AI algorithms in question, the social outcome might become unintentional. As an illustration, an AI system may end up de facto eternalising biases and relying on which personalised offers or marketing communications should not leave out particular demographic data. The companies should further guarantee that their AI systems are inclusive and equitably formulated and provide equitable access to marketing choices to all buyers, regardless of their heritage.

Practical and social implications of this research point to the fact that the policies of encouraging consumer trust and adjusting the marketing strategies on the AI-control to digital literacy are essential. Firms must focus on creating trust in the form of transparency and personalisation to enhance intentions of the purchase, and at the same time, to modulate the complexity of AI tools in the form of consumption knowledge. Emotional connections and better brand commitment levels can be achieved as the marketing efforts become personalised with the use of AI. Socially, the enhancement of digital literacy, particularly of the underserved groups serving as enablers to the consumers, will enable them to make increasingly sound decisions. Moreover, such ethical AI as ensuring the security of data protection and the open description of the role of AI is of paramount importance to continue the trust of consumers and the establishment of a fair digital market. Developing digital and ethical AI utilisation, companies and society can utilise the benefits of AI-guided marketing tactics in a sustainable and efficient manner.

8. Limitations and Future Research Directions

This paper offers good information on the role of AI-based marketing control on consumer behaviour, which is, however, limited. An important restriction is the focus on a single geographical region (India), which can restrict the generalizability of the results to other markets with different consumer behaviour and cultural contexts. In future, it may be able to present the findings of the study to other contexts, such as the presence of developed markets, to see whether the effects of controlled marketing strategies by AI have the same impact on consumer behaviour across the different types of population groups. The other limitation is the belief placed on self-reported information that can be distorted, as in social desirability or inappropriate callback. In future investigations, an experimental or longitudinal study would be appropriate to determine causality and to track consumer behaviour in the long run. The research reviews several aspects of AI-controlled marketing, whereas, at the same time, it does not fully explore the possible adverse consequences, such as the protection of information or automation transfer. It would be possible to investigate these issues further and analyse how companies can balance the need to personalise with protecting the consumer.

Finally, this research study only deals with the direct impact of strategies under the control of AI, disregarding possible moderating variables like demographic data of the consumers or psychological traits. The effectiveness of AI marketing tools and a more nuanced knowledge about how consumers of different types respond to AI-controlled marketing might be explored in future research on how age, education, or personality factors impact the effectiveness of AI marketing tools. In general, future studies should be focused on widening the frames of the current study by considering different geographical frames, applying different research methods, and studying the possible adverse outcomes of AI marketing. This shall provide a deeper insight into how AI can be useful in formulating consumer behaviour design and criteria in the use of more efficient and accountable marketing plans.

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Agri-business Supply Chain Scenario in India: A Systematic Literature Review with Special Reference to Jharkhand

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Abstract

Purpose: The purpose of this study is to explore the existing state of the Indian agri-business supply chain and specifically of the state of Jharkhand through an extensive literature review.

Methodology/Approach: The methodology used here is a *Systematic Literature Review* (SLR) on the area of agri-business supply chain. In accordance with the PRISMA guidelines, 268 papers were selected for review from various databases, including ScienceDirect, Emerald, Wiley, and Taylor & Francis. These papers were published between 2014 and 2024, and in early 2025. VOS viewer software is used for Bibliometric analysis.

Findings: Analysis shows that research on the agri-business supply chain in the Indian context is at a nascent stage, with very few papers specifically for Jharkhand. According to the NABCON study in 2022, food losses in India's supply chain are estimated at 6.4%, equivalent to 1.52 lakh cr. Issues found in Jharkhand include poor infrastructure, limited rural road connectivity, limited market information for farmers, a high number of intermediaries, and poor coordination among supply chain partners. Significantly, storage capacity in Jharkhand is very low (15%) compared to agri-food production, whereas the All India average is 22%.

Implications: **U**sing Bibliometric analysis, the present study extensively reviews the literature from 2014 to February 2025 on agri-business supply chains, including their barriers and prospects. Findings highlight growing interest in applying Industry 4.0 technologies such as Blockchain, IoT, and AI to enhance performance and sustainability. However, challenges such as storage, transport, rural infrastructure, farmer awareness, and market access require substantial government support and policies to enhance overall system performance. **Originality/Value:** India is basically an agricultural country. The Government of India invests heavily in agriculture. Also, the state of Jharkhand has strong growth potential. Yet, limited research on supply chains hinders sustainability. This study adds to the agribusiness literature by focusing on Jharkhand.

Keywords: *Agri-business Supply Chain, Challenges, Post-harvest Losses, Cold Chain Management, Industry 4.0, Sustainability.*

Paper Type: Literature review

1. Introduction

1.1 *Agriculture Scenario in India: at a Glance*

Agriculture has an essential role in the Indian economy. 54.6 per cent of the total workforce is involved in agriculture and related sector activities. Current research shows that agriculture and allied sector activities account for 18.4% of India's Gross Value Addition (GVA) for the year 2022-'23 (Ministry of Agriculture report, 2023). India is the world's 2nd-largest producer of agricultural products (food grains), with 329.69 million tons in 2022-'23, accounting for 16.3% of India's GDP in 2022-'23 (Ministry of Agriculture, 2023).

1.1.1 *Agriculture Scenario in Jharkhand*

Jharkhand, a newly created state of India in 2000, was formerly a part of Bihar. The rural economy in the state is dominated by smallholder rainfed agriculture farming (Singh, 2015). Agriculture and related activities play a pivotal role in Jharkhand's development, driving employment generation, supplying essential raw materials and fostering rural livelihoods. Approximately 80 percentage of the rural population is engaged in agriculture.

The share of agriculture and related activities in the Gross State Value Added was 11.6% in 2023-'24 in Jharkhand. The state has a net cropped area of 1.0 million hectares, which is 12.85% of the state's total land area. The total agricultural land in the state is 2.7 million hectares, approximately 35% of the total land (Jharkhand Economic Survey Report, 2023). The main crops of the state are paddy and wheat. The production of paddy and wheat in the state was 3.2 million tons and 0.48 million tons, respectively, in the year 2023-'24. The state also produced a good quantity of vegetables, totalling 4.35 million tons, in 2023-'24.

1.2 *Agri-business Supply Chain*

The *'Food and Agriculture Organisation of the United Nations*' defines agri-business supply chain management as the '*process through which agricultural produce is transformed into value-added final products and then delivered to the consumer'.* This process begins on the farm after harvesting and continues through storage, transportation, processing, packaging, and finally to retail (FAOUN, 2019)

The Literature on Agribusiness supply chains has evolved significantly over the last four decades. A timeline of the evolution of agribusiness literature, with key concepts, is provided in *Table 1.*

Overall, the literature shows a clear progression from traditional supply chains to modern, technologically integrated, consumer-oriented, sustainability-driven agribusiness supply networks, reflecting a broader transformation in the field of Agribusiness supply chains. Many concerns in the agricultural industry affect the supply chains of various agricultural commodities in India. Problems plaguing India's agri-business supply chain system include: small-scale farmers' monopoly on production; supply chain fragmentation; lack of scale economies; inadequate processing and value addition;

Table 1: Evolution of Agribusiness supply chain literature: Timeline of key themes

Period	Focus Area	Key Themes	Research Orientation
Before 1990s	Agricultural production and marketing	Price spread	Efficiency & margins
1990s	Supply chain management	Logistics, Coordination, Post-harvest loss	Cost and logistics
2000s	Global Value Chains due to Globalisation	Perishability, contract farming, Cold chains, optimisation *models*	Competitiveness
2010s	Sustainability	Sustainability, resilience, traceability, risk management	Environmental & social performance
2020s	Digitalisation	Blockchain, IoT, AIuse, Circular Economy	Transparency, technology usage

(Source : Somashekhar et al., 2014; Khandelwal et al., 2021; Diego et al., 2024)

inadequate storage and transportation; and inadequate marketing and advertising infrastructure. All these issues are imperative for making this sector sustainable (Somashekhar *et al.,* 2014).

1.3 Theoretical Background and Research Questions

The FAOUN report from 2019 indicates that approximately 14 per cent (1.4 billion tons) of agricultural produce is lost in the supply chain from post-harvest to retail. Minimising agricultural food loss is recognised as a significant way to reduce production costs and enhance supply chain efficiency. In addition to profitability, this poses a considerable challenge to environmental sustainability. The increasing focus on food loss and waste is evident in the United Nations Sustainable Development Goals (SDGs), specifically target 12.3, which aims to halve per capita global agri-food waste and reduce food loss within the supply chain by 2030 (FAOUN, 2019).

Although there is no universally accepted definition of food loss and waste, the concept of food from agriculture being lost or wasted is surprisingly straightforward. Food loss and waste are defined as a decline in food quantity or quality that occurs at any point in the supply chain, as per FAOUN report, 2019. In developed nations, food waste mostly happens at the consumer and retail levels. However, in poor countries, the leading cause of food loss is inadequate infrastructure throughout supply chains (Youthika, 2020).

According to the 2019 FAOUN report, Central and Southern Asia had the most post-harvest losses in the supply chain, at about 21%. India accounts for 85-90% of the observation points in Southern and Central Asia. Estimates of the actual quantum of food losses along the supply chain in India vary widely across studies. According to the (NABCONS, 2022) report, losses in the agri-food sector are 6.4%, equivalent to Rs. 1.52 lakh crore. A survey by (Nuthalapati, et al., 2022), estimates losses based on (FAOUN, 2019) data at 8.2%, amounting to Rs. 3.15 lakh crores per year in India. Again, the reported food losses across all countries amount to approximately 3.3 gigatons of CO2 emissions, equivalent to 7% of total global greenhouse gas emissions.

All these issues, as identified, are very imperative and need serious attention. By improving supply chain efficiency, losses can be reduced dramatically. This, in turn, will benefit the 'quality of life' of the 'bottom of the pyramid' people who are the actual producers. Unfortunately, research in this area is minimal. The motivation for the current study stems from a broad view of the agribusiness scenario, where significant investment is underway but remains relatively unsustainable. With this, the rationale of the study is established.

We now raise the following research questions to be addressed in this study. Based on the PCC (population, concept, and context) framework, the following research questions have been raised.

RQ1. *What are the existing agribusiness supply chain processes in India and in Jharkhand, based on existing literature?* This question is framed to identify inefficiencies in the supply chain that lead to post-harvest losses.

RQ2. *What technologies and digital innovations have been adopted across the agribusiness supply chain in India, and particularly in Jharkhand? How will Industry 4.0 technology improve the efficiency of the agribusiness supply chain?*

RQ3. *What gaps exist in the current literature, and what future research directions can be proposed for a sustainable, efficient Agribusiness supply chain?*

The area requires a deep study of related articles with divergent views and ideas, with minimal bias, to identify gaps in the literature. Systematic Literature Review allows for the possibility of 'combining various works on the same subject, highlighting their shared features, contrasting their dissimilarities, and expanding the work in some way' (Yadav *et al.,* 2022). The SLR is appropriate for mapping, assessing and synthesizing disparate pieces of literature to develop the knowledge base within a field.

Given the above systemic advantages, the SLR was found suitable for analyzing articles on the Agribusiness supply chain. Authors have used a combination of SLR and Bibliometric analysis to study the literature. Bibliometric analysis is a statistical analysis of publications to identify research patterns, trends and impact within a specific field. This helps identify prominent themes, influential authors, and emerging trends within the field. To summarize, bibliometric analysis was used to identify prominent themes and emerging trends in the subject. In contrast, SLR was used to conduct a thorough literature review and identify gaps.

2. Literature Review

Researchers identified literature review as *'a concise overview of a subject area that facilitates the identification of particular research inquiries'* (Rowley & Slack, 2004). The function it plays in locating, assessing, and interpreting the existing corpus of documents is methodical, explicit, and reproducible (Fink, 1998).

2.1 *Methodology*

2.1.1 The Search Strategy based on 'Keywords'

Table 2: Keywords

	Areas Identified	*Keywords*
1	Agri-business Supply Chain Management.	a. Agri-business supply chain (ASCM) with reference to India and Jharkhand. b. Sustainability
2	Technology and its impact on the efficiency of the agri-business supply chain.	a. Industry 4.0 technology in the Agri-business supply chain. b. Supply chain efficiency.
3.	Losses in the supply chain after harvest / Infrastructure.	a. Post-harvest loss b. Storage and cold chain infrastructure in India and Jharkhand.

(Source: Author's, 2025).

2.1.2 Inclusion and Exclusion Criteria: Criteria used for inclusion and exclusion of articles are given in *Table 3.*

Table 3: Inclusion and Exclusion criteria

Criteria	*Inclusion*	*Exclusion*
Type of Literature	Peer-reviewed articles, government reports, and Books	Opinion articles, Blogs
Focus	Agribusiness supply chain	Supply chain in other Industries.
Language	English-language publications	Non-English publications
Keywords	As mentioned in Table 1	-
Year of Publication	Between 2014-2025 Feb	Before 2014

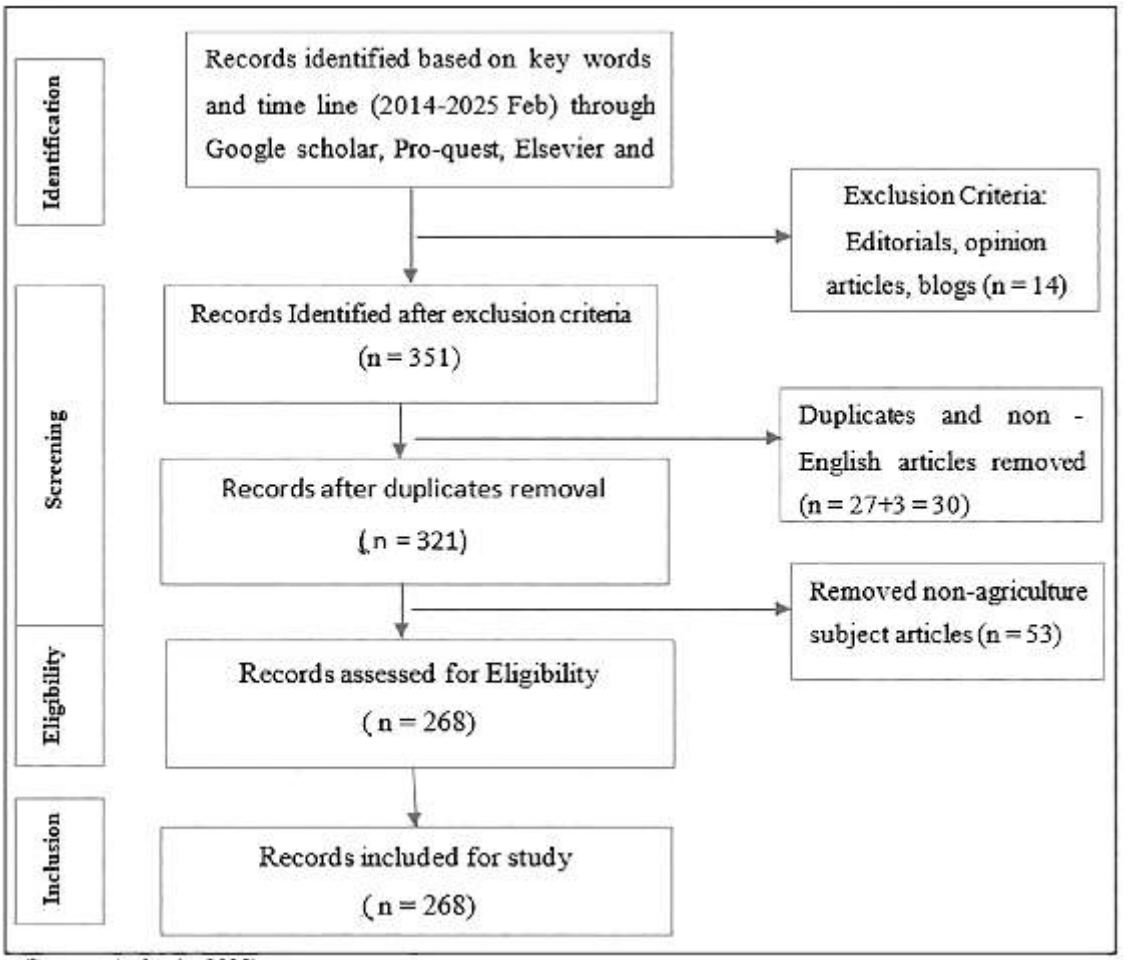
Source: Author's, 2025

The PRISMA (Preferred Reporting Items for Systematic reviews and Meta-analysis) method was used to sort the collected articles for a systematic review. PRISMA is widely used for systematic literature review and meta-analysis (Singh et al. 2024). The PRISMA procedure follows a detailed protocol that is replicable, scientific, and transparent, and includes several stages (Moresi, 2022). *Figure 1* below shows the PRISMA procedure followed for records sorting.

