ISSN 0975-895X
E-ISSN 2581-7450
Vol. 20, Issue 2, 2025
Peer Reviewed Journal

SFIMAR RESEARCH REVIEW

ST. FRANCIS INSTITUTE OF MANAGEMENT & RESEARCH (SFIMAR)
and
ST. FRANCIS INSTITUTE OF MANAGEMENT & RESEARCH - PGDM
Approved by AICTE, DTE, An ISO 9001:2015 Certified
Gate No.5, Mount Poinsur, S.V.P. Road, Borivali West, Mumbai 400103.
Mob. : +91 9619499199, +91 9619499099
Email: srr@sfimar.org Website : www.sfimar.org

SFIMAR RESEARCH REVIEW (SRR)

Journal of St. Francis Institute of Management and Research

Table of
Content ...

Editorial...

We are pleased to announce the release of **Volume 20, Issue 2** of the SFIMAR Research Review, a biannual, double-blind, peer-reviewed, open-access journal published by St. Francis Institute of Management and Research. The journal is committed to sharing information with real-world applications in a variety of management fields and is published with **ISSN 0975-895X/2581-7450** to ensure the international standard of quality and is dedicated to disseminating knowledge. We hope that this journal will continue to inspire important, innovative, and experiential ideas in the field.

There are five thought-provoking research papers in this issue.

- **Dr E Venkatesan & Dr V Thangavel** investigate the Recent advancements in artificial intelligence have led to increased adoption of machine learning and deep learning techniques in financial risk management. Deep learning models, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks, have demonstrated strong potential for analysing high-dimensional financial data.
- **Ms. Bhavana B. Solanki** presents that Unified Payments Interface (UPI) has expanded quickly and is currently the top digital retail payment system in India and has grown rapidly. She proposes a complicated relationship that is impacted by changes in policy, merchant acceptance, and differences between rural and urban locations. Examined are merchant discount structures, financial inclusion, and policy implications for payment regulation.
- **Dr Aashis Joshi** compares the performance of two different financial environments on the Indian equity market and the cryptocurrency market. In his experiment, he indicated four popular, widely used technical indicators, which are Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Bollinger Bands, and Stochastic Oscillator.
- **Mr Praveen Kumar and Mr Puviyarasan** evaluated the essential elements influencing the performance of supply chains in MSMEs in Coimbatore and used SEM methodologies to increase operational efficiency and its digital adoption challenges.
- **Ms Ann Jose, Dr S Bhawiya Roopa & Dr Sibu C Chithran** investigate overconfidence bias among Indian equities investors using secondary data analysis from NSE Market Pulse reports and the SEBI Investor Survey 2025. Perceived knowledge, excessive risk-taking, overtrading, solo decision-making, skill overestimation, inadequate diversification, and demographic tendencies are some of the ways that overconfidence shows up.

We hope this issue will be enlightening and enriching for our readers. We would like to express our profound appreciation to all the authors, reviewers, editorial board members and support personnel whose hard work made this publication possible. Your ongoing contributions support the SFIMAR Research Review's dedication to high standards in academic research. We anticipate your continued participation and support in upcoming editions.

Prof. Dr Shalini Sinha
Chief Editor

AN AUTOMATED APPROACH TO CREDIT RISK ANALYSIS IN LOAN PROCESSING USING DEEP LEARNING TECHNIQUES

***Dr E. Venkatesan, **Dr V. Thangavel**

ABSTRACT

Risk analysis is a fundamental component of loan processing in the banking sector, where accurate assessment of borrower creditworthiness is essential for reducing financial risk and maintaining institutional stability. The rapid growth of digital banking systems has led to the generation of large and complex financial datasets, making conventional risk evaluation methods increasingly inadequate. This study proposes a structured risk analysis framework for loan processing based on deep learning techniques to support intelligent and automated decision-making. A dedicated data preprocessing stage is incorporated to improve data quality, where a median filter is employed to manage noise, missing values, and outliers commonly found in banking data. The framework explores the use of multiple deep learning models, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks, for modelling loan-related risk factors. By integrating advanced preprocessing methods with deep learning-based analysis, the proposed approach aims to strengthen the reliability, consistency, and scalability of risk assessment processes in modern banking environments.

Keywords: Loan Processing, Credit Risk Assessment, Banking Sector, Deep Learning, Median Filter, Data Preprocessing, Financial Risk Analysis.

Introduction :

The banking sector plays a fundamental role in economic development by channelling funds from savers to borrowers through structured lending mechanisms. Loan processing is one of the most critical banking operations, as it directly influences profitability, liquidity, and long-term financial stability. Ineffective assessment of borrower risk can lead to loan defaults, increased non-performing assets, and systemic financial challenges. Consequently, robust risk analysis is essential for ensuring sound credit decisions and sustainable banking practices (Ghosh, 2019; Saunders & Allen, 2010).

Traditionally, credit risk assessment has been performed using statistical techniques such as logistic regression, discriminant analysis, and rule-based scoring systems. These approaches rely on predefined assumptions and limited financial indicators, which restrict their ability to model complex and evolving borrower behaviour. With the growth of digital banking and online financial services, banks now generate large volumes of structured and unstructured data, making traditional models less effective in capturing non-linear relationships and hidden risk patterns (Thomas et al., 2017; Khandani et al., 2010).