The Emerald Insight, Elsevier, ScienceDirect, Springer, Wiley, MDPI, and IEEE databases were searched using the keywords listed in *Table 2*. The searches in this study focused on the agribusiness supply chain in the Indian context, especially in Jharkhand, as well as in other parts of the world. Post-harvest losses and the efficiency of ASCM were also another focus area. Initially, 365 articles were identified, and after screening the records against inclusion and exclusion criteria, 268 were included in the systematic literature review. During screening, 14 articles were excluded because they were opinion articles, blogs, or editorials. 30 articles were excluded for non-English language, and 53 articles were excluded because they were from non-agriculture fields.

2.2 *Data Extraction*

The article's data was extracted, synthesised, and analysed using a Microsoft Excel data form (Yuvraj *et al.,* 2023). This helped with data extraction for research papers. *Table 4* presents the parameters of the research papers, extracted and arranged in a matrix in the Excel sheet. All 268 research papers were reviewed, and a summary of each paper, including the article identifier, bibliographic information, methodology used, findings, conclusion, limitations, and future scope of research, was recorded.



(Source: Author's, 2025)

Figure 1: Prisma Flow Diagram

Table 4: Data extraction from research publications

Sl.	*Parameter*	*Description*
1	Article information	Digital Object Identification
2	Bibliographic Details	Author(s) Names, Publication date and Journal name.
3	Methodology	Methodology used: SLR, Conceptual, Mathematical modelling, Statistical method, Descriptive, Primary data and Secondary data.
4	Findings	What are the conclusions of the articles.
5	Limitations of the study	Constraints of the Article as enumerated by the Authors
6	Future Research Areas	Research areas in which further study can be pursued.

Source: Author's, 2025

2.3 *Systematic Literature Review*

Here, we used a six-step approach as follows (Siddh *et al.,* 2017) and (Palazzo & Vollero, 2022) for the Systematic Literature review. *The steps are explained as:*

Step 1: Time Period: Set the study period. The period chosen for the evaluation of literature is 2014-2024, with the early period of 2025, with special focus on the area of study. The ten years were chosen to cover all significant developments in the field since the emergence of Industry 4.0.

Step 2: Compilation of Research Articles: Article papers were chosen from the reputed management/management-related publishing houses. They are Emerald Insight, Elsevier, Science Direct, Springer, Wiley, MDPI, and IEEE. These databases are commonly used for bibliometric analysis and literature review (Soni & Kodali, 2011; Palazzo & Vollero, 2022).

Step 3: Selection of Articles: The research papers were selected based on the keywords listed in *Table 1*. In total, 365 relevant research papers were selected from the databases mentioned in step 2 using the keywords above.

Step 4: Classification of research publications: Duplicate papers were eliminated from the collection, and only relevant publications were retained. In this later step, to create a more representative sample set, the sample size was reduced according to the following policy: articles/papers should focus on agriculture, food, agri-produce supply chain efficiency, post-harvest losses, and the use of technology to improve efficiency in India, specifically in Jharkhand. After filtering, 268 research papers were selected for further analysis.

Step 5: Research publication categorization: Research articles are organized into the following classes: year-wise publications, journal-wise publications, and country-wise classification, which present the classification of research studies. The origin of the first author is used to decide the country-region/state-wise classification of the research paper within India.

Step 6: Concluding remarks: The analysis in this paper is qualitative; it is not suitable for applying any statistical methodologies. Hence, no hypothesis framing or testing was carried out. The research papers have been critically analyzed, and gaps have been identified. The contribution of this study is to identify the grey areas that require serious attention.

3. Analysis

This section initiates the interpretation phase of the review, which builds on earlier compiled articles. Guided by the TCCM framework, all the articles were analysed across four dimensions: Theories (T), Characteristics (C), including the variables Context (C) covering the countries studied; and Methods (M), which consists of the methodologies used in the selected articles. This analysis is summarized visually in *Table 5*, which outlines the TCCM framework used to map the selected articles (Paul, 2019a). This theory will help in answering RQ1 and Rq2.

Table 5: TCCM Framework of the Reviewed Literature

Theories (T)	***Characteristics (C): Variables***	***Context (C): Country***	***Method (M)***
Short supply chain	Post-harvest food loss	Austria	Bibliometric Analysis
Cloud-based Supply Chain System	Logistics Management	Australia	Systematic Literature Review
Digital Agricultural Architecture	Sustainability	Brazil	DEMATEL (Decision Making Trial and Evaluation Laboratory) method
Integrated Agriculture Supply Chain Management	Cold Chain	China	Multi-criteria Decision making
Artificial Intelligence approach	Storage capacity	Canada	Structural Equation Modelling (SEM)

Supply chain aggregate	Circular Economy	Colombia	Interpretive structural
Production planning			modelling
Knowledge Management	Supply Chain Efficiency	Denmark	Case study
Total Quality Management	Usage of technology: Blockchain, AI, IoT	Egypt	Optimisation, Linear Programming
Decentralized Agribusiness supply chain.	Traceability	Germany	PRISMA guidelines
Unified theory of Acceptance and Use of Technology (UTAUT)	Agri-food quality	Indonesia	DELPHI technique
Technology Acceptance Model(TAM)	Stakeholders	India	Partial Least Squares-Structural Equation Modelling (PLS-SEM), SLR
Data-driven Approach		Iran	Data Envelopment Analysis (DEA)
Supply chain practice view (SCPV)		Italy	Quantitative Survey methodology
		Japan	Autoregressive Integrated Moving Average (ARIMA)
		Kenya	Stochastic Programming.
		Morocco	Simulation techniques
		Malaysia	Mixed Integer Non-linear Programming model
		Peru	Multi-Objective Linear Programming
		Portugal	Value Stream Mapping
		Poland	Descriptive Analysis
		Russia	ANOVA Test
		Saudi Arabia	Analytical Hierarchy Process (AHP)
		Spain	Confirmatory Factor Analysis and Exploratory Factor Analysis
		Sri Lanka Sweden	Systematic Literature Review Interpretive tructurals modelling

		Thailand	PLS-SEM
		Tunisia	Descriptive Analysis
		Turkey	Fuzzy set qualitative comparison analysis
		USA	SLR, Case study, PLS-SEM
		UK	Case study, PRISMA, SLR
		Ukraine	Simulation modelling
		Vietnam	Statistical method through SPSS

Source: Author's illustration; Adapted from Paul (2019a)

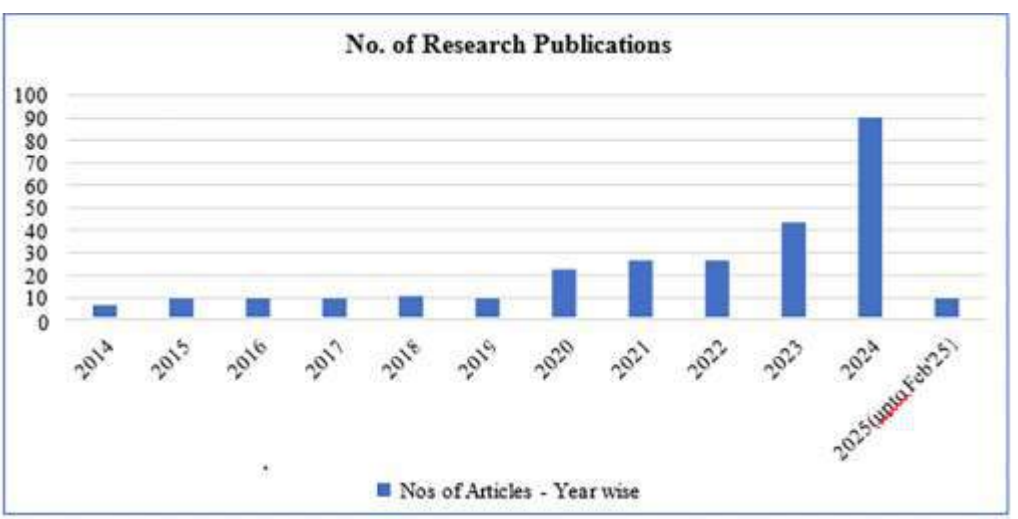
The collected research papers are analyzed and categorized based on various parameters as enumerated below.

3.1 *Year-wise Publications*

Figure 2 shows the number of articles collected per year for the period 2014-'24 and early papers of 2025. It can be seen that research papers on the subject have increased gradually, with the most extensive collection in 2024. Emphasis has been placed on the latest publications and on research related to the Indian context. A total of 268 research papers have been chosen for the study. Out of which, approximately 72 percentage are original articles, 11

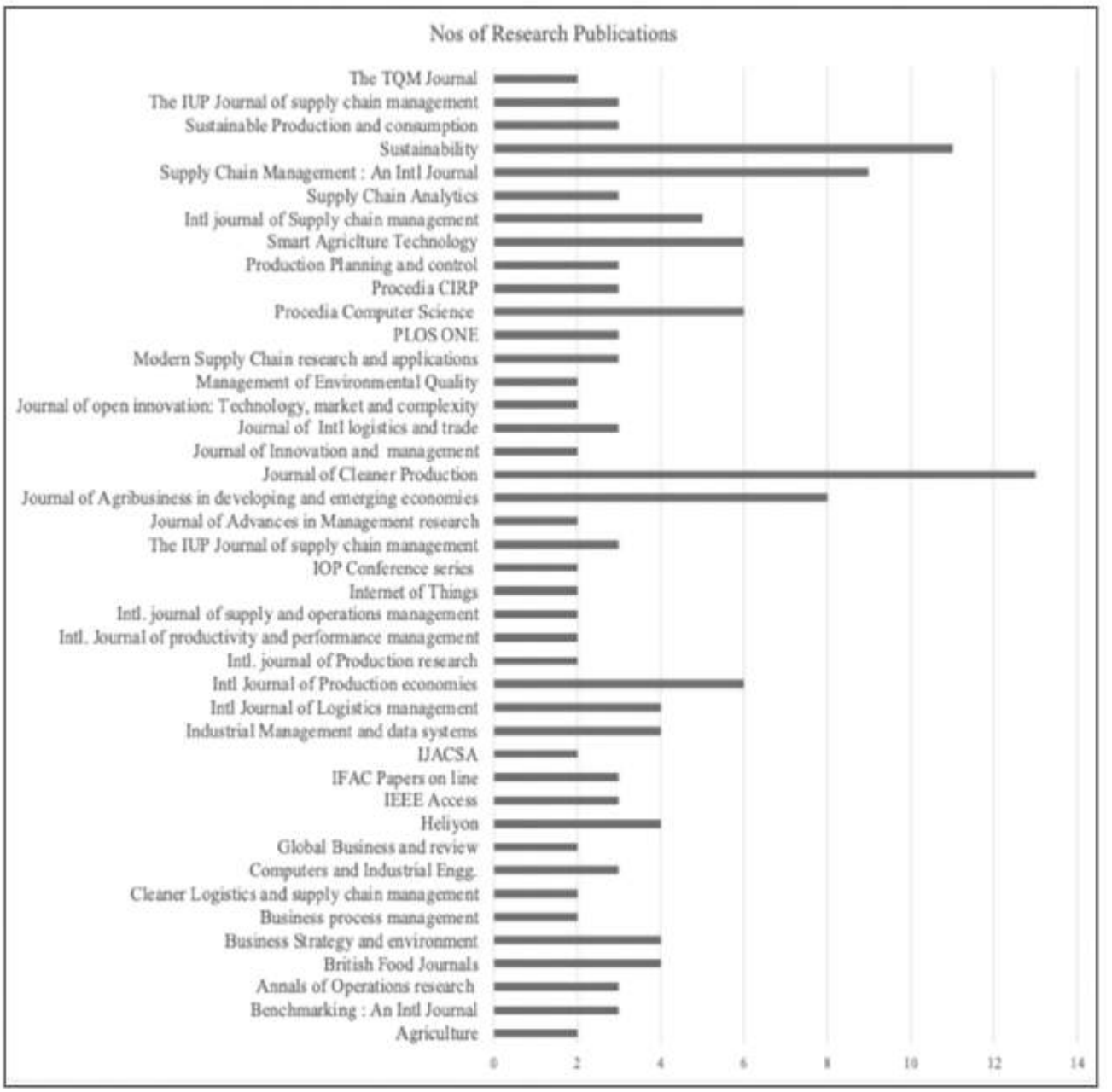
3.2 *Journal-Based Categorization of Research Papers*

This categorisation is based on the journals in which the research papers were published (*Fig. 3*). Approximately 60% of the research papers were published in 42 journals, as indicated in the cluster graph below. The articles were collected from 154 journals from various databases. The chart below shows that the most research articles were published in the *Journal of Cleaner Production* (13 papers) *and Sustainability* (11 papers). It is also found that only 10 percentage of the articles were published in agricultural journals, and the rest were in interdisciplinary areas of supply chain and technology. The recently published articles show extensive use of technology.



Source: Author's, 2025

Figure 2: Number of Research Publications: Year-wise



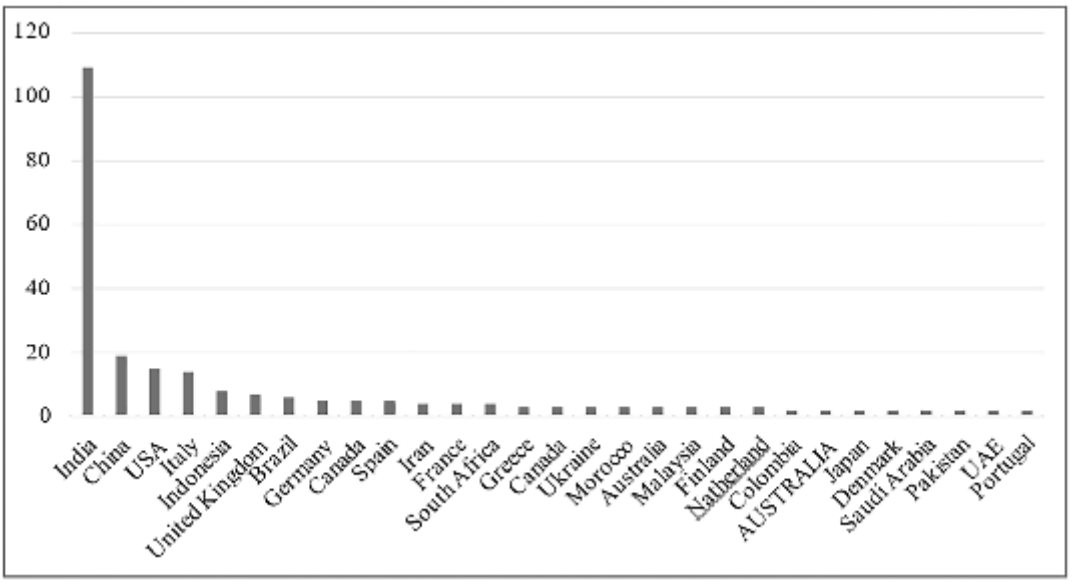
Source: Author's, 2025

Figure 3: Journal-wise classification

3.3 Classification based on Countries of the First Author ('Context' of TCCM Framework)

The chart below (*Figure 4)* shows the country of the first author-based classification of research papers. The maximum number of documents is from India, China, the USA, and Italy.

3.4 Classification based on Geographical region/state in India('Context' of TCCM Framework) Of 109 research publications on India, the sub-classification was based on region/state (only Jharkhand), as shown in *Table 6*. Only 24 articles/reviews focus on specific states/regions.



Source: Author's, 2025

Figure 4: Classification based on Country of first Author

Table 6: Classification based on the Geographical region within India

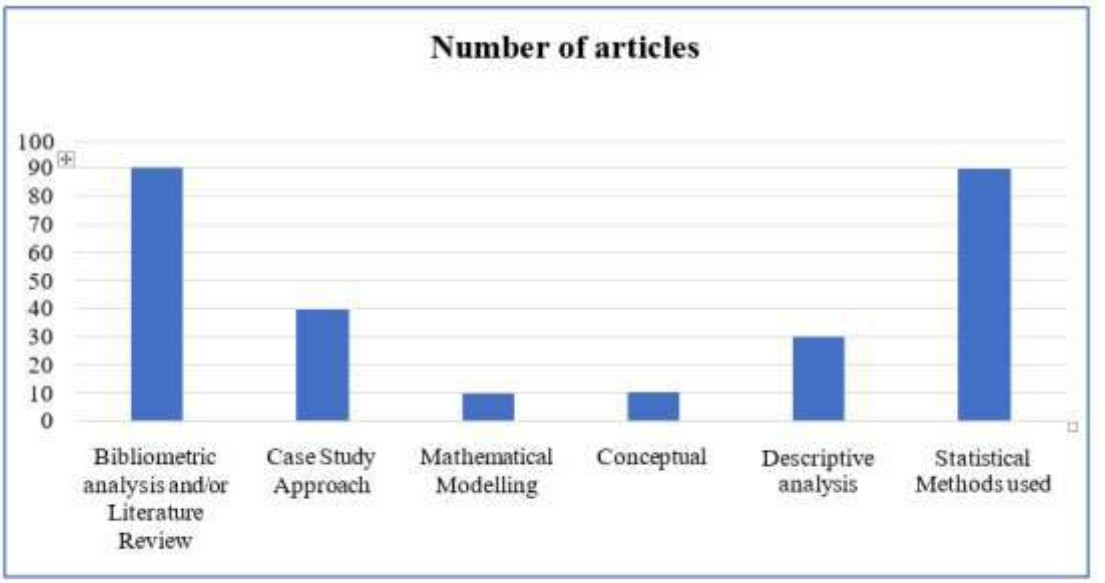
Sl.	Region/state name within India	No. of research papers
1	Eastern Region (including Jharkhand)	6
2	Northern Region	11
3	Central Region	2
4	Western Region	1
5	Sothern Region	4
6	Jharkhand	4

Source: Author's, 2025

However, except for four papers (Parwez, 2014; Somashekhar et al., 2014; Choudhary, 2024), none of the research papers has an analysis of the agri-business supply chain management as a whole system. Priorities are frequently centred on post-harvest losses, logistics, information technology applications, food safety and quality, and perishability (Khandelwal *et al.,* 2021).

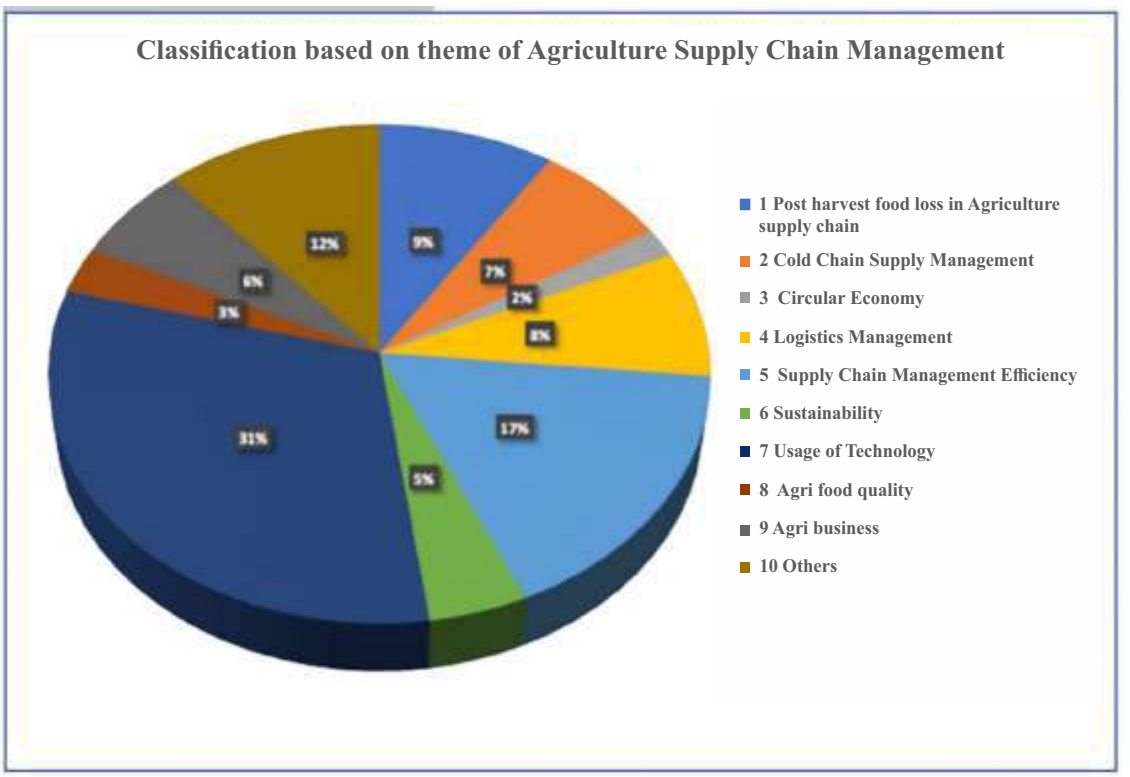
3.5 *Classification based on Statistical tools used ('Method' of TCCM Framework)*

The research papers have been classified by the analysis method used. *Figure 5* indicates that the maximum number of researchers (34%) have used bibliometric analysis and/or literature review, followed by statistical methods (32%), case study (15%), descriptive analysis (12%), Conceptual (4%) and Mathematical modelling (3%). It is also observed that in recent periods, articles have used mathematical programming/modelling methods, such as fuzzy logic models and optimization models, for analysis (Ngyun *et al.,* 2021; Sharma *et al.,* 2024). This indicates increased use of scientific methodology in discussions of issues in the agricultural supply chain (Rahbari & Mohammadi, 2025). This augurs well for future research in the subject field (Dadsena & Paul, 2024). The data source used in the study was as follows: 11% (30 articles) used primary source data, 8% (22 articles) used secondary source data, and the remaining articles used literature reviews, conceptual analyses, etc



Source: Author's, 2025

Figure 5: Classification based on the methodology/tools applied



Source: Author's own creation

Figure 6: Themes in Agri-business Supply Chain literature

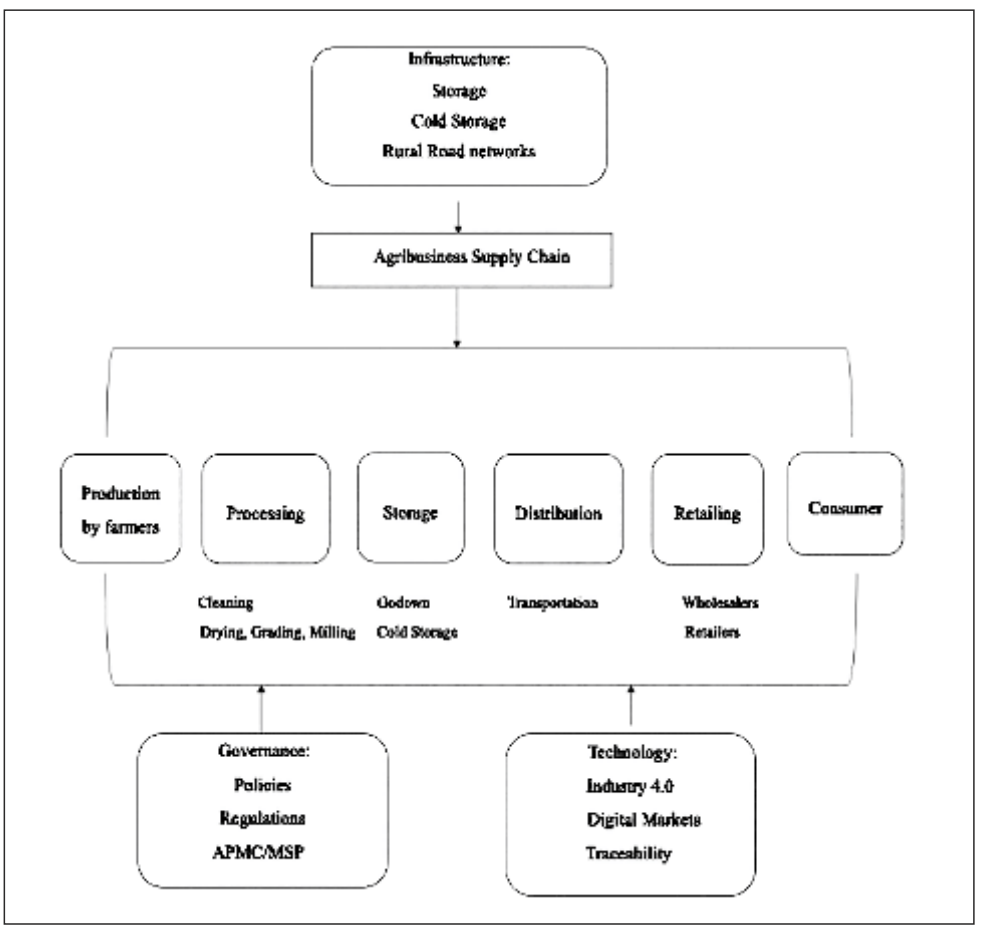
3.6 *Classification based on the Theme ('Characteristics' of TCCM Framework)*

The research publications are also categorized based on the central Theme addressed in the articles. *Figure 6* indicates the themes of agri-business supply chain, usage of technology (31.3 percentage) being the highest followed by Supply chain efficiency (17 percentage), Post harvest food loss (9.3 percentage), Logistics Management (8 percentage), Cold supply chain (7.1 percentage), Agri-business (6.3 percentage), sustainability (4.5 percentage), Agri-product quality (3 percentage), Circular economy (2 percentage) and others (12 percentage).

The analysis of the research papers indicates that the use of the latest technologies, like Blockchain, IoT, Artificial Intelligence, Industry 4.0 technology, etc., in improving the efficiency and transparency in the agriculture supply chain management has been widely discussed, though primarily a conceptual analysis, as implementation of these technologies is yet to be fully completed in the field.

The TCCM analysis presented in *Table 5* above provides a framework for the Theory of Integrated agribusiness supply chain management in India, with a reference to Jharkhand, based on the classification of the literature selected above. A proposed conceptual frameworkThe relationship between infrastructure-technology-governance as a function of structural infrastructure capacity, digital technology adoption, and institutional governance mechanisms is displayed in Fig 7.

This framework will improve supply chain efficiency, reduce post-harvest losses, and enhance farmers' incomes through technology, traceability, and sustainability.



Source: Author's, 2025

Figure 7: Agribusiness Supply Chain

3.7 *Analysis of Bibliometric Networks*

A bibliometric analysis has been conducted using VOSviewer. This software is used to construct and view bibliometric networks based on various parameters Eck & Ludo, 2010). In this analysis, the Author keyword co-occurrence network and Co-authorship parameters have been used.

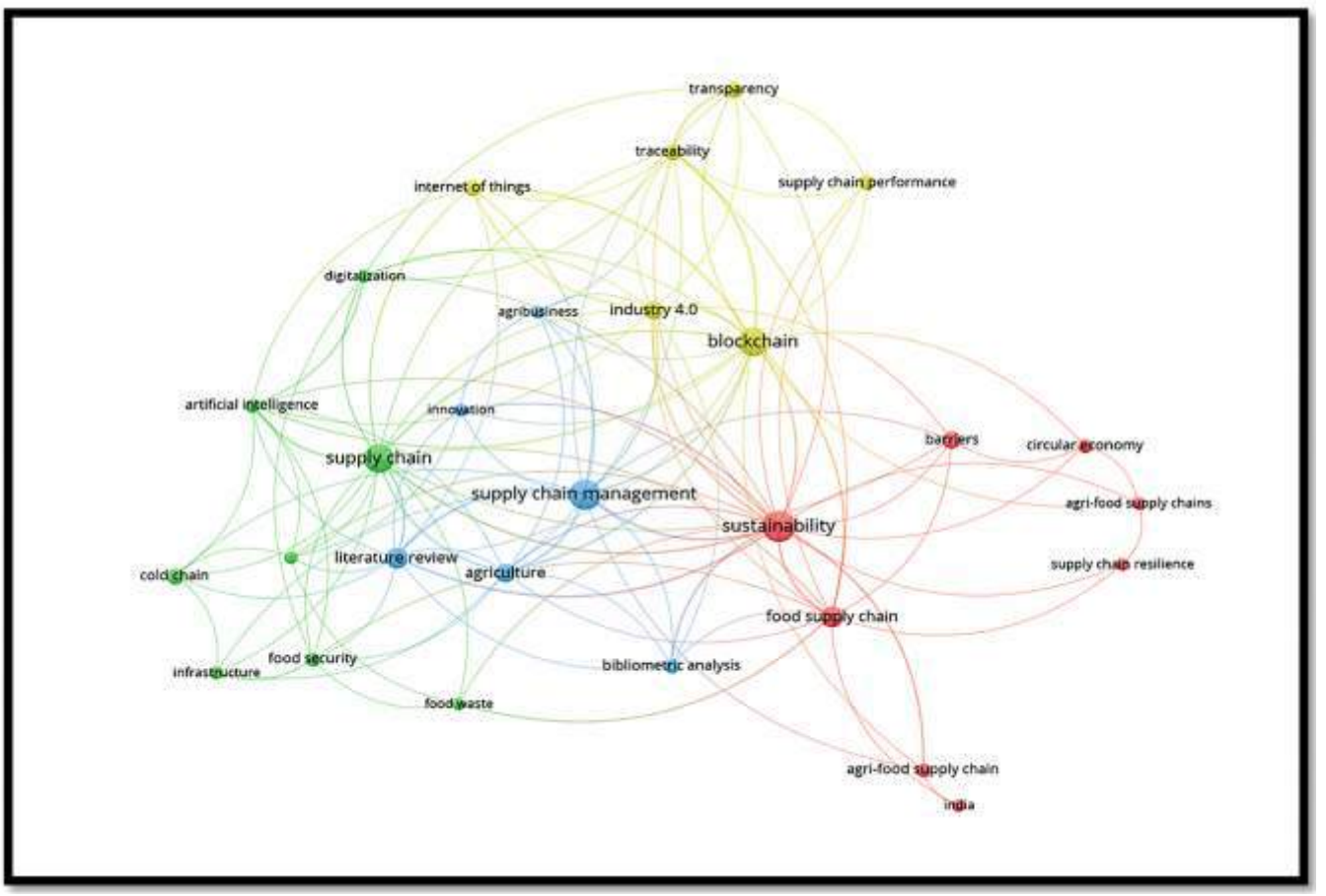
Keyword: Co-occurrence Map

A co-occurrence link is a link between two sources that both contain the same term (keyword) (Tsoulfas *et al.,* 2023). The use of a keyword map allows for the identification of unique themes within this study topic. To shape future research and development in this area, it is essential to use this analytical technique to identify knowledge gaps and key issues (Zrelli & Rejab, 2024).

Figure 8 shows the keyword network map, having 28 keywords distributed among four clusters. The limit for the number of repetitions of a keyword was set to 5. Of the 705 keywords, 28 met the threshold criteria. The keywords have been divided into four groups depending on their links.

Group 1, depicted in Red colors, combined the topics of *'agri-food supply chain, circular economy, food supply chain, India, supply chain resilience and sustainability'*. The above topics and their interlinkages indicate that this cluster addresses the state of agri-food supply chains and the barriers to their successful implementation. The topics of highly prevalent 'sustainability' and 'circular economy' indicate the most highlighted areas and the future of the agri-business supply chain.

Group 2, in Green, contains eight topics: *'artificial intelligence, cold chain, digitalization, food security, food waste, infrastructure, machine learning, and supply chain'.* Supply chain is the most common topic. Interlinked topics in this cluster indicate the introduction of artificial intelligence and digitalization in this field. Cold chain, being the second most highlighted topic, is also an area of interest, as many research papers have reported a poor supply chain infrastructure.