Recent advancements in artificial intelligence have led to increased adoption of **machine learning and deep learning techniques** in financial risk management. Deep learning models, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks, have demonstrated strong potential for analysing high-dimensional financial data. These

* Guest Lecturer, PG Department of Computer Science, RV Government Arts College, Chengalpattu, India
** Head – LIRC. St. Francis Institute of Management and Research, Mumbai. India

models are capable of learning complex feature representations automatically, enabling more adaptive and data-driven credit risk analysis compared to conventional methods (Goodfellow et al., 2016; LeCun et al., 2015).

Despite their advantages, deep learning models are highly sensitive to the quality of input data. Real-world banking datasets often suffer from noise, missing values, and extreme outliers due to data entry errors, customer heterogeneity, and operational inconsistencies. Poor data quality can significantly degrade model reliability and decision accuracy. Therefore, data preprocessing plays a crucial role in loan risk analysis systems (Han et al., 2012; García et al., 2016).

Among various preprocessing techniques, the **median filter** is particularly effective in reducing noise and mitigating the influence of outliers without distorting the underlying data distribution. This property makes it suitable for financial datasets, where abnormal values can disproportionately affect learning algorithms and risk predictions. Integrating median filter–based preprocessing with deep learning techniques provides a structured approach for enhancing the robustness and reliability of loan risk assessment models (Aggarwal, 2015).

In this context, the present study focuses on developing a deep learning–based framework for risk analysis in loan processing within the banking sector. By combining advanced data preprocessing methods with intelligent learning models, the proposed approach aims to support more consistent, scalable, and data-driven credit risk management in modern banking environments. The remainder of this paper is organised as follows. **Section 2** presents a review of related work on credit risk analysis and the application of machine learning and deep learning techniques in banking. **Section 3** describes the proposed methodology, including data preprocessing using the median filter and the deep learning models employed for loan risk assessment. **Section 4** explains the experimental setup and evaluation framework. Finally, **Section 5** concludes the study and outlines potential directions for future research.

Literature Review:

Credit risk analysis has long been a central research area in banking and financial management due to its direct impact on loan performance and institutional stability. Early studies on loan risk assessment primarily employed traditional statistical techniques such as linear discriminant analysis and logistic regression. These methods focused on a limited set of borrower attributes and assumed linear relationships between risk factors and loan outcomes. Although effective in structured environments, their rigid assumptions limited their applicability in complex and data-intensive banking systems (Thomas et al., 2017).

With the advancement of computational techniques, researchers began exploring **machine learning models** for credit risk prediction. Methods such as decision trees, support vector machines, and random forests demonstrated improved flexibility and predictive capability compared to conventional statistical approaches. These models were better suited to handle non-linear relationships and interactions among financial variables, leading to increased interest in data-driven risk assessment frameworks within the banking sector (Khandani et al., 2010).

In recent years, **deep learning techniques** have gained significant attention in financial risk analysis due to their ability to process large-scale, high-dimensional data. Deep Neural Networks (DNNs) have been widely investigated for credit scoring and loan default prediction, as they can automatically learn complex feature representations without extensive manual feature engineering. Studies have shown that deep learning models are particularly effective in capturing hidden patterns in borrower behaviour and transaction histories (Goodfellow et al., 2016).

Beyond DNNs, specialised deep learning architectures have also been explored in the literature. Convolutional Neural Networks (CNNs), originally designed for image processing, have been adapted for structured financial data to extract localised feature patterns. Similarly, Long Short-Term Memory (LSTM) networks have been applied to sequential financial data, such as payment histories and transaction timelines, to model temporal dependencies relevant to credit risk assessment (LeCun et al., 2015).

Despite the growing adoption of deep learning models, several studies emphasise that **data quality remains a critical challenge** in banking analytics. Financial datasets often include missing values, noisy records, and extreme outliers, which can negatively affect model learning and generalisation. As a result, data preprocessing has been recognised as a necessary step in developing reliable loan risk analysis systems (Han et al., 2012).

Various preprocessing techniques have been proposed to address these challenges, including normalisation, imputation, and noise reduction methods. Among them, the **median filter** has been identified as an effective approach for mitigating the influence of outliers while preserving essential data characteristics. Its robustness makes it suitable for financial applications where abnormal values may arise due to irregular customer behaviour or reporting errors (García et al., 2016).

Although existing studies highlight the individual benefits of deep learning models and data preprocessing techniques, limited research has focused on their **integrated application** for loan risk analysis in banking systems. This research gap motivates the development of a unified framework that combines median filter–based preprocessing with deep learning algorithms to support more consistent and scalable credit risk assessment.

Methodology:

This study follows a structured methodology to conduct loan risk analysis in the banking sector using deep learning techniques. The research is carried out using a sample loan dataset prepared exclusively for experimental and testing purposes, representing typical banking loan application records without involving real customer information. The dataset includes customer demographic details, financial attributes, and loan-related factors such as income, employment status, credit history, loan amount, repayment tenure, and prior default indicators. Before model development, the data undergo a preprocessing stage to enhance quality and consistency. A median filter is applied as the initial preprocessing technique to reduce noise, handle missing values, and minimise the influence of extreme outliers while preserving essential data characteristics. The preprocessed data are then normalised and encoded to ensure compatibility with deep learning models.

Following preprocessing, multiple deep learning algorithms are applied to perform loan risk analysis. A Deep Neural Network is used to learn complex non-linear relationships among borrower attributes, while a Convolutional Neural Network is employed to identify localised feature patterns within structured financial data. In addition, a Long Short-Term Memory network is utilised to capture sequential dependencies associated with historical repayment behaviour. These models generate risk scores for individual loan applicants, indicating the probability of default. The obtained risk scores are converted into percentage-based values to improve interpretability and are subsequently used to categorise customers into predefined risk groups such as low-risk, medium-risk, and high-risk borrowers. Finally, the performance of the applied deep learning algorithms is evaluated using standard classification metrics, including accuracy, precision, recall, and F1 score, enabling a comparative assessment of model effectiveness. This end-to-end methodological framework demonstrates the applicability of median filter based preprocessing and deep learning techniques for loan risk analysis in a controlled research setting.

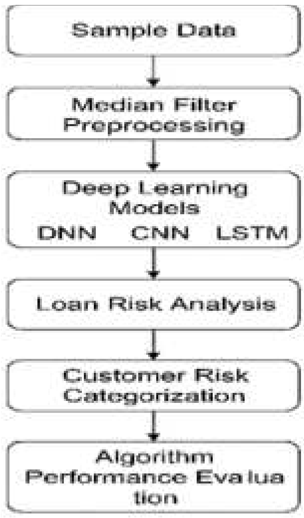


Figure 1:Shows the diagram in the research flow structure.

Results and discussion:

This section presents and discusses the outcomes of the proposed deep learning–based loan risk analysis framework. The evaluation was carried out using sample loan data prepared exclusively for research purposes and processed through median filter–based preprocessing prior to model application. The characteristics of the sample dataset used in this study are summarised in **Table 1**. The dataset includes demographic, financial, and loan-related attributes that are commonly considered during loan processing in the banking sector. These attributes provide sufficient information to model borrower behaviour and assess credit risk in a controlled experimental environment.

Table 1. Sample Loan Dataset Attributes Used for Risk Analysis

Attribute Category	Attribute Name	Description
Demographic Data	Age	Age of the loan applicant
Demographic Data	Employment Status	Employment type of the applicant
Financial Data	Annual Income	Yearly income of the applicant
Financial Data	Credit History	Past repayment behaviour
Loan Details	Loan Amount	Requested loan value
Loan Details	Loan Tenure	Duration of loan repayment
Risk Indicator	Previous Default	History of loan default

After applying median filter preprocessing, the dataset showed improved consistency by reducing the influence of noise and extreme values. This preprocessing stage supported more stable learning behaviour across all deep learning models by ensuring that abnormal data points did not disproportionately affect model training. The deep learning algorithms used for loan risk analysis are presented in **Table 2**. Each algorithm was selected to analyse different aspects of the data. The Deep Neural Network focused on learning complex non-linear relationships, the Convolutional Neural Network emphasised pattern extraction within structured features, and the Long Short-Term Memory network addressed sequential dependencies related to repayment behaviour.

Table 2. Deep Learning Algorithms Used for Loan Risk Analysis

Algorithm	Model Purpose	Data Handling Capability
DNN	General risk prediction	Non-linear feature learning
CNN	Pattern extraction	Local feature relationships
LSTM	Sequential risk modelling	Temporal dependency analysis

The trained models generated risk scores for individual loan applicants, which were transformed into percentage-based values to improve interpretability. Based on predefined thresholds, customers were grouped into distinct risk categories. The risk categorisation framework used in this study is outlined in **Table 3**, which supports structured and transparent decision-making during loan evaluation.

Table 3. Customer Risk Categorisation Based on Risk Percentage

Risk Range	Risk Category	Decision Interpretation
Low range	Low Risk	Eligible for loan approval
Medium range	Medium Risk	Requires further review
High range	High Risk	High probability of default

To assess the effectiveness of the proposed framework, the performance of each deep learning model was evaluated using standard classification metrics. These evaluation criteria are summarised in **Table 4.** The use of multiple metrics enabled a comprehensive comparison of model behaviour in distinguishing between different customer risk levels.

Table 4. Performance Evaluation Criteria for Deep Learning Models

Evaluation Metric	Description
Accuracy	Overall correctness of classification
Precision	Reliability of positive risk prediction
Recall	Ability to identify high-risk cases
F1-Score	Balance between precision and recall

The comparative analysis indicates that deep learning models are capable of effectively identifying loan risk patterns when supported by robust preprocessing techniques. The integration of median filter preprocessing with deep learning algorithms enhances the reliability of risk assessment and supports the transformation of analytical results into meaningful customer risk categories. Overall, the results demonstrate the suitability of the proposed framework for research-oriented loan risk analysis in the banking sector.