(Source: VOS viewer output)

Figure 8: Mapping of keyword occurrence

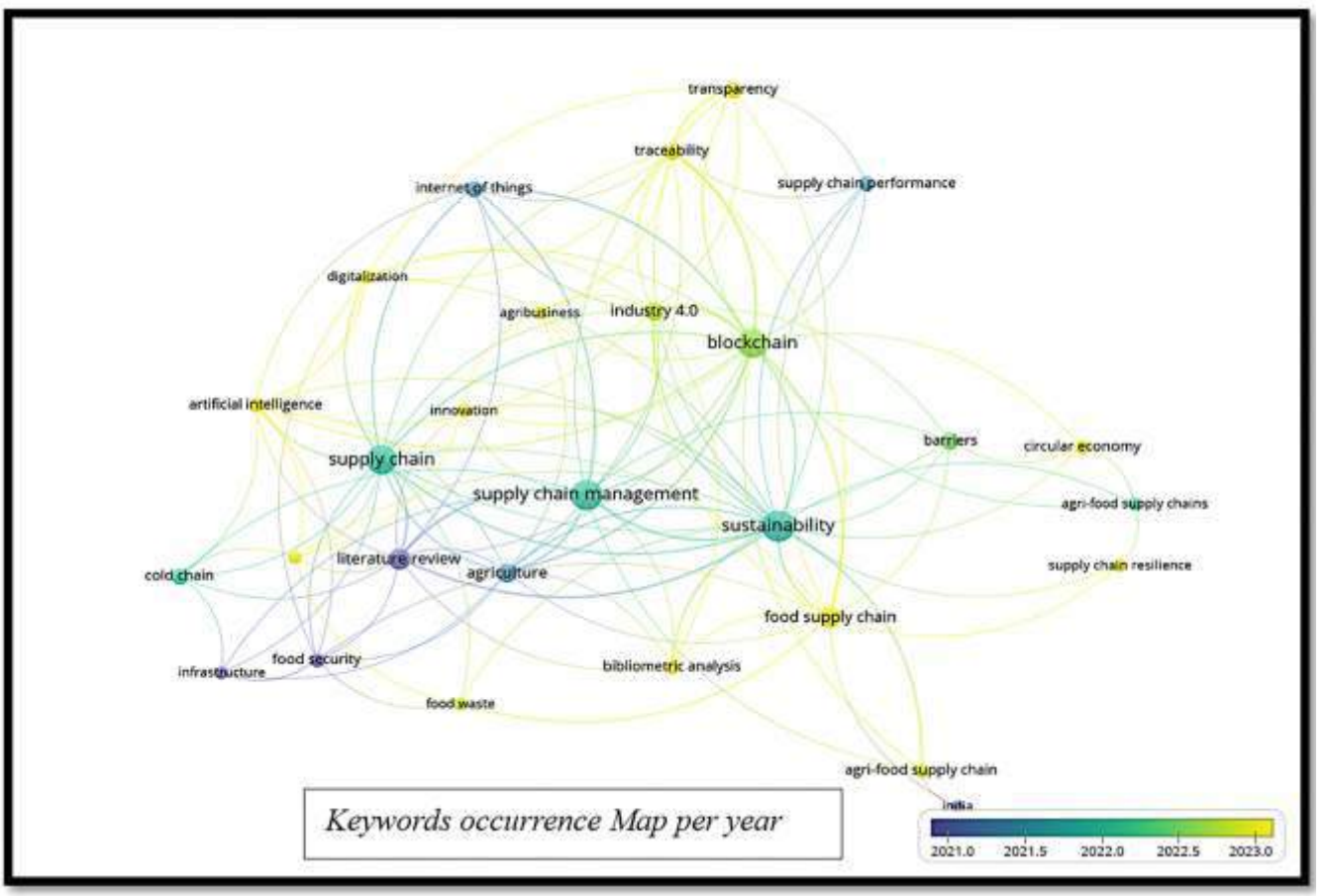
Group 3 in Blue color has six topics: *'agri-business, agriculture, bibliometric analysis, innovation, literature review, and supply chain management'*. Supply chain management is the most highlighted item. The topics in this group focus on literature reviews and innovation in this field. Significantly, agri-business is highlighted as the topic of future discussion.

Group 4 in Yellow color called the 'technology group', which comprises *'blockchain, Industry 4.0, Internet of Things, supply chain performance, traceability and transparency'*. Blockchain is the most common topic. It has been found that customers increasingly know the product's origin and quality, and this can be ensured only through the application of technology.

Figure 9 shows the year-wise history of the subject as reported in the literature and the keywords used throughout the time period (Singh *et al.,* 2024)

Co-Authorship: Network Visualization

When two or more scholars collaborate to write a publication, a co-authorship link is created (Tsoulfas *et al.,* 2023). To create a network visualisation of co-authorship interlinking, a single document was set as the minimum number of records per author, and 862 authors participated in the network. Only 27 authors participated in the co-authorship network, as visible in *Figure 10.* Six Groups of color red, green, blue, yellow, purple and light blue have been created in the network. Red, green, blue, and yellow each have five authors, the purple cluster has four, and light blue has three, as shown in *Table 7*



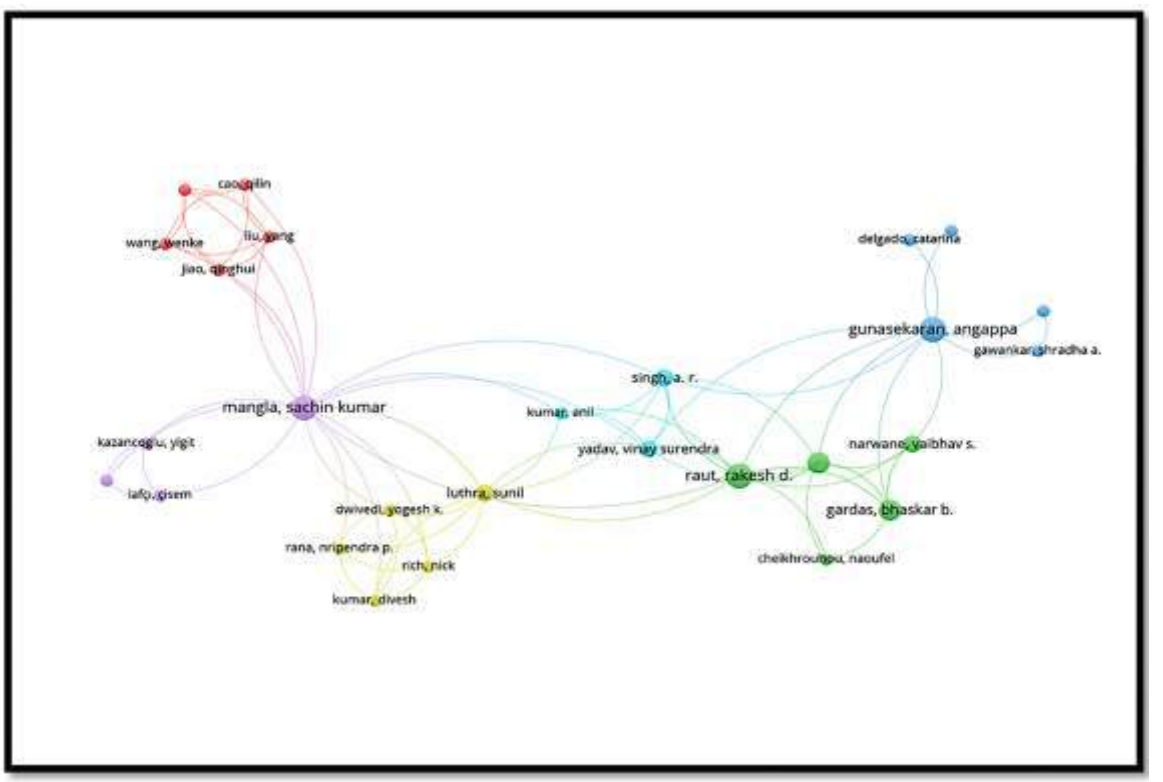
(Source: VOS viewer output)

Figure 9: Keywords occurrence overlay visualization

Table 7. Group of Authors as per Co-authorship map

Sl. No.	Group 1 (Red)	Group 2 (Green)	Group 3 (Blue)	Group 4 (Yellow)	Group 5 (Purple)	Group 6 (Blue)
1	Cao, Qiln	Cheikhrouhou, Naoful	Delgado, Caterina	Dwivedi, Yogesh	Kazancogular, Yigit	Kumar, Anil
2	Jiao, Qinghui	Gardas, Bhaskar	Gawankar, Shraddha	Kumar, Divesh	Lafci, Cism	Singh, A.R.
3	Liu, Yang	Narkhede, Balkrishna	Gunashekhar, Angappa	Luthra, Sunil	Mangla, Sachin Kumar	Yadav, Vinay.
4	Wang, Wenke	Narwane, Vaibhav	Kamble, Sachin	Rana, Nripendra	Sezur, muruvett	
5	Zhou, Cheng	Raut, Rakesh	Mani, Venkatesh	Rich, Nick		

Source: VOS viewer output



Source: VOS viewer output

Figure 10: Network visualization of Co-authorship

2. Discussion

The main aim of this article is to examine existing agribusiness supply chain research in the Indian context, specifically in Jharkhand. This will help identify areas of concern. The bibliometric analysis and TCCM concept provide a detailed analysis of the selected Literature on ASCM, and some key themes emerge.

The keyword co-occurrence map in *Figure 8* shows how common specific keywords are in the academic literature on this topic, with node size indicating each term's relative frequency. A node's size indicates the frequency with which it co-occurs with other keywords; each node represents a keyword. The association between keywords is indicated by the closeness of two nodes (Zrelli & Rejab, 2024).

Keyword co-occurrence also indicates that the topics discussed in the literature are mostly blockchain, artificial intelligence, innovation, IoT, transparency, traceability, and the circular economy. This suggests that research has paid more attention to the implementation of technology in this area.

Figure 9: The keyword overlay visualization map shows the year-wise development of the Theme. In 2021, the most discussed topics were food security, infrastructure, and agriculture. Since 2022, the focus has shifted to supply chain management, sustainability, and cold chain. Since 2023, the focus has shifted to technological advancement in this area.

The co-authorship map in Figure 10 clearly shows fragmented cooperation among scholars on the topic. This also indicates that more and more scholars are conducting research in this area, which is well-suited to academia.

Now, we try to discuss the research questions we raised in the previous section based on the above analysis.

Answer to Research Question 1

Of the 268 research papers selected for study, 109 are related to the Indian context. The scholars have used primary data for analysis in 17 papers (19%) and secondary data in 11 papers (12%). This indicates that scholars in this area have not conducted thorough field research. All 109 articles about the Indian Context have been categorized. Highest number of articles, 31 numbers(28%) pertains to application of I4.0 technology in ASCM, followed by ASCM Bottlenecks at 24%, such as Fragmented markets, Inadequate storage capacity, lack of market awareness among farmers, High number of intermediaries, etc., followed by Sustainability(14%), post-harvest losses(10%), Cold Supply Chain(7%), supply chain efficiency(6%), Logistics(5%), food processing(3%) and Circular economy(2%).

Based on the above analysis, the following are inferred:

• *Fragmented market:* Productivity losses of 20-30% due to fragmented markets, poor infrastructure, limited knowledge among farmers about climate, prices, and markets, and a high number of intermediaries in the Indian context. In a survey, 63.6% of respondents, stakeholders, have cited inefficient logistics and transportation facilities (Choudhary, 2024).

• *India's storage capacity:* The study reveals that storage capacity shortages are one of the reasons. India has a total storage capacity of 71 million metric tons, against food grain production of 329 million tons. Similarly, for horticulture production, the capacity of cold storage is 38 million tons, compared with the output of 353 million tons (Ministry of Agriculture, 2023).

Jharkhand's storage capacity: As per the available literature, there is no research paper on Agricultural storage infrastructure in Jharkhand. The study on the analysis of cold storage capacity utilization (Kumar & Gaurav, 2024) and the analysis of the vegetables market in Ranchi district have been conducted previously (Singh & Singh, 2017). Jharkhand has produced food grain (Rice and wheat) of 3.68 million tons, while the available storage capacity is only 5.66 lakh metric tons during the period 2023-'24 (Jharkhand Economic Survey, 2025). As far as the capacity of cold storage in the state of Jharkhand is concerned, it is meagre at 2.36 lakh ton, while the production of horticultural products in the state was 5.57 million ton during the year 2022-'23 (Ministry of Agriculture, 2023).

- *Refrigerated transport facility:* The requirement for refrigerated transport vehicles for perishable products in India is also very high. The requirement is for 61826 vehicles, while the availability is only 9000, resulting in a 85% gap (Beriya, 2021).
- *High number of intermediaries*: The agricultural supply chain in India spans multiple channels. The channels include: i. Farmer-consumer, ii. Farmer-retailer-consumer, iii. Farmer-wholesaler-retailer-consumer, iv. Farmer-commission agent-wholesaler-retailer-consumer, and v. Farmer-village merchant-wholesaler-retailer-consumer. Regulated markets offer no alternative options for producers to sell their produce. The existing mandi system involves numerous intermediaries, resulting in significant value loss (Somashekhar *et al.,* 2014).

- *Coordination among all supply chain members*: Supply chain contracts are critical agreements that govern pricing and the exchange of goods among supply chain participants. It facilitates the efficient distribution of goods, services and information among all members (Choudhary, 2024).

Answer to Research Question 2

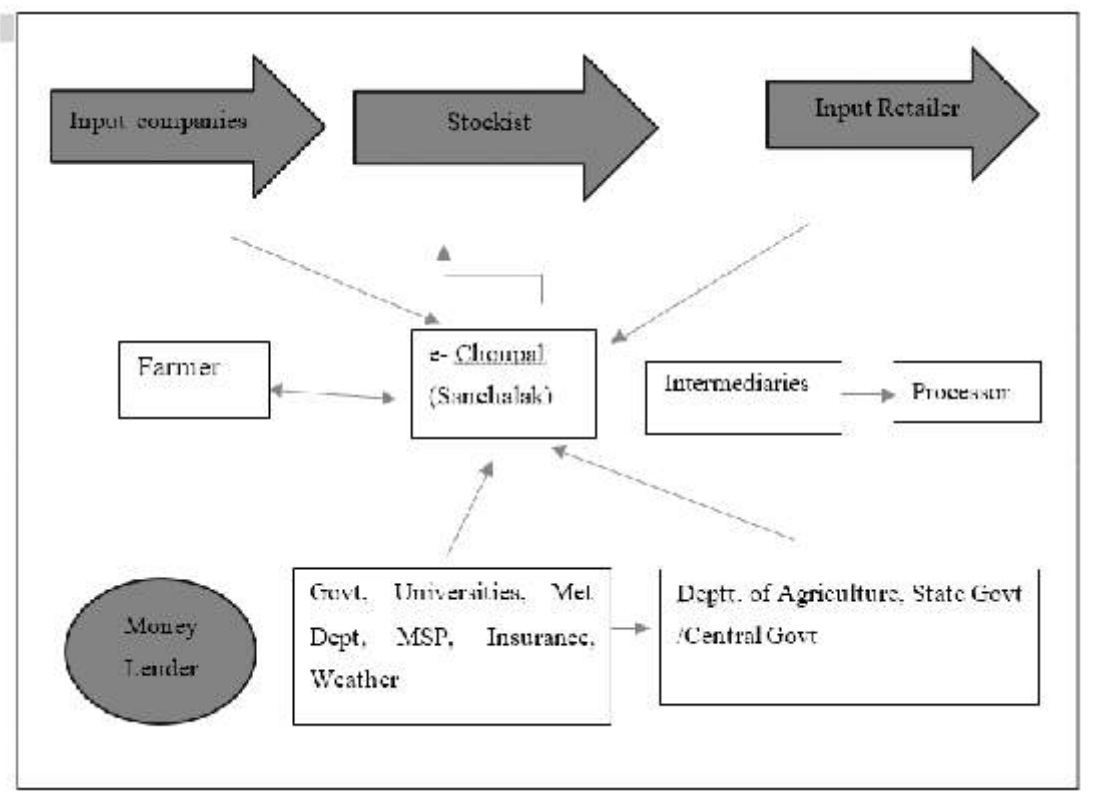
The Indian agri-business supply chain is complex and challenging to manage due to its disorganised nature and the presence of numerous intermediaries. The primary reasons for inefficiency in the supply chain are gaps in basic infrastructure, underuse of information technology, and a lack of coordination among stakeholders (Parwez, 2014).

However, based on the available literature, the following are inferred:

- The application of Industry 4.0 technologies within established organizations is attracting the attention of business and academia (Costa *et al.,* 2023).
- Machine learning can be used effectively to forecast sales of agricultural products. (Amine, et al., 2024) used this technique to predict sales of phytosanitary items in Morocco, which was found to be highly accurate, with a Mean Absolute Error (MAE) of 0.0035 and a Root Mean Square Error (RMSE) of 0.0066.
- One of the most recent and rapidly expanding technologies, blockchain has the potential to revolutionise the agriculture industry by enhancing supply chain transparency and ensuring the integrity, security, and traceability of data. Without the need for a trusted third party, blockchain technology improves agribusiness supply chain management (Mokgomola *et al.*, 2024). In a study in North America involving 130 firms, it was found that adopting blockchain technology has significantly improved operational performance, including labour productivity, operating cycle time, and profitability (Culot *et al.,* 2024).

Above are a few examples from outside India of how the use of I4.0 technologies has improved ASCM efficiency.

- In the Indian context, not much has been done to implement the latest digital technologies; however, there is sufficient literature on the conceptual work on



Source : Parwez, 2014

Figure 11: ITC e-Choupal Supply Chain model

implementing blockchain, ICT, and AI. Two literature reviews discuss the use case study.

- One example is the e-Choupal project by ITC (Indian Tobacco Company). Information and communication technology (ICT) platform e-choupal facilitates multi-location trade. ITC provides village-level e-choupal through a Sanchalak, a lead farmer who interfaces with the computer. On the e-choupal website, ITC provides data on weather, contemporary agricultural practices, prices and market information from government sources. All the above information is provided to farmers on a personalized basis, as per their requirements. *Figure 11* shows the e-choupal structure. This was started as a project business model, but currently operates across states of Madhya Pradesh, Uttar Pradesh, Andhra Pradesh, Haryana, Karnataka and Rajasthan (Parwez, 2014).
- East India Distilleries (EID) Parry has initiated the project 'Parry's Corner' to assist farmers by offering value-added services that enhance their income and increase farm productivity in the Chennai region. Local self-help groups are utilising the ICT platform for e-commerce activities. This has facilitated the development of social networks. Social networks enable the dissemination of ICT platforms (Mudda *et al.,* 2017).
- The agri-food supply chain faces significant challenges in ensuring the availability, confidentiality, and integrity of distributed systems. Blockchain offers a potential solution, but its adoption in India's agri-food sector is still emerging. Because India is a developing country, digitalising the supply chain will take time. A survey of 200 supply chain members. In Punjab, it was found that on-the-ground barriers continue to slow blockchain implementation, suggesting that full adoption will take longer (Sharma *et al.,* 2023).
- IoT (Internet of Things) can help turn agriculture into an innovative sector. In developing countries like India, adoption is still in its early stages. IoT could improve energy management, dematerialisa-tion, bio control, ecological feedback, and automated systems.
- It enables interconnected objects to share information and has wide applications in agricultural supply chain management (Narwane *et al.,* 2022).
- The researcher found no literature on the use of ICT in the agribusiness supply chain in Jharkhand.