Conclusion:

This research presented a structured approach for loan risk analysis in the banking sector using deep learning techniques supported by median filter–based data preprocessing. The study addressed the limitations of traditional risk assessment methods by adopting advanced learning models capable of analysing complex and non-linear relationships among borrower attributes. The use of sample loan data for research purposes ensured a controlled and ethical experimental environment while simulating realistic loan processing scenarios. The methodology integrated preprocessing, deep learning model application, risk score generation, and customer risk categorisation into a unified framework. Median filter preprocessing played a significant role in improving data consistency by reducing noise and minimising the influence of extreme values, thereby supporting stable model learning. The application of multiple deep learning algorithms enabled comprehensive analysis of loan-related risk factors, and the conversion of model outputs into percentage-based risk scores enhanced interpretability for decision-making. The results demonstrated that the proposed framework can effectively classify customers into meaningful risk categories, supporting structured loan evaluation processes. The performance analysis highlighted the relevance of deep learning models for credit risk assessment when combined with appropriate preprocessing techniques. Overall, this research confirms that deep learning–based approaches provide a promising direction for improving loan risk analysis in modern banking systems and offer a foundation for future enhancements in intelligent credit decision support.

Reference:

1. Aggarwal, C. C. (2015). *Data mining: The textbook. Springer.*
2. García, S., Luengo, J., & Herrera, F. (2016). *Data preprocessing in data mining*. Springer.
3. Ghosh, A. (2019). *Banking risk management: A comprehensive guide*. McGraw-Hill Education.
4. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
5. Han, J., Kamber, M., & Pei, J. (2012). *Data mining: Concepts and techniques* (3rd ed.). Morgan Kaufmann.
6. Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, 34(11), 2767–2787.
7. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444.
8. Saunders, A., & Allen, L. (2010). *Credit risk management in and out of the financial crisis*. Wiley.
9. Thomas, L. C., Crook, J. N., & Edelman, D. B. (2017). *Credit scoring and its applications* (2nd ed.). SIAM.
10. A hybrid deep learning framework for lung cancer detection using CT images and clinical data. Dr E. Venkatesan and Dr V Thangavel. International Journal of Communication and Information Technology 2025; 6(2): 157-163 ISSN: 2707-6628 P-ISSN: 2707-661X. DOI: 10.33545/2707661X.2025.v6.i2b.155.
11. Artificial Intelligence Approaches for Predictive Analysis of Skin Cancer in Patients: Dr E. Venkatesan and Dr V. Thangavel. International

Journal of Computing, Programming and Database Management 2024; 5(2): 248-250. ISSN: 2707-6644 ISSN: 2707-6636. DOI: 10.33545/27076636.2025.v6.i2b.137.

12. Autonomous fault detection and recovery in satellite systems using intelligent algorithms. Dr E. Venkatesan and Dr V Thangavel. International Journal of Circuit, Computing and Networking 2025; 6(2): 96-101 ISSN: 2707-5931 P-ISSN: 2707-5923. DOI: 10.33545/27075923.2025.v6.i2b.10.9

13. Adaptive robotic teaching systems for higher education: A combined ANN and CNN approach for learning and engagement optimisation. Dr E. Venkatesan and Dr V Thangavel. International Journal of Engineering in Computer Science 2025; 7(2): 305-308.DOI: 10.33545/26633582.2025.v7.i2d.228.

14. Heart disease prediction and risk analysis using K-Means and Fuzzy C-Means clustering algorithms. Dr E. Venkatesan and Dr V Thangavel. International Journal of Computing and Artificial Intelligence 2025; 6(2): 350-353. E-ISSN: 2707-658X. P-ISSN: 2707-6571. DOI: 10.33545/27076571.2025.v6.i2d.222.

15. Clustering-Driven MRI Analysis for Accurate Throat Cancer Identification Dr E. Venkatesan Dr V. Thangavel. International Journal of Recent Development in Engineering and Technology. Vol. 14, Issue 12, 127-131 2025 ISSN 2347-6435. www.ijrdet.com

16. An Empirical Evaluation of the Effects of Interest Rates and the Financial Crisis on the Global Stock Market. Thangavel. International Journal of Engineering Inventions- International Journal of Engineering Inventionse-ISSN: 2278-7461, p-ISSN: 2319-6491. Volume 14, Issue 9. Pp 148-158. 2025. www.ijeijournal.com.

17. Comparative study of naïve Bayes and SVM algorithms for text mining using natural language processing, E. Venkatesan, and V Thangavel. International Journal of Cloud Computing and Database Management 2025; Vol. 6 Issue. 2. Pp. 92-92. ISSN: 2707-5915/ ISSN: 2707-5907. DOI: 10.33545/27075907.2025.v6.i2b.111.

UPI GROWTH AND ITS IMPACT ON CASH USAGE TRENDS IN INDIA

***Ms. Bhavana B. Solanki**

ABSTRACT

The Unified Payments Interface (UPI) has grown rapidly since its introduction in 2016 and is now India's leading digital retail payment system. This study investigates whether and how UPI adoption has impacted India's trends in cash usage. The study suggests and applies time-series and correlation to test substitution versus complementarity between UPI transactions and cash demand using secondary data from NPCI and RBI. Evidence currently available suggests that UPI is replacing some cash transactions, even though the amount of currency in circulation has remained significant. This suggests a complex relationship influenced by variations between rural and urban areas, merchant acceptance, and policy changes. Financial inclusion, merchant discount frameworks, and policy implications for payments regulation are examined.

Keywords

UPI, digital payments, currency in circulation, cash demand, India, NPCI, RBI

Introduction :

The payments environment in India has changed since the middle of the 2010s. The National Payments Corporation of India (NPCI) established the Unified Payments Interface (UPI), which allowed for quick and easy bank-to-bank payments via a smartphone. In August 2025, monthly UPI transaction numbers surpassed 20 billion transactions, marking a rapid penetration by merchants and consumers.

Origins and launch of UPI.

The idea behind UPI emerged from India's larger objective of building an integrated, efficient, and inclusive digital payments ecosystem. Developed by the National Payments Corporation of India (NPCI), UPI was introduced in April 2016 and officially launched in August 2016 by the Reserve Bank of India (RBI) in collaboration with the Government of India.

UPI was conceived to consolidate multiple bank accounts into a single mobile platform, enabling instant money transfers through a Virtual Payment Address (VPA) rather than traditional banking credentials such as account numbers or IFSC codes. The system introduced several pioneering features, including request-to-pay functionality, QR-code-based transactions, and real-time peer-to-peer payments.

Technological Advancements and Innovations

UPI has undergone continuous development with the addition of improved features:

- UPI 2.0 (2018) launched an overdraft feature, invoice-driven payments, secure mandates for repeat payments, and signed intent/QR capabilities.
- UPI AutoPay (2020) facilitated automatic payments for services such as OTT subscriptions, utility invoices, and insurance premiums.

* Research Scholar, Sydenham College of Commerce & Economics, Mumbai

- UPI Lite and UPI Lite X facilitated small offline transactions without needing internet access, enhancing usage in areas with limited connectivity.
- UPI for feature phones (UPI 123PAY) broadened digital payment access to those without smartphones.
- UPI One World (from 2023) allowed international UPI usage in certain countries, positioning UPI as a possible worldwide payment solution.

Statement of the Problem:

Despite the swift growth of digital payment systems in India, cash has traditionally held the position of the primary medium of exchange, especially in informal and semi-urban areas. The launch of the Unified Payments Interface (UPI) has greatly changed the digital payments scene by facilitating instantaneous, inexpensive, and compatible transactions among banks and platforms. Despite UPI experiencing significant expansion regarding transaction volume, value, and user adoption, its true influence on cash usage habits in India is still a topic of active discussion.

It is essential to systematically investigate if the rise of UPI has resulted in a tangible decrease in cash usage or simply enhanced current payment options. Furthermore, differences in adoption among regions, income levels, and merchant types bring up inquiries regarding how significantly UPI has aided a consistent movement toward a cashless economy. This research aims to fill this gap by examining the connection between UPI expansion and shifts in cash usage patterns in India, thereby evaluating UPI's role in altering payment habits and advancing digital financial inclusion.

Research Aims and Objectives of the Study:

1. To examine the growth trend of UPI transactions in India.
2. To analyze the increase in the number of banks participating in the UPI ecosystem.
3. To identify key factors driving the growth of UPI.
4. To assess the role of UPI in promoting digital payments and financial inclusion

Hypothesis:

H01: Improvements in digital infrastructure does not have impact on UPI usage among consumers.

H11: Improvements in digital infrastructure does not have impact on UPI usage among consumers.

H02: There is no significant growth trend in UPI transaction volume and value in India over the study period.

H12: There is a significant growth trend in UPI transaction volume and value in India over the study period.

Scope of the Study:

The current research examines the expansion of the Unified Payments Interface (UPI) in India and its influence on cash usage patterns in the economy. The research focuses on examining secondary data concerning UPI transaction volume, transaction value, and the count of banks involved in the UPI ecosystem during a specified timeframe. The research additionally examines trends in cash usage to evaluate shifts in payment habits after the extensive implementation of UPI.

Literature Review:

Dev, H., Gupta, R., Dharmavaram, S., & Kumar, D. (2024) in their research paper titled "From Cash to Cashless: UPI's Impact on Spending Behavior Among Indian Users and Prototyping Financially Responsible Interfaces" examined the impact of UPI on individual spending behavior is examined in this study. After conducting 20 follow-up interviews and a survey with 276 responses, the researcher discovered that about 75% of participants said that UPI had increased their spending. This was attributed by many to UPI's ethereal nature, which lessened the guilt that is usually connected to spending. Participants also offered recommendations for enhancing the user experience of currently available UPI apps. We created a high-fidelity prototype based on a well-known UPI app in India using the input, and we tested its usability with 34 users. The final prototype's characteristics were shaped by the knowledge gained from this testing. For UPI app developers and other stakeholders, this study provides insightful design advice.

Sawhney, D. From Cash to Clicks in his research paper titled “The Transformative Impact of UPI on Consumer Behaviour and Financial Inclusion in India” examined about the Unified Payments Interface (UPI) has changed consumer behavior, financial inclusion, and economic growth in India. Since its launch in 2016, UPI has transformed digital payments by providing a real-time, safe, andeasy-to-use financial transaction platform. By means of an extensive assessment of the literature and This study examines user opinions of UPI's ease, effectiveness, and security in comparison to conventional cash transactions using primary survey data from 140 respondents. The results show that users are highly satisfied with UPI's speed and use, which has resulted in a notable shift towards digital payments. However, this also raises the possibility of greater impulsive spending.