Answer to Research Question 3

We investigated a systematic literature review of 268 selected articles. Of 268 articles, 109 (40%) pertain to India, and the majority of these research papers have been published in the last five to six years. This indicates that there is growing awareness of agricultural supply chain management among scholars, yet there is little research on the field as a whole system. Based on the literature reviewed, t*he following gaps are observed:*

1. ASCM (Agribusiness supply chain management), as a coordinated system, has not been discussed in detail by scholars in the collected research publications. A lot of literature is available on perishability, food safety and quality, ICT applications in ASCM, logistics, and post-harvest losses.
2. Very little (only 4) literature is available about the agricultural products in the state of Jharkhand. This literature does not explicitly discuss the ASCM.
3. A sizable number of research publications (84.31%) are available on the use of Information technology worldwide, including about India. These concepts are at a nascent stage, and, as such, no use cases in the field are available in India or in Jharkhand.
4. The researchers' use of primary data in their publications is minimal, while the use of conceptual or descriptive methods is widespread. The use of primary field data will provide a clearer picture for analysis.
5. Since there are no research publications available on ASCM as a coordinated system in India, the factors contributing to inefficiency in ASCM have also not been thoroughly discussed.

Based on the above discussion and available literature, a comparison can be made between developed economies, India, and Jharkhand with respect to the Agribusiness Supply chain, as presented in Table 8.

6. Implications

This work presents multiple avenues for Managers and researchers, as well as theoretical ramifications.

6.1 Managerial Implications

The findings of this study affect agribusiness supply chain professionals. Managers must focus on innovation and current technologies to boost the efficiency of the

Table 8: Comparison of Agribusiness Supply Chain Management

Sl no.		Developed Economies(USA, China, UK, Japan)	India	Jharkhand
1	Farm Size	Large-scale	Marginal holder, less than 1 acre (68%)	Marginal holder less than 1 acre (82%)
2	Coordination	Vertical	Semi-Coordinated	Informal trader-led
3	Technology	Advanced (AI, Blockchain, etc.)	Emerging	Emerging
4	Infrastructure	Strong	Moderate but uneven	Under developed
5.	Market orientation	Export driven	Domestic + export	Local Subsistence

Source: (Sheetal & Karuna, 2024), (Ministry of Agriculture, 2023), (Jharkhand Economic Survey, 2025), (Somashekhar et al., 2014).

agribusiness supply chain. Blockchain, AI, and IoT can greatly benefit stakeholders. Consumers will receive higher-quality agricultural products using technology. The research also highlights government-dependent issues like storage and transportation infrastructure, rural road networks, farmer awareness, market access, and more. System efficiency can be significantly increased with government backing and the right policy.

6.2 Theoretical Implication

This study has substantial theoretical consequences. The study shows limited research in this area. Perishability, agricultural produce quality, and supply chain technology have been studied, but the supply chain system has not. This study examines the agribusiness supply chain system as a whole, unlike previous studies. This study highlights the essential research gaps discussed above and the critical research needs. The study reveals that future studies should adopt a comprehensive approach when addressing the agricultural supply chain.

6.3 Research Implications

This study reviews the literature from 2014 to February 2025 to provide academics with a complete understanding of the agri-business supply chain. A bibliometric analysis was used to identify the most common keywords in the literature review. The survey found that researchers are interested in applying I4.0 technologies like Blockchain, IoT, and AI to agriculture. This improves performance and system sustainability.

7. Conclusions, Limitations and Future Research Directions

The present study is based on a systematic literature review of the current state of agribusiness in the Indian context, specifically in Jharkhand. A systematic review of 268 research publications was conducted. These publications were categorised by year, journal, country of origin of the first author, and methodology/statistical tools used. We perform a Bibliometric analysis of the literature using VOSviewer and discuss the results accordingly.

The literature review indicates that most of the research was published between 2020 and 2025. This shows the growing interest among academicians, researchers, and scholars in this field of study. Literature discussing the agri-business supply chain as a whole coordinated system is minimal. The researchers/scholars have shown greater interest in components such as the perishability of agricultural produce, food safety, IT applications, and logistics.

The Indian agri-business chain is more difficult than in developed countries due to its unorganised structure, numerous intermediaries, limited infrastructure, and lack of real-time farmer information. Inefficiencies in post-harvest supply chains result in losses. The systematic review emphasised the use of information technology. Blockchain enhances transparency and traceability. IoT helps farm surveillance, supply chain coordination, and cold chain supplies. AI can predict weather and production demands. Drone technology can be used to monitor and sprinkle

Table 9: Proposed Future Research Directions

Sl No.	*Suggested Future Research Directions*
1	Scholars and academicians should conduct more research on the agri -supply chain in India, despite the government's significant investments; this area remains underexplored.
2	Future studies should explore the use of Technology 4.0 (such as Artificial Intelligence, the Internet of Things, and Blockchain) in the agri -supply chain in India to improve efficiency and reduce post-harvest losses.
3	Studies on the availability and use of transport and storage infrastructure in India.
4	More research should be conducted on emerging themes such as the Circular Economy, Sustainability and the effects of climate change on the agri-supply chain.

(Source: Author's 2025)

fertiliser on farmland. Government assistance is required to build infrastructure and transport facilities.

The present study also has some limitations. Despite the researcher's efforts to collect literature from all available databases, the bias towards selecting literature on the Indian context may have led to the omission of some good articles. Also, only English-language research publications have been selected for review, which may introduce bias. There are many emerging areas where future research could be conducted. The same is outlined in *Table 9*

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Impact Investing: A Bibliometric Analysis and Topic Modelling Using Latent Dirichlet Allocation (LDA)

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Abstract

Impact Investing has gained increasing attention among millennial investors as a way to address social responsibility by directing funds towards inequality, climate change, and sustainable development. This study examines the intellectual, social, and conceptual structures of the field. VOSviewer and Biblioshiny(R) were used to analyse the performance and network structure of 759 peer-reviewed research papers published between 2000 and 2024. Topic modelling using the Latent Dirichlet Allocation (LDA) is also performed to identify hidden thematic structures in the literature. The study offers a new methodological contribution to this domain by combining topic modelling with bibliometric analysis. The findings highlight the interdisciplinary nature of the field, with results spanning finance, economics, psychology, and environmental studies. Key themes and further research needs are highlighted. The findings benefit researchers, regulators, and industry professionals in better understanding impact investing.

Keywords: *Impact investing, bibliometric analysis, topic modelling, LDA, sustainable finance*

1. Introduction

The term "impact investing" was coined by the Rockefeller Foundation in 2007 to describe "investments aiming for both financial return and positive social or environmental impact" (Höchstädter and Scheck, 2015). Subsequently, it has emerged as an important component of the broader sustainable finance ecosystem, attracting growing attention from academics, policymakers, and institutional investors. The Global Impact Investing Network (GIIN) reports that total assets under management (AUM) amount to USD 1.571 trillion worldwide (Hand et al., 2024). The majority of this share comes from developed regions, primarily Western, Northern, and Southern Europe (95%), followed by emerging markets with headquarters in Sub-Saharan Africa, Southeast Asia, the Middle East, and North Africa (5%). Scientific research in this domain is expanding into diverse subfields (Migliavacca et al., 2022), prompting scholars to assess scientific output quantitatively. Previous research has focused on definitions, measurement frameworks, and performance outcomes, but the literature is scattered in terms of conceptual clarity, analytical approaches, and practical implementation. With increasing global attention to the Sustainable Development Goals (SDGs) and sustainable finance, it is important to examine the growth and thematic evolution of this domain systematically. To address this gap, the current study combines bibliometric analysis with topic modelling to analyse the literature indexed in the Scopus database. To the best of our knowledge, this is the first-ever study to apply topic modelling in this domain. Specifically, the study seeks to answer the following research questions:

1. What are the developments in the domain of impact investing?
2. Who are the highly prolific authors in this field?
3. Which journals are prominent in the field?
4. What contributions have different countries made to the field?
5. What intellectual and collaborative structures exist within impact investing research?
6. Which research themes and topics are most explored?
7. What are the potential future avenues for impact investing research?

This study makes several contributions. First, it offers a systematic bibliometric review of the impact investing literature. Second, it uses topic modelling to detect key thematic clusters and emerging trends. Third, network analyses reveal the field's intellectual structure. These insights will help practitioners and policymakers understand key trends and suggest ways to foster a more standardised, transparent impact-investing ecosystem.

This paper proceeds as follows. Section 2 discusses relevant literature. Section 3 explains document extraction and review strategy. Section 4 shows the detailed analysis and results. Section 5 gives future research directions. Section 6 provides policy and theoretical implications, and Section 7 concludes.

2. Literature Review

2.1 Evolution of Impact Investing

Impact investing differs from traditional investing by targeting "positive social and environmental effects alongside financial returns" (Mahat et al., 2025). Related terms are often used interchangeably in this context. These include socially responsible investing (SRI) (Dorfleitner & Nguyen, 2016; Marshall et al., 2021), sustainable investing (Seifert et al., 2024; Kleffel & Much, 2023), responsible investing (Pilaj, 2017; Drut, 2010), ethical investing (Mishra et al., 2023; Renneboog et al., 2008), value-based investing (Shen & Venkatesan, 2019), triple bottom line investing (Nica et al., 2025) and social investing (An et al., 2023).

Financial markets have witnessed a rise in sustainable investment options (De Jong & Rocco, 2022; Rahim et al., 2024; Birk et al., 2024), alongside increasing institutional investor participation (Barber et al., 2021). Supportive regulatory frameworks and technological advancements contributed to this increased participation (Seow, 2025). Pension funds consider both financial and non-financial returns while incorporating sustainability into portfolio construction (Hoepner & Schopohl, 2020). Responsible investment behaviour is influenced by institutional and regulatory environments in pursuit of sustainability-oriented initiatives (Hoepner et al., 2021). Industry standards and best practices for measuring and managing environmental impact have evolved over time (Jain & Tripathi, 2023). Government initiatives and policy incentives create favourable conditions for the growth of impact investing and its integration into mainstream financial markets (Paulsy & M, 2024; Thomas et al., 2024).

2.2 Previous Bibliometric Studies on Impact Investing

Academic interest in this field has surged over the past decade, as seen by the rising number of publications. Bibliometric analysis, first introduced by Alan Pritchard

(1969), is useful for charting this growth. Scholars have increasingly applied such methods to examine research trends across various areas of sustainable finance, such as 'green banking', 'ESG investing', and 'sustainable investment'.

A review of 753 papers identified five key thematic clusters: sustainable development, sustainability, corporate social responsibility (CSR), sustainable investment, and environmental economics (MC, 2024). Another study emphasised the prevalence of social impact bonds and noted that green bonds and impact funds are largely untapped themes (Chiappini et al., 2023). Terms such as "corporate social responsibility," "sustainable development", and "ESG investing" are receiving growing attention in academic research (Rathore et al., 2024). Mobilising finance to tackle climate change has also emerged as an important topic (Talukder et al., 2025).

Existing studies have primarily relied on bibliometric techniques to examine publication trends, influential authors, and thematic clusters (Shome et al., 2023). Typically, these studies used citation analysis, co-authorship networks, and keyword co-occurrence to map the field's intellectual structure. However, such approaches may not fully capture the underlying thematic patterns in large volumes of academic text. A review of the Scopus database suggests that no prior bibliometric study has used LDA-based topic modelling to examine the evolution of the literature's themes systematically. The present study addresses the identified gap.

2.3 Topic modelling

"Topic modelling is a text-mining tool that identifies hidden themes or subjects within a set of documents" (Hankar et al., 2025). This method operates on the premise that every text has multiple themes, each linked to a set of frequently occurring words (Kherwal & Bansal, 2020). The temporal analysis of topic models enables researchers to track how research themes evolve over time periods (Griffiths & M., 2004). It complements bibliometric analysis by identifying latent themes in large document corpora (Cobelli & Blasi, 2024). Given the impact investing context, there is a need for such techniques to support deeper thematic exploration (MC, 2024; Migliavacca et al., 2022).

"Latent Dirichlet Allocation (LDA)", introduced by David Blei, Andrew Ng, and Michael Jordan (Blei et al., 2003), is a powerful tool for topic modelling. It has gained widespread adoption in natural language processing and computational text analysis (Nasution et al., 2023). It has been used for market prediction based on financial news (Garcia-Mendez et al., 2023) and sentiment mining of consumer financial complaints (Bastani et al., 2019). It was also applied to detect themes in financial fraud (Soltani et al., 2023) and to research mapping in crowdfunding (Rejeb et al., 2024). Topic modelling using LDA has become an increasingly common approach in bibliometric and scientometric studies. It helps to identify emerging research themes by analysig abstracts or full texts of research papers (Asmi et al., 2026).

3. Document Extraction and Review Strategy

The bibliometric review strategy outlined by Öztürk et al. (2024) is followed in this paper, which includes defining research aims, selecting the database, downloading the dataset, conducting the analysis, and summarising insights to recommend future research directions.

3.1 Document extraction

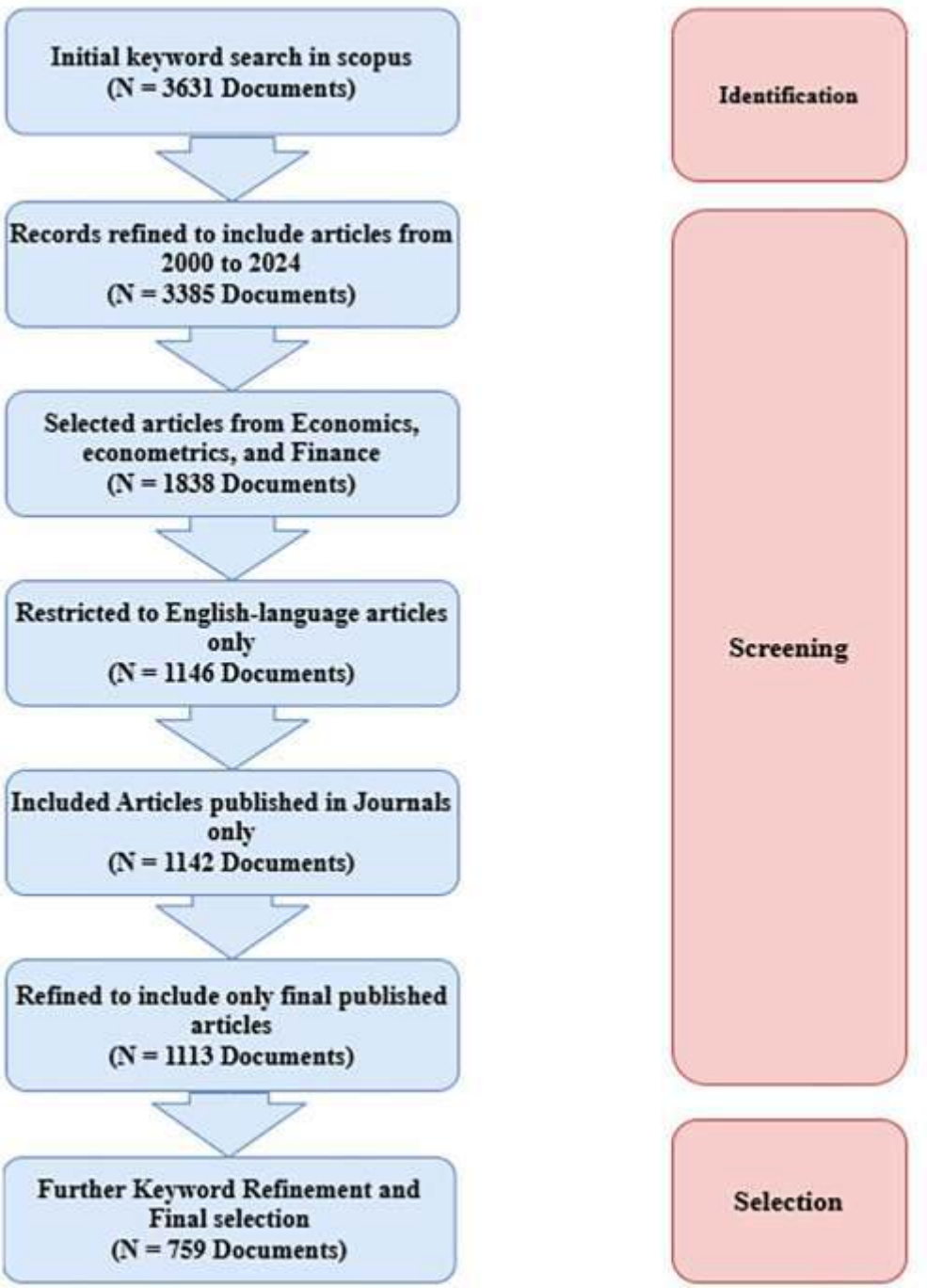
Documents were collected from the Scopus database to retrieve all the published articles. Scopus is most reliable and widely used database for bibliometric analysis in social science research (Rathore & Maheta, 2025). Publications with the following keywords: "impact investing," "sustainable investing," "responsible investing," "ESG investing," "socially responsible investing," and "ethical investing" were included. Figure 1 give details of various filters applied during document extraction.