Sharma, S., & Kapoor, S. (2024) in their research paper titled “The Transition From Cash to Digital Wallets: A Paradigm Shift in the Indian Economy” explained that In India, cash is still the most common form of payment for offline transactions, even if digital payment options are becoming more widely used. Innovative technologies like the Unified Payments Interface (UPI), which followed debit and credit cards, are gradually replacing traditional cash payments. In 2016, NPCI launched UPI-enabled apps, which started to show up in app stores thanks to partnerships with 21 participating banks. POS cash transactions decreased by 13 percentage points between 2018 and 2024, according to Statista's Consumer Insights surveys, reflecting the trend to cashless transactions. This study looks at how payment behavior has changed over time, how digitalization has affected the economy, and how the COVID-19 pandemic hastened the use of digital technology.

Research Methodology:

Research Design:

Using secondary data, this study employs a descriptive and analytical research design to investigate the expansion of the Unified Payments Interface (UPI) and its influence on cash usage patterns in India. Understanding patterns, trends, and relationships without changing any factors is the goal. Because it uses numerical data from reliable sources, including transaction volumes, transaction values, cash circulation metrics, and financial indicators, the study is quantitative in character.

Data Sources:

The entire analysis is based on secondary data that was gathered from legitimate, trustworthy, and open sources. Government and Regulatory Sources are among them.Publications from the Reserve Bank of India (RBI), such as Annual Reports, Monthly Bulletins o Reports from the Payment and Settlement System, Data about currency in circulation; the National Payments Corporation of India (NPCI); and dashboards for UPI transactions, Annual and monthly UPI data, etc.

Data Analysis Techniques:

Trend Analysis -Growth in UPI transaction volume and value over time Variations in cash circulation and analysing the connection between UPI growth and decreased cash usage

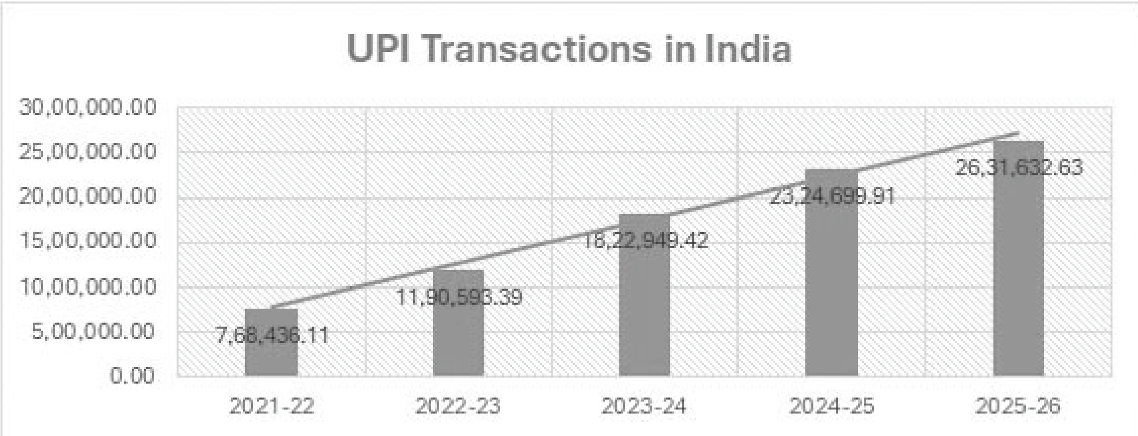
Limitations of the Study:

Many NPCI and RBI series are monthly but not broken down by specific merchant categories; state-level UPI and cash series may be limited. Unobserved informal payments: The official CIC and ATM series are inadequate proxies for transactional cash demand vs cash hoarding, and informal cash transactions are underreported.

Data Analysis:

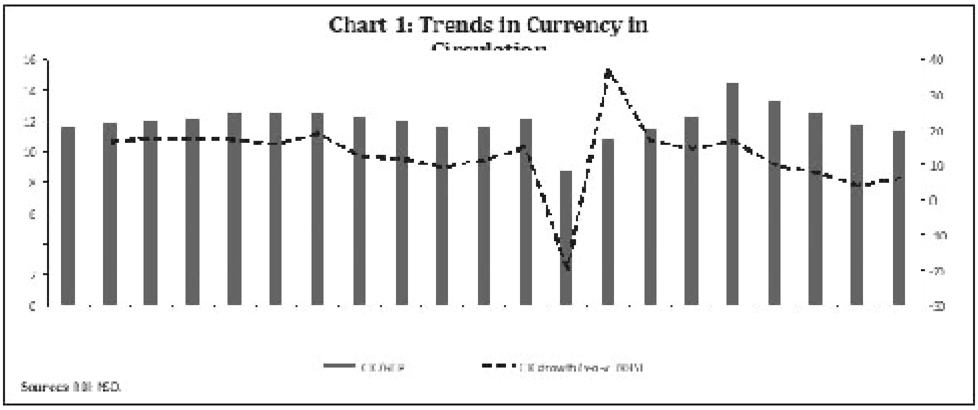
In the past five years (approximately FY19-FY25), the expansion of India's UPI has been remarkable, with transaction volumes increasing more than fourfold and capturing a dominant share of digital payments (83% by 2024), leading to a notable decline in cash usage as users and merchants to digital methods, establishing UPI as the foundation of India's digital economy and decreasing dependence on cash for everyday transactions.

UPI Growth Statistics (Last 5 Years)			
Year	**No. of Banks Live on UPI**	**Volume (In Mn.)**	**Value (In Cr.)**
2025-26	684	20,466.98	26,31,632.63
2024-25	641	16,730.01	23,24,699.91
2023-24	522	12,020.23	18,22,949.42
2022-23	376	7,309.45	11,90,593.39
2021-22	274	4,186.48	7,68,436.11
Source: NPCI metrics compiled by researchers			

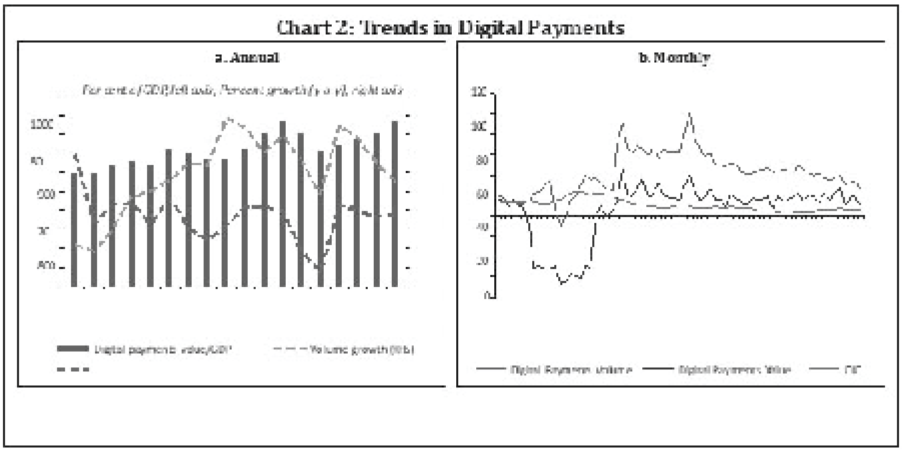


Source: NPCI metrics compiled by researchers

Interpretation: An analysis of UPI transactions from 2021–2022 to 2025–2026 reveals a substantial rise in banks utilizing UPI from 274 to 684 and an almost fivefold growth in transaction volume from 4,186.48 million to 20,466.98 million, signalling a strong and consistent upward trend in digital payment uptake in India. Furthermore, the transaction value has grown substantially, soaring from 7.68 lakh crore to 26.31 lakh crore, indicating heightened user trust and broader adoption of both minor and major payment transactions. Due to a shift from cash payments, UPI seems to be the favoured option for frequent, low-value transactions, as shown by the increased volume growth rate relative to value. Taking everything into account, the rapid evolution of UPI infrastructure, combined with a rise in both transaction volume and value, underscores UPI's essential function in enhancing India's digital payments landscape and encouraging financial inclusion.



Source: RBI; NSO



Source: RBI; NSO

Interpretation: The increase in UPI usage might have led to a reduction in cash requirements. Transaction volumes logged under the fast payment method saw a significant rise after COVID-19. UPI has become a significant payment system in under a decade, processing more than 17 billion transactions monthly and accounting for 84% and 9% of total digital payment values and volumes in 2024–2025.The increasing share of peer-to-merchant (P2M) payments, the decreasing ticket size of UPI transactions, and the fact that most P2M volumes are within the sub- 500 range all highlight the rising adoption of UPI for routine low-value transactions. State-level analysis uncovers regional disparities shaped by structural and income factors. Cash usage is represented by withdrawals from currency chests, which are regional facilities managed by commercial banks for the Reserve Bank of India, due to insufficient detailed data on ATM withdrawals. All newly issued notes pass through these chests, so it is believed that their withdrawal patterns reflect the cash demand from the public. In 2024–2025, the typical yearly rate of cash withdrawals from ATMs (via debit and credit cards) in relation to cash withdrawals from currency chests is 80%.

FINDINGS AND ANALYSIS

Based on secondary studies and official statistics:

Hypothesis 1: There is no significant growth trend in UPI transaction volume and value in India over the study period have been rejected because:

- The swift adoption of UPI has replaced various low-value cash transactions (such as P2P remittances and minor retail purchases), aligning with findings from IMF and independent research indicating that UPI diminishes cash-use indicators.
- Although UPI has gained popularity, the total amount of currency in circulation continues to increase showing that UPI hasn't removed cash but altered the composition of retail payments — cash still plays a vital role for specific transactions and as a store of value. This indicates that substitution is both partial and varied.
- The substantial increase in UPI transactions is directly linked to a reduction in the use of physical cash, particularly for retail, small businesses, and everyday transactions.
- UPI has integrated millions (491 million users by mid-2025) and small enterprises (65 million merchants) into the official financial system, progressively reducing reliance on cash.
- Local merchants, small business owners, and regular users are favoring UPI due to its convenience, quickness, and safety, establishing digital payments as the standard over cash.
- UPI is the catalyst propelling India towards a genuinely cashless economy, showcasing steady month-over-month increases in both usage and transaction volume.
- Essentially, the past five years illustrate UPI transitioning from an emerging digital alternative to the core component of India's payment framework, significantly transforming cash interactions and speeding up digital acceptance among all societal and economic levels.