Table 1 summarises the scholarly research between 2000 and 2024. 759 peer-reviewed articles met the research criteria. Among these, 136 research papers were single-authored. A total of 1,633 researchers contributed to these articles, which included 34,723 references. An average of 44.41% citations were observed per extracted paper. International co-authorship (27.27%) indicates a moderate level of global collaboration. An annual growth rate of 23.04% and a strong citation impact indicate rapid developments in this research field.

3.2 Review Strategy

The VOS-Viewer, introduced by Van Eck & Waltman (2010), was used to generate scientific maps for co-citation analysis, co-word analysis and bibliographic coupling. Biblioshiny(R), introduced by Aria & Cuccurullo (2017), was used to identify leading authors, journals, countries, and thematic maps.

LDA-based topic modelling was applied to publication abstracts to identify latent thematic structures that conventional analyses overlook. The results have helped identify possible directions for further research in impact investing. Table 2 summarises the techniques and software used for analysis.



Source: Author's elaboration

Figure 1: Research article selection process

Table 1: Documents Description

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2000:2024
Sources (Journals, Books, etc.)	237
Documents	759
Annual Growth Rate %	23.04
Document Average Age	6.26
Average citations per doc	44.41
References	34723
DOCUMENT CONTENTS	
Keywords Plus (ID)	368
Author's Keywords (DE)	1852
AUTHORS	
Authors	1633
Authors of single-authored docs	136
AUTHORS COLLABORATION	
Single-authored docs	150
Co-Authors per Doc	2.6
International co-authorships %	27.27
DOCUMENT TYPES	
article	759

Source: Biblioshiny(R)

Table 2: Techniques and Tools

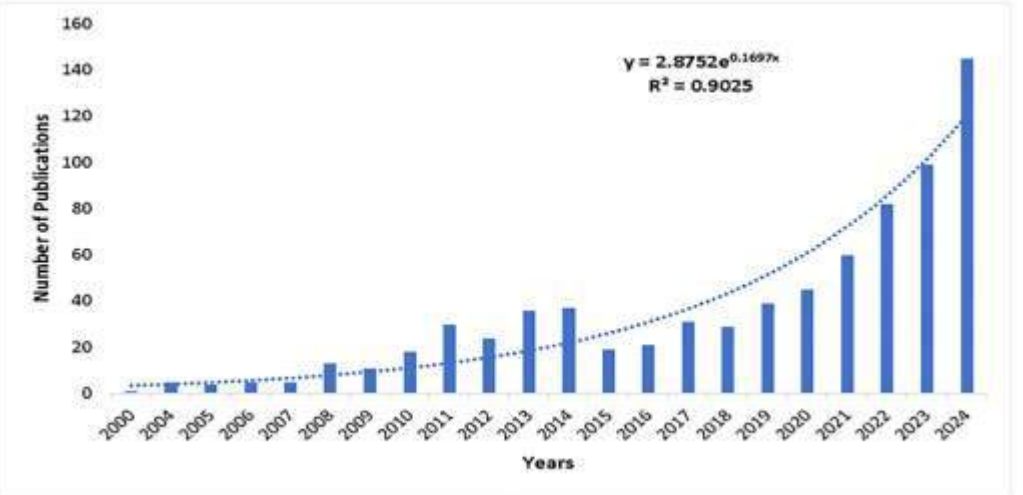
Research Question	Technique	Software
What are the developments in the field of impact investing?	Publication trend analysis & seminal papers	MS Excel & Biblioshiny(R)
Who are the highly prolific authors in this field?	Author Productivity Analysis	Biblioshiny(R)
Which journals are prominent in the field?	Source analysis & Bradford's Law	Biblioshiny(R)
What contributions have different countries made to the field?	Country Productivity Analysis	Biblioshiny(R)
What intellectual and collaborative structures exist within impact investing research?	Co-Citation analysis & Bibliographic Coupling	VOS-Viewer
Which research themes and topics are most explored?	Keyword Co-occurrence & Thematic Map	VOS-Viewer & Biblioshiny(R)
What are the potential future avenues for Impact investing research?	Topic Modelling	R Studio

Source: Author's elaboration

4. Analysis and interpretations

4. 1 Performance Analysis

4.1.1 Publishing Pattern



Source: Author's elaboration

Figure 2: Scholarly publication trend

Fig. 2 illustrates the quantity of annual publications on impact investing. The figure demonstrates a fast exponential growth rate on an annual basis, but it is not uniformly distributed. The exponential regression equation $y=2.8752 e^{0.1697x}$ suggests a positive publication trend with an average annual increase of 16.79%. An R-squared value of 0.9025 indicates a strong exponential growth trend over time.

The key observations are as follows:

- The first article published in a Scopus-indexed journal appeared in 2000.
- No research articles were published between FY 2001 and 2003.
- There was very limited research between FY 2004 and 2008.
- Publications began to increase significantly post-FY 2010 and peaked at 37 in FY 2014. More than 50% of the articles were published post-FY 2020.

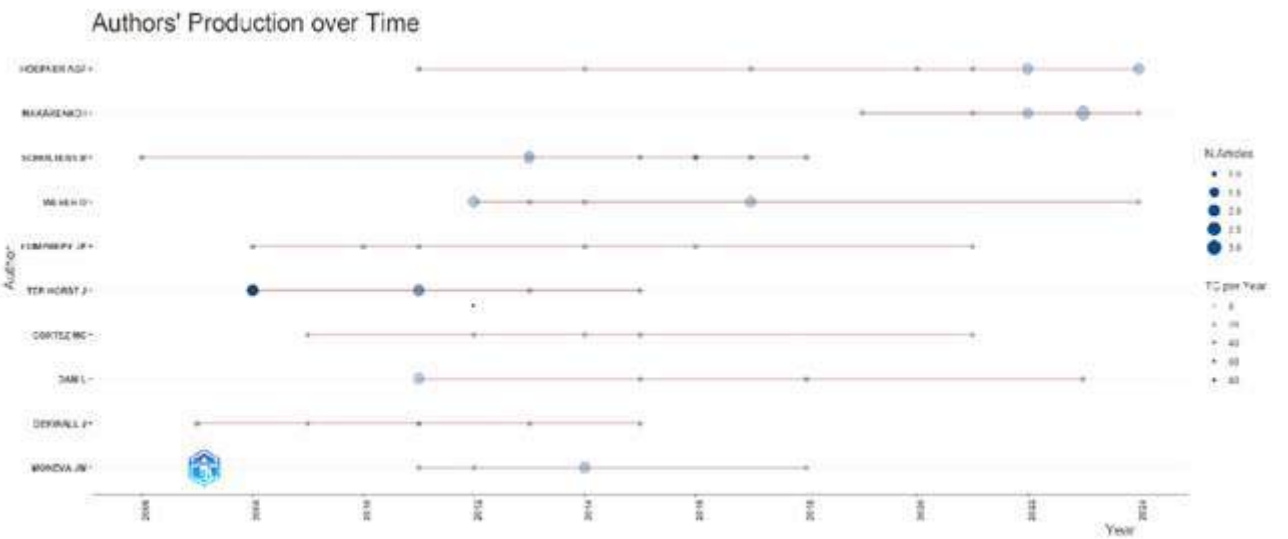
Traditional finance literature has focused on risk-return principles. Non-financial goals, such as social or environmental outcomes, have not received much attention. Mainstream academic interest was limited by the perception that subjects like 'ESG' (Environmental, Social, and Governance) and 'SRI' (Socially Responsible Investing) were ancillary or ideological. However, the increase in publications post FY-2010 shows rising interest among investors and academics for impact investing.

4.1.2 Top Authors

Table 3: Prolific Authors

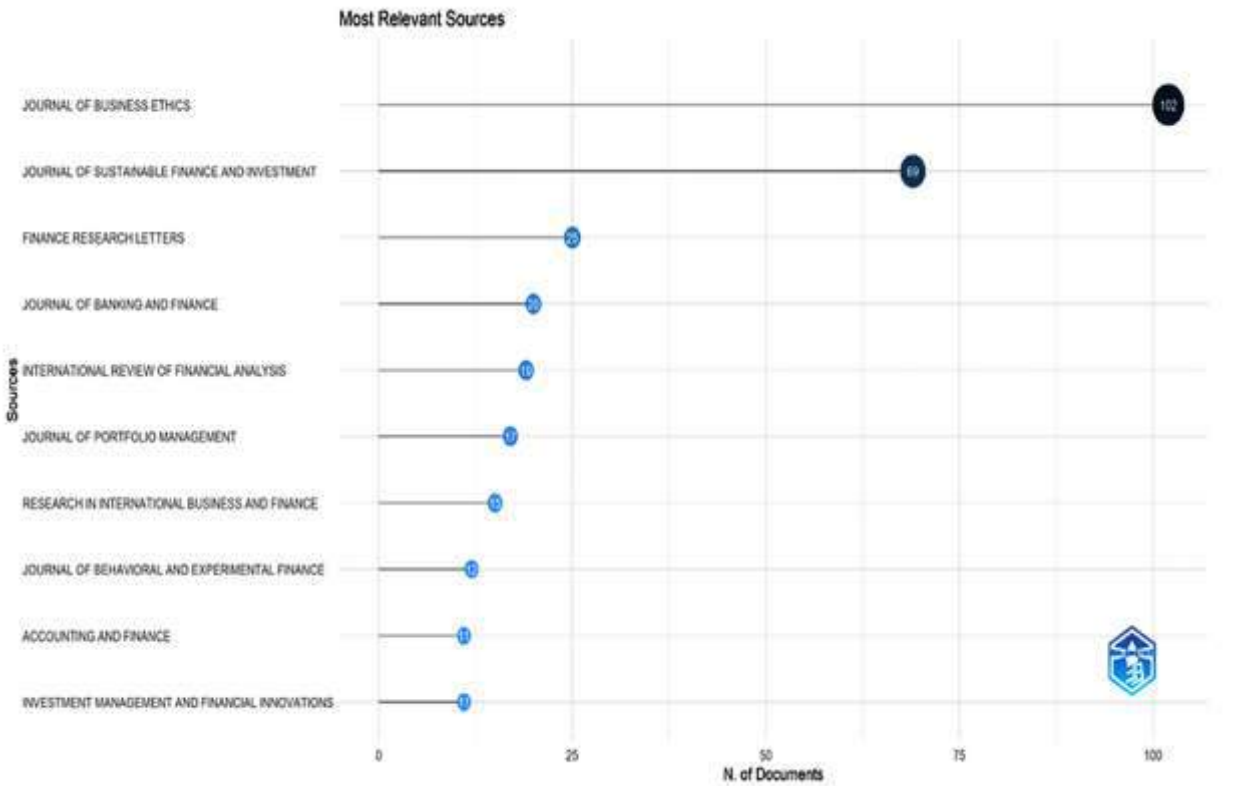
Authors	Articles	H index	Current affiliation	Country
Hoepner AGF	9	33	University College Dublin	Dublin
Makarenko I	8	15	University of Helsinki	Finland
Scholtens B	7	62	University of Saint Andrews	Scotland
Weber O	7	47	York University	Canada
Humphrey JE	6	17	University of Queensland	Australia
Ter Horst J	6	23	Tilburg University	Netherlands
Cortez MC	5	23	University of Minho	Portugal
Dam L	5	22	University of Groningen	Netherlands
Derwall J	5	20	Maastricht University	Netherlands
Moneva JM	5	49	University of Zaragoza	Spain

Source: Author's Elaboration



Source: Biblioshiny(R)

Figure 3: Temporal Trends in Author Output



Source: Biblioshiny(R)

Figure 4: Top sources by document count

Table 3 shows the top ten authors in the discipline, including their number of publications, H-indices and institutional affiliations. Andreas Hoepner (University College Dublin) ranks first with 9 publications and an H-index of 33. Inna Makarenko (University of Helsinki) ranks second with 8 publications and an H-index of 15. Bert Scholtens and Olaf Weber each contributed seven publications. Jacquelyn E. Humphrey and Jenke Ter Horst had six publications each. Other prominent contributors include Maria Cen Cortez, Lammertjan Dam, Jeroen Derwall and Jose M. Moneva, each of whom have authored five papers.

Fig. 3 shows the leading authors in the field. The dominance of prominent authors changed over time. Ter Horst J is active in the years 2008 to 2011, with a longer publication span but lower article counts per year. Hoepner AGF and Makarenko I, with larger bubbles, show higher article count and strong citation impact.

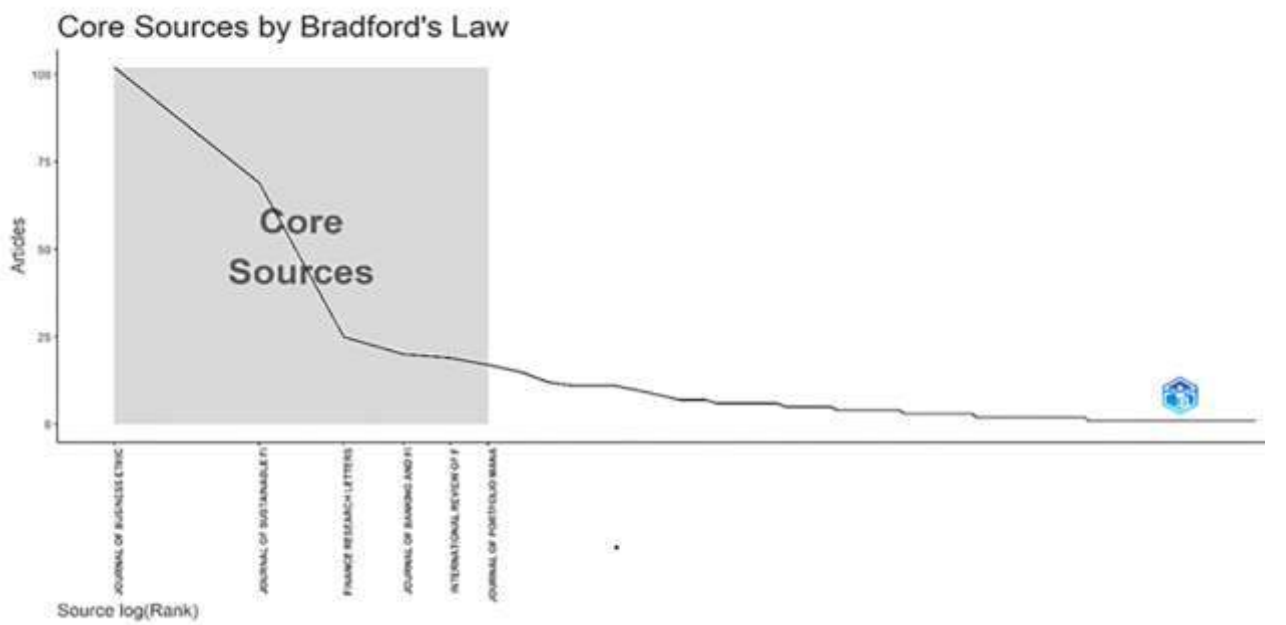
4.1.3 Leading Journals

Fig. 4 shows the leading journals indexed in this field. The "Journal of Business Ethics" with 102 publications demonstrates its prominence. This journal discusses ethical issues in investment and finance. The "Journal of Sustainable Finance and Investment" ranks second with 69 publications. This journal focuses on sustainable, impact-driven investment strategies. "Finance Research Letters" ranks third with 25 publications. Findings show that mainstream finance journals are also interested in sustainability.

Fig. 5 presents Bradford's Law of Scattering, used to determine the core journals. The values on the x-axis display the logarithm of the source rank. The values on the y-axis represent the number of articles published by each source. The literature is distributed unevenly across journals, with a few journals accounting for the majority of publications.

4.1.4 Seminal Papers

Table 4 lists the top-cited articles in the field. "The impact of corporate social responsibility on the cost of bank loans" is the most cited article with 1251 citations, followed by Edmans A (2011)'s article with 1210 citations. "Socially responsible investments: Institutional aspects, performance and investor behaviour" holds third position with 1058 citations.



Source: Biblioshiny(R)

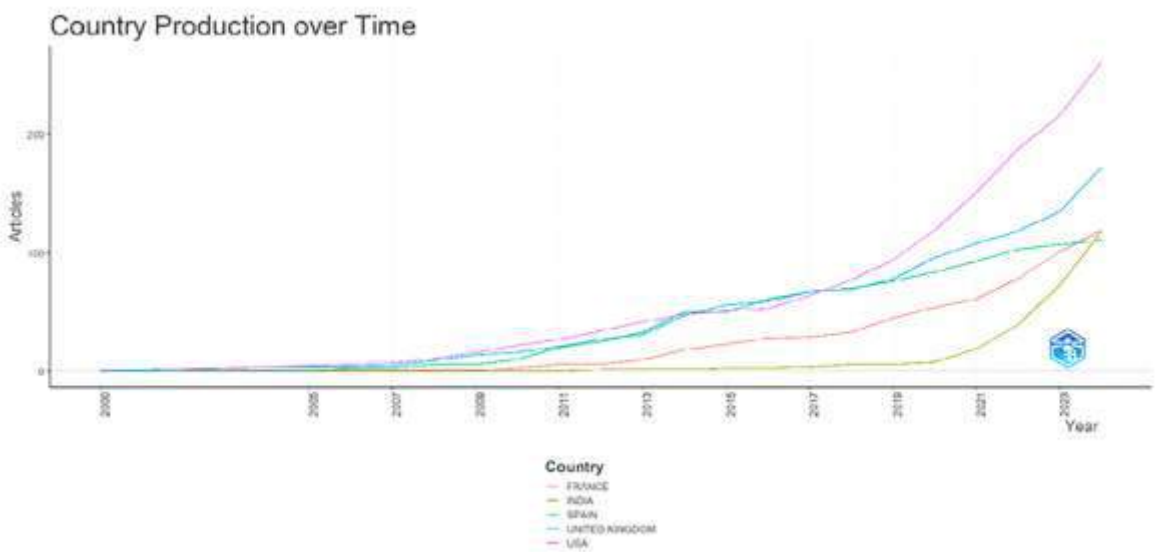
Figure 5: Bradford's Law

Table 4: Seminal papers as per total Scopus citations

Rank	Title & authors	Total citations
1	"The impact of corporate social responsibility on the cost of bank Loans" (Goss and Roberts, 2011)	1251
2	"Does the stock market fully value intangibles? Employee satisfaction and equity prices" (Edmans,2011)	1210
3	"Socially responsible investments: Institutional aspects, performance, and investor behaviour" (Renneboog et al., 2008)	1058
4	"Corporate green bonds" (Flammer, 2021)	899
5	"Responsible investing: The ESG-efficient frontier" (Pedersen et al., 2021)	756
6	"Sustainable investing in equilibrium" (Pastor et al.,2021)	706
7	"The effect of pro-environmental preferences on bond prices: Evidence from green bonds" (Zerbib, 2019)	681
8	"The effect of socially responsible investing on portfolio performance" (Kempf, 2007)	499
9	"The price of ethics and stakeholder governance: The performance of socially responsible mutual funds" (Renneboog, 2008)	497
10	"ESG Integration and the Investment Management Process: Fundamental Investing Reinvented" (Duuren et al., 2016)	400

Source: Author's Elaboration based on R outputs

4.1.5 Top Countries:



Source: Biblioshiny(R)

Figure 6: Cross-country publication growth

Fig. 6 shows the production of countries over time. The UK and the USA were early contributors to this field. Publications began to increase significantly in all five countries after 2009. Until about 2014, Spain held the lead, followed by the USA and UK, which had notable upticks. India's growth accelerated after 2020, driven by rising interest in ESG, climate finance, and sustainable development. There was significant growth in articles from the USA beyond 2015, reaching almost 250 articles in 2024. USA is a prominent leader in this field. The study observes an increase in academic focus and growing interest in sustainable finance. The trendlines reflect the dynamic and expanding nature of this research field.

4.2. Network Analysis

4.2.1 Co-Citation of References

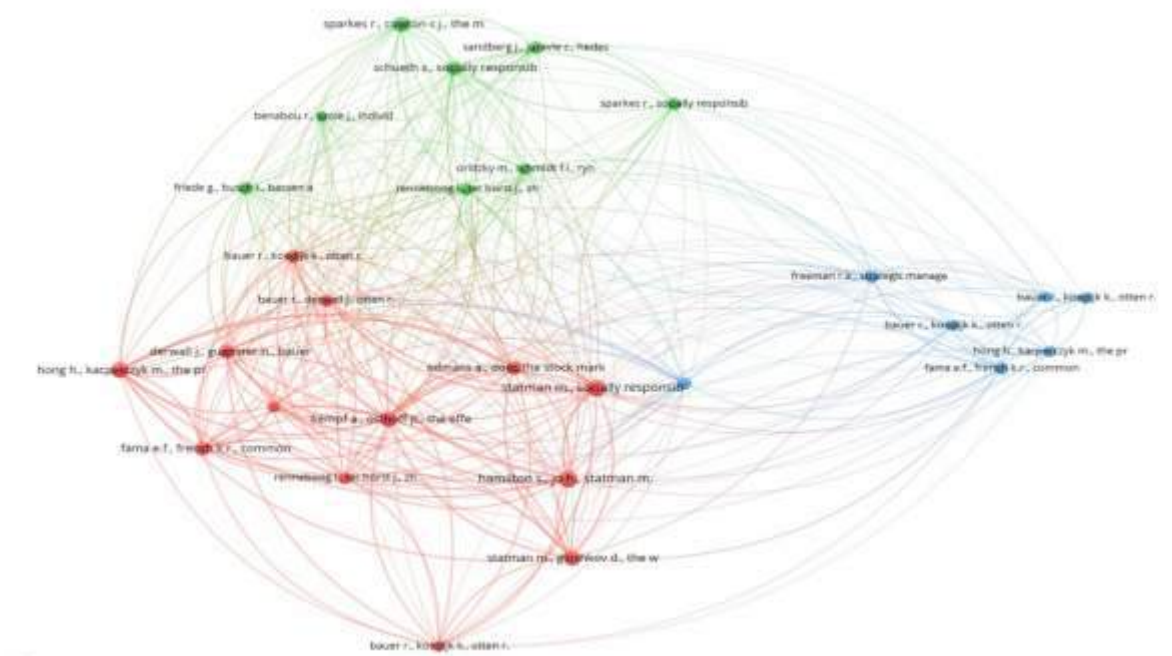
"Co-citation is the frequency with which two documents are cited together by other documents" (Liu & Chen, 2012).

Fig. 7 was created using VOSviewer, where coloured nodes identify clusters of co-cited authors, and connecting lines represent their connections.

- The red cluster is the densest, featuring authors such as Fama E.F., Hamilton S., Statman M., and Renneboog L., who focus on asset pricing, socially responsible mutual funds, socially responsible investing, and ESG investing.
- The green cluster features authors such as Sparkes R., Schueth S., Busch T., and Benabou R., who focus on social norms and motivations behind ethical investing, the stakeholder approach, and ethical mutual funds.
- The blue cluster features authors such as Freeman R. E., Bauer R., Hong H., and French K. R., who focus on concepts related to SRI, investor preferences, and firm behaviour.

Together, these clusters represent the coexistence of qualitative finance and integrative ESG approaches.

4.2.2 Keyword Analysis



Source: VOSviewer

Figure 7: Co-citation of References

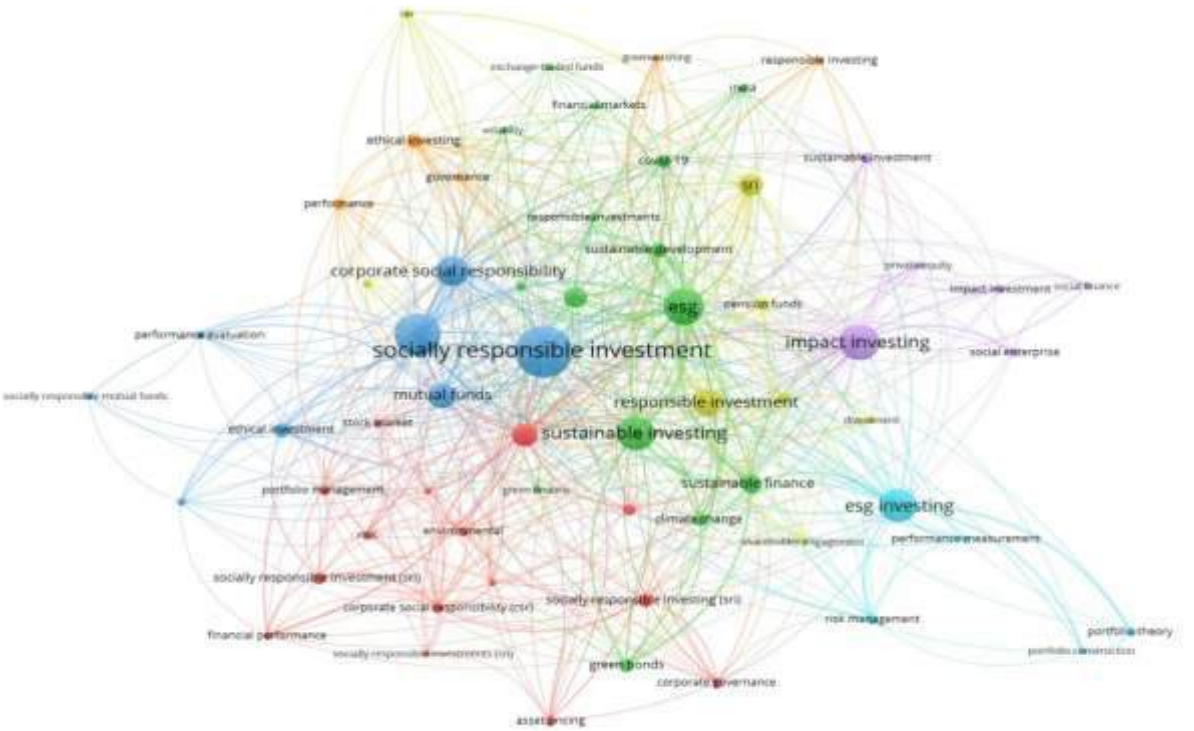


Figure 8: Keyword Co-occurrence network map

Fig. 8 highlights essential topics that define the framework of impact investing research. An explanation of this network is given in Table 5.

Table 5: Major clusters and keywords

Keyword	TO	TLS	DC	EC
Cluster 1: ESG				
esg	88	192	285	1
Sustainable investing	81	120	271	0.71
responsible investments	59	68	51	0.09
socially responsible investments	40	53	139	0.27
sustainable finance	35	75	110	0.38
sustainable development	24	46	92	0.25
Green bonds	22	41	68	0.23
covid-19	21	43	78	0.21
climate change	20	38	72	0.2
sustainable investments	12	17	52	0.07
India	11	25	50	0.14
financial markets	11	20	38	0.12
green finance	9	12	32	0.06
volatility	8	17	33	0.06

Keyword	TO	TLS	DC	EC
exchange-traded funds	8	13	30	0.07
Cluster 2: Socially Responsible Investment				
Socially responsible investment	146	172	464	0.81
socially responsible investing	108	133	358	0.73
Corporate Social Responsibility	67	123	209	0.69
Mutual funds	53	86	164	0.47
Ethical Investment	23	45	76	0.25
Performance evaluation	10	20	32	0.09
socially responsible mutual fund	8	9	23	0.06
Cluster 3: sustainability				
sustainability	46	99	170	0.53
socially responsible investing (sri)	21	28	72	0.07
socially responsible investment (sri)	17	25	62	0.06
corporate social responsibility(csr)	16	37	60	0.12
environmental	14	28	69	0.12
asset pricing	14	19	46	0.13
portfolio management	13	22	54	0.08
corporate governance	13	22	52	0.12
financial performance	11	21	38	0.12
stock market	10	18	45	0.09
risk	10	17	33	0.08
sustainable and responsible investment	9	16	42	0.05
socially responsible investments (sri)	8	9	31	0.03
Cluster 4: Responsible investment				
responsible investment	59	68	213	0.39
sri	43	86	154	0.52
pension funds	16	37	76	0.15
fiduciary duty	11	22	47	0.11
divestment	9	17	37	0.08
shareholder engagement	8	20	33	0.09
csr	8	26	38	0.19
Cluster 5: Impact Investing				
Impact investing	87	94	325	0.47
sustainable investment	16	24	76	0.14
impact investment	12	19	50	0.06
social enterprise	10	19	46	0.08
Private equity	9	17	36	0.1
Social finance	8	13	35	0.06
Cluster 6: ESG investing				
ESG investing	77	79	219	0.23
Risk management	14	25	51	0.1
Performance measurement	11	17	32	0.06
Portfolio construction	8	14	22	0.05

Keyword	TO	TLS	DC	EC
Cluster 7: ethical investing				
ethical investing	25	50	90	0.25
performance	16	31	55	0.17
responsible investing	12	19	47	0.13
governance	10	23	44	0.13
greenwashing	8	23	39	0.16

TO= Total occurrence, TLS= Total Link Strength, DC= degrees of centrality, EC= Eigenvector centrality

Source: Author's elaboration

Table 5 presents seven main themes: ESG, socially responsible investment, sustainability, responsible investment, impact investing, ESG investing, & ethical investing. The accompanying statistics show the total occurrence of each keyword; the total link strength (TLS) is used to measure the strength of connections between keywords (Chalissery et al., 2023); the degree of centrality (DC) represents the number of connections which any keyword has in the network; and eigenvector centrality (EC) is used to assess the importance of each keyword (Donthu et al., 2021).

Cluster 1 (Green) - ESG: The largest cluster in the network is ESG, containing fifteen terms. The word "ESG" appears 88 times and is linked to 285 other terms. An eigenvector value of 1 indicates that a node is central in the network. A total link strength (TLS) of 192 indicates strong connectivity. Other frequent keywords in this cluster are "sustainable investing," "responsible investments," "sustainable finance," "sustainable development," "green bonds," "COVID-19," "exchange-traded funds," and "financial markets."

Cluster 2 (Dark Blue) - Socially Responsible Investment: The second-largest cluster in the network has 7 keywords. The term "socially responsible investment" appears 146 times and has an eigenvector value of 0.81, indicating high influence. A centrality score of 464 indicates that it is connected to many other terms in the network. A TLS of 172 suggests frequent co-occurrence. Other notable keywords in this cluster are "socially responsible investing," "corporate social responsibility," "mutual funds," "ethical investment," "performance evaluation," and "socially responsible mutual funds."

Cluster 3 (Red) - Sustainability: The third-largest cluster consists of 13 terms. The term "sustainability" appears approximately 46 times and links to 170 other terms. An eigenvector value of 0.53 indicates that sustainability is an important thematic connector. Other prominent keywords in this cluster are "socially responsible investment," "environmental," "asset pricing," "financial performance," "portfolio management," "corporate governance," "stock market," and "sustainable and responsible investing."

Cluster 4 (yellow) - responsible investment: The fourth-largest cluster contains seven keywords. "Responsible investment" occurs 59 times and is connected to 213 other keywords. It has an eigenvector value of 0.39. Other important keywords in this cluster are "SRI," "pension funds", and "CSR."

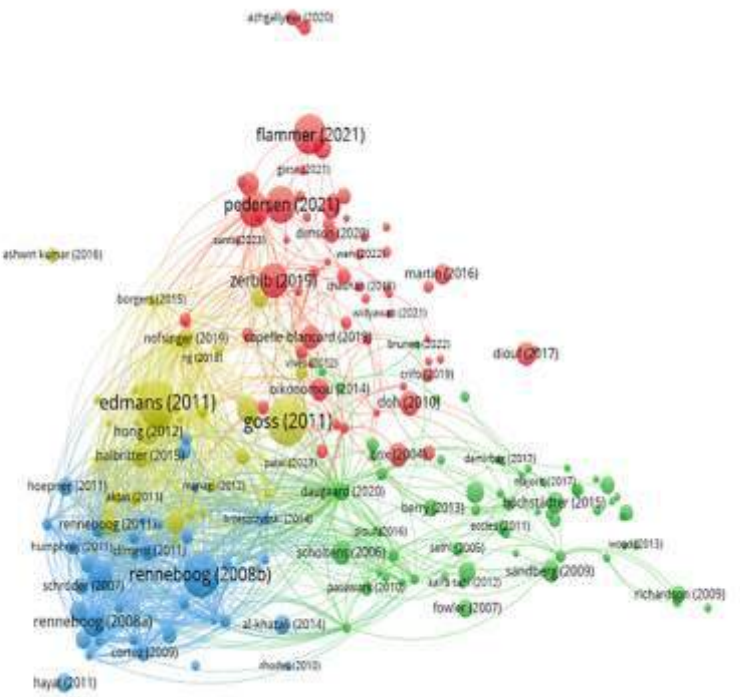
Cluster 5 (purple) - Impact investing: The fifth cluster in this network is impact investing, with six words. The word "impact investing" appears approximately 87 times. It is connected to 325 other keywords, with a TLS of 94 and an eigenvector centrality of 0.47, indicating its significance within the research field. Other popular terms in this cluster are "sustainable investment," "impact investment," "social enterprise," "private equity," and "social finance."

Cluster 6 (light blue) - ESG investing: The sixth-largest cluster in the network, is ESG *investing,* with four more keywords. ESG investing is the dominant keyword in this cluster, with a centrality score of 219. An eigenvector centrality of 0.23 indicates that it is a secondary node and is connected to many other main topics.

Cluster 7 (orange) - ethical investing: The final cluster in this network is ethical investing, with 5 keywords. Ethical investing occurs 25 times, with a TLS of 50. It is connected to 90 other keywords in the network. It has an eigenvector value of 0.25, which shows that ethical investing is a secondary node, linked to many other main topics.

4.2.3 Bibliographic Coupling

'Bibliographic coupling finds connections between publications through shared references' (Kessler, 1963).



Source: VOSviewer

Figure 9*:* Bibliographic Coupling

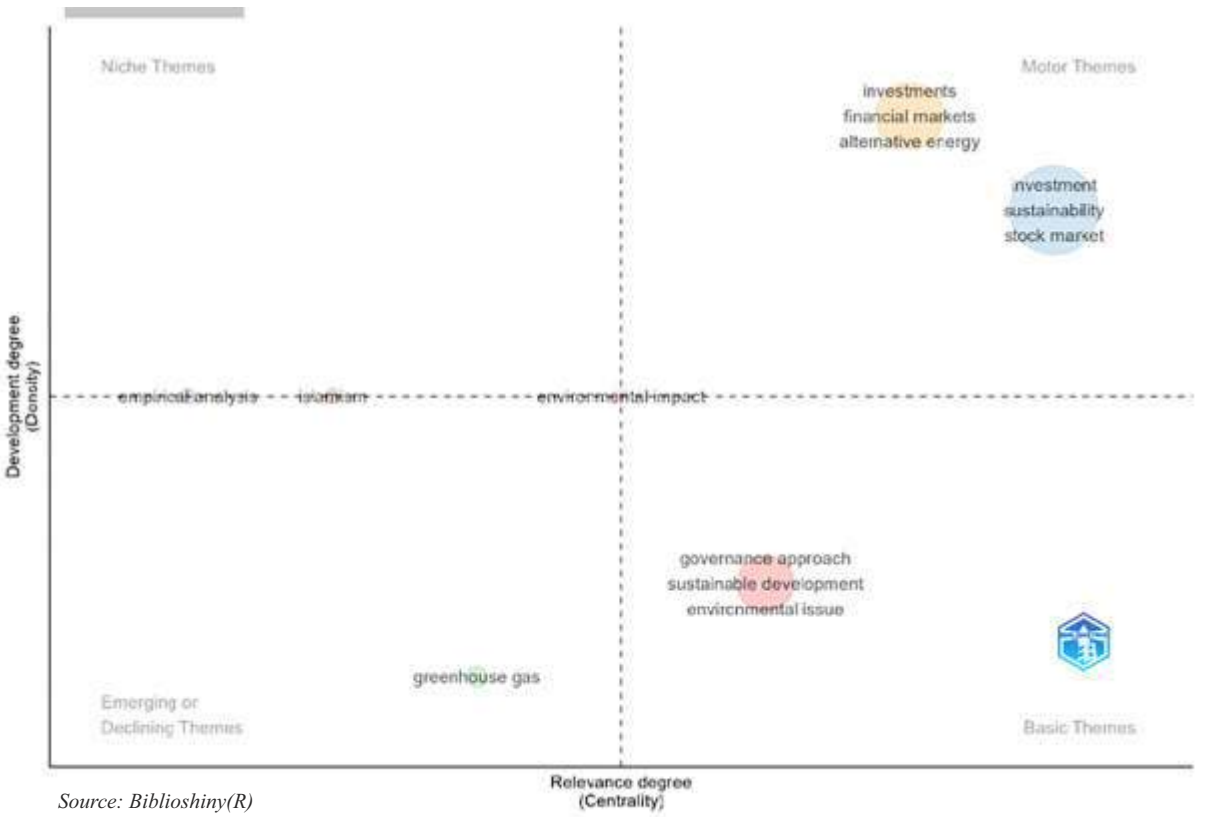
The conceptual structure of a research field is shown in Fig. 9. Each node represents a publication, and the links indicate common references. The dimensions of each node represent citation impact, and colours represent clusters of closely related documents.

- The red cluster includes works by Flammer (2021), Pederson (2021), Zerbib (2019), Wen (2022), and other authors, with a focus on sustainable finance, ESG integration, and climate-related financial policies.
- The yellow cluster includes works by Edmans (2021), Hong (2012), Goss (2011), and other authors, with a focus on hybrid themes linking corporate finance and ESG.
- The blue cluster includes works by Renneboog (2008b), Hoepner (2011), and Schroder (2007), which connect topics such as fund performance, SRI and ESG frameworks.
- The green cluster includes works by Sandberg (2009), Daugaard (2020), and Richardson (2009), which focus on ethical, social and philosophical aspects of impact investing.

4.2.4 Thematic Map

Figure 10 shows various themes for the research field, based on their progress and applicability

- The upper right quadrant (motor themes) includes words such as “investment,” “sustainability,” “stock market,” “investments,” “financial markets,” and “alternative energy.” These topics are very influential and are used to bridge different areas of research.
- The lower-left quadrant is associated with emerging or declining themes in which "greenhouse gas" is highlighted with low centrality and density.
- “Empirical analysis” and “Islamism” are near the boundary between niche and emerging themes, indicating limited presence in the research network and minimal development.
- The top-left quadrant contains no niche themes, which suggests a lack of specialised themes.
- “Environmental impact” is moderately central but not well developed.
- The bottom-right quadrant includes basic themes with clusters such as “governance approach,” “sustainable development,” and “environmental issue.” These themes are foundational in the research field.



Source: Biblioshiny(R)

Fig. 10: Thematic Map

Table 6: Topic Modelling Results

Topic	Top Terms	Annotation
1	Responsible, socially, investment, results, performance	SRI results
2	Impact, investors, sustainable, investment, performance	Impact investment performance
3	Social, sri, investors, market, ESG	Responsible investment markets
4	ESG, impact, responsible, performance, investment	ESG investment
5	Funds, sri, investment, social, ESG	SRI Funds
6	Investment, funds, financial, sri, risk	Financial risk in ESG investing

Source: Author's elaboration

4.3 Topic modelling results

"Topic modelling" was performed using LDA implemented in the R packages *tm* and *topicmodels*. After text preprocessing, a document-term matrix was constructed, and terms that appeared in fewer than 1% of documents were removed. The LDA model was estimated using the Variational Expectation Maximisation algorithm with six topics. The top terms for each topic were extracted to interpret the dataset's thematic structure.

The top five terms for each topic are shown in Table 6. The first topic, "SRI Results", highlights the financial outcomes of SRI. The second topic, "Impact investment performance," is focused on aligning impact investments with sustainability. The third topic, "Responsible investment markets", highlights the increasing investor interest and participation in these markets. The fourth topic, "ESG Investment", shows increasing integration of ESG into investment decisions. The fifth topic, "SRI Funds", focuses on funds that align with ESG criteria. The last topic,

"Financial risk in ESG Investing", highlights risks associated with ESG investments.

5. Future research directions

5.1 Behavioural Finance

The theory of planned behaviour, risk perception, and internal motivation are some of the factors that drive investors' interest in impact investing (Rathee & Aggarwal, 2022). Factors such as awareness, beliefs, age, and income (Ahamed et al., 2023); governing behaviour (Rathee & Aggarwal, 2023); and framing effects (Pant & Mishra, 2025) are the key drivers of investment decisions. However, there is limited research on how risk perception, personality types, and cognitive biases affect investors' choices regarding impact funds (Vega et al., 2025; Menon & Rai, 2025). In the future, researchers should explore how such aspects, along with regional and external variables, influence investor behaviour (Pasquino & Lucarelli, 2025; Kraussl et al., 2024).

5.2 Technology and AI

Artificial intelligence has transformed many aspects of financial markets, including ESG and socially responsible investing. Antončič (2020) noted that big data analytics can correct self-reporting biases and provide deeper insights into a firm's ESG performance. Given these advancements, further research should examine how different aspects of AI, such as machine learning, natural language processing, and predictive analytics, affect investments in sustainable funds (Kumar et al., 2025; Hadhri et al., 2025).

5.3 Corporate Governance

Strong corporate governance enhances transparency, accountability, and ethical business practices and is vital for assessing the credibility and effectiveness of impact investing (Hoepner & Schopohl, 2018). Research shows that companies with robust governance systems attract long-term investors (Aggarwal et al., 2025; Asteriou et al., 2024). Governance factors such as board diversity, stakeholder relations, and executive accountability also influence a firm's ESG performance and contribute to building investor trust (Miranda et al., 2023). Future research should investigate how various governance factors affect the scale and efficiency of impact investments across different institutional and national contexts (Agrawal & Hockerts, 2021).

5.4 Environmental Factors

Investors are increasingly interested in investments that advance sustainability, reduce carbon footprints, and address climate change (Gurrib et al., 2023; Senadheera et al., 2021; Gao & Hoepner, 2024). However, these investors face challenges, including low expected returns, high investment risks, and insufficient market capacity. Such challenges constrain investments in renewable energy and sustainable infrastructure projects (Taghizadeh-Hesary & Yoshino, 2020). Companies with strong environmental strategies tend to be more resilient over time and deliver better risk-adjusted returns (Wang et al., 2024; Hasnaoui, 2025). Better corporate environmental performance generally leads to superior returns (Shmelev & Gilardi, 2025). As environmental risks become increasingly financially significant, future research can examine how different environmental performance indicators shape investor preferences and capital allocation in impact investing across sectors and regions.

5.5 Performance

There is limited empirical evidence on financial performance and risk implications across sustainable markets and assets (Agrawal & Hockerts, 2021; Schlütter et al., 2024). Very few studies have examined how impact investing portfolios align with the United Nations Sustainable Development Goals (SDGs) and whether they generate measurable sustainability outcomes. Future studies should investigate how financial performance, risk exposure, and SDG alignment jointly shape the effectiveness and scalability of impact investing strategies (Talukder et al., 2025; Vega et al., 2025).

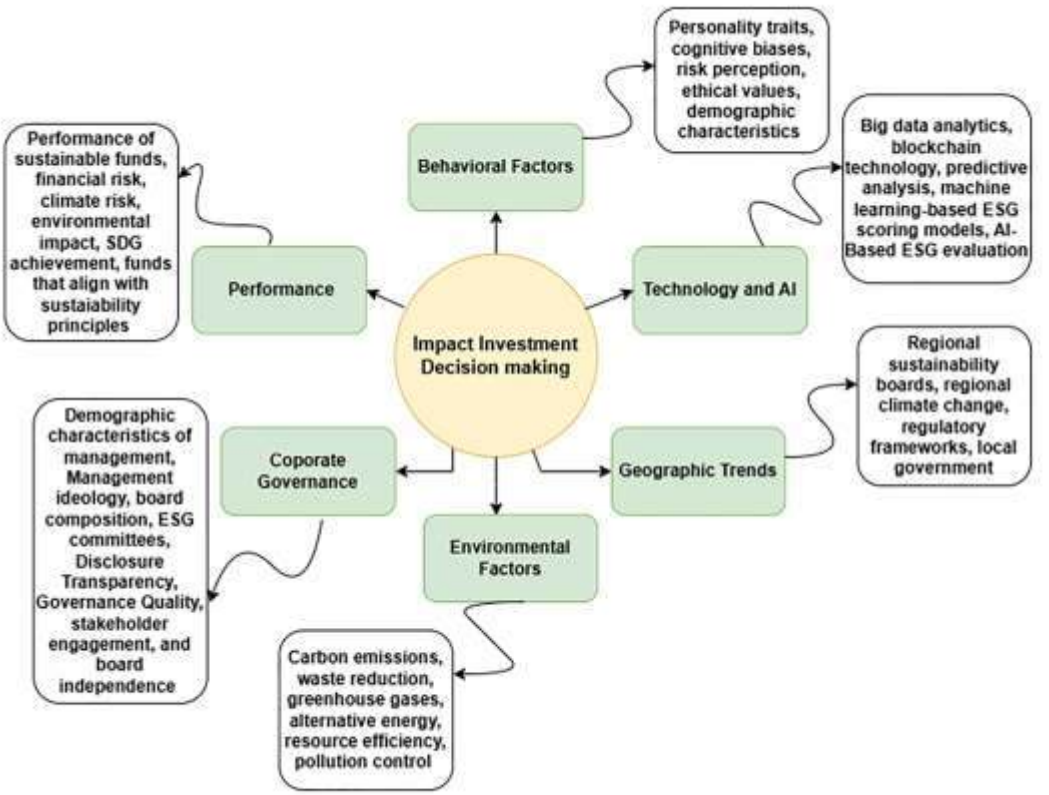
Fig. 11 presents various variables that can help extend the impact investing literature.

6. Implications

6.1 Policy Implications

The findings of this study have important suggestions for regulators, institutional investors, and policymakers.

- Policy makers should improve investor confidence and comparability across markets through regulations and disclosure systems, such as the EU Taxonomy and SEC climate risk disclosure rules.
- Policy makers should employ artificial intelligence and other advanced technology-driven tools to detect greenwashing and sustainability misreporting.



Source: Authors' elaboration

Figure 11: Future research directions

- Regulators and institutional investors should encourage governance reforms through enhanced reporting requirements and incentives for credible impact investments.
- The Global Impact Investing Network (GIIN) and the United Nations-supported Principles for Responsible Investment (UNPRI) should establish shared principles and best practices, and facilitate cross-country collaborations to develop a global impact investing ecosystem.
- The government should link climate policies with investment incentives such as tax relief for green bonds, or subsidies for renewable energy funds, etc., to mobilise more capital for sustainability.

6.2 Theoretical Implications

The findings of this study have important theoretical implications for both Behavioural finance and psychology. The presence of themes such as socially responsible investing, sustainability, and ESG in this analysis supports the idea that investor choices now incorporate environmental and sustainability motives. Behavioural finance literature shows that investors' decisions are influenced by factors such as ethical values, framing effects, mental accounting and other considerations. Behavioural finance theories (Shefrin & Statman, 2000) provide a useful framework for understanding why investors allocate capital to sustainable funds, even if these funds offer lower financial returns. For example, these findings extend behavioural finance theory by highlighting the role of pro-social preferences, moral satisfaction, and environmental awareness in shaping sustainable investment behaviour.

From a psychological perspective, impact investing can also be explained using theories such as the Theory of Planned Behaviour (Ajzen, 1991), Social Norm Theory (Gilbert et al., 1998), and Prosocial Behaviour Theory

(Batson, 2014). Investment decisions are influenced not only by financial considerations but also by attitudes, social expectations, and intrinsic motivations to contribute to societal welfare. Social influence from peers, family members, and professional networks may encourage investors to choose socially responsible investments. Additionally, investors may experience moral satisfaction and reputational benefits from supporting sustainable and socially beneficial projects. These psychological drivers highlight that impact investing behaviour extends beyond traditional risk-return considerations.

7. Conclusion

Impact investing exemplifies a collective belief in sustainable development and has experienced rapid scholarly expansion in the last decade. Spurred by increasing academic interest, this study charts the development of the impact investing literature over the past 20 years. This paper expands the literature by applying bibliometric analysis and the LDA technique for topic modelling in an innovative way.

The study is based on 759 scholarly articles published between 2000 and 2024. The paper discusses top journals, top authors, and most cited papers. It also explores co-citation maps, the collaboration networks, and keyword co-occurrence to reveal thematic trends and intellectual connections. Using LDA-based topic modelling, the research investigates the thematic evolution and trending topics in impact investing scholarly research and offers an agenda for future research.

The results show a significant increase in impact investing studies, as evident by the growing number of academic publications, contributing authors, and countries involved. Thematic map analysis highlights new focus areas such as greenhouse gases, air pollution, and environmental impact. LDA-based topic modelling reveals that impact investing research is expanding into various fields, including behavioural finance, corporate finance, portfolio management, and sustainability, reflecting the discipline's diverse nature.

Nonetheless, this research has some limitations. Peer-reviewed articles from the Scopus database are the only data source, which limits the study's scope. Future research could apply the same methodology across multiple databases (such as ProQuest, Web of Science, or JSTOR) to achieve broader coverage. This study included only English-language articles, excluding relevant work in other languages. Future investigations could incorporate multilingual sources to enhance external validity. Finally, while co-citation network analysis was used, future research could employ alternative methods (such as self-organising maps or continuous space modelling) to examine the field's conceptual structure in greater detail.

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