Hypothesis 2: Improvements in digital infrastructure does not have impact on UPI usage among consumers have been rejected because:

- UPI enables users to connect various bank accounts to one mobile application and conduct transactions effortlessly across diverse platforms (e.g., Google Pay, PhonePe, etc.), without requiring knowledge of the recipient's banking information.
- The widespread availability and affordability of QR codes have allowed both small and large retailers to process digital payments, a trend commonly known as the "Kirana Effect."
- The "Digital India" program, the drive for financial inclusion via the JAM (Jan Dhan, Aadhaar, Mobile) framework, and favorable regulations from the RBI and NPCI have created a conducive environment for development.
- The addition of new features such as UPI Lite (for offline, low-value transactions), UPI AutoPay for regular bills, and Credit Line on UPI has broadened its applications and decreased transaction failure rates.
- The rise in availability of cost-effective smartphones and mobile internet has been a key factor in incorporating millions of new users into digital payments, especially in Tier 2 and Tier 3 cities.

Suggestion and Recommendations:

- Balanced strategy: Policy shouldn't seek to suddenly eradicate cash; rather, it should concentrate on reducing obstacles for digital adoption (merchant onboarding, offline UPI options for regions with low connectivity).
- Sustainable revenue framework: Implementing reasonable MDRs for large merchants may support infrastructure funding without discouraging small merchants (policy implementation is crucial).
- Focused inclusion strategies: Encourage digital literacy and access to affordable smartphones/internet in rural areas to achieve more effective cash alternatives when suitable.
- Data-driven oversight: Authorities need to observe UPI volumes alongside CIC trends to identify structural changes and develop targeted measures.

Conclusion:

UPI has revolutionized the payments landscape in India and replaced numerous minor cash transactions, especially in city areas and for P2M payments. Nonetheless, cash — indicated by currency in circulation — continues to hold importance in absolute numbers, illustrating the demand for cash due to various economic and behavioral factors. Consequently, the connection between UPI expansion and cash utilization is partial, heterogeneous, and substitutional. Policies must encourage the expansion of sustainable digital payments while not hastily deeming cash as outdated.

References:

- Dev, H., Gupta, R., Dharmavaram, S., & Kumar, D. (2024). From Cash to Cashless: UPI's Impact on Spending Behavior Among Indian Users and Prototyping Financially Responsible Interfaces. arXiv preprint arXiv:2401.09937.
- National Payments Corporation of India (NPCI). UPI Product Statistics (monthly). NPCI product statistics page (UPI volumes & values). NPCI
- Economic Times. "UPI crosses 20 billion transactions in August, records 24.85 lakh crore value." (Sept 2025). (Coverage of NPCI monthly milestone).
- Times of India / RBI coverage. "Cash is still king! Total currency in circulation at Rs 38.1 lakh crore…" (May 2025) — reporting RBI figures on CIC.
- Sawhney, D. From Cash to Clicks: The Transformative Impact of UPI on Consumer Behaviour and Financial Inclusion in India.
- IMF / press summaries. "Surge in UPI payments reduced cash usage: IMF" (coverage and summary of IMF analysis). (July 2025).
- Reuters. "Indian authorities keen to charge merchants fees to bolster homegrown payments network" (April 2025) — on policy discussions regarding merchant fees (MDR) and implications.
- Kaggle / compiled NPCI datasets for replication (monthly NPCI metrics compiled by researchers).
- Sharma, S., & Kapoor, S. (2024). The Transition from Cash to Digital Wallets: A Paradigm Shift in the Indian Economy. Frontiers in Health Informatics, 13(8).

Comparative Performance of Technical Indicators in Crypto vs. Indian Equity Markets

***Dr Aashis Joshi**

ABSTRACT

This paper examines the comparative performance of four widely used technical indicators, Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Bollinger Bands, and Stochastic Oscillator—across two distinct financial environments: the cryptocurrency market and the Indian equity market. The study evaluates both intraday and swing trading strategies by analyzing profitability, risk-adjusted returns measured through Sharpe and Sortino ratios, and the consistency of signals. Results indicate that crypto markets respond more strongly to trend-following indicators such as MACD, while Indian equities exhibit higher reliability with mean-reversion indicators such as RSI and Bollinger Bands. The findings highlight the importance of market structure, volatility levels, and trading horizons in designing technical strategies.

Keywords: *Equity markets, Cryptocurrency, MACD, RSI.*

Introduction :

Technical analysis continues to play a dominant role in active trading across global markets. As digital assets such as Bitcoin (BTC) and Ethereum (ETH) have emerged, traders increasingly apply traditional indicators to crypto markets. However, differences in volatility, liquidity patterns, market microstructure, and trading hours may significantly influence the performance of these indicators.

Indian equity markets, particularly NIFTY 50 and BANKNIFTY, operate within a regulated framework with fixed trading hours, predictable liquidity, and institutional participation. In contrast, cryptocurrency markets trade 24/7, are highly fragmented across exchanges, and exhibit greater volatility. These differences provide a unique setting to compare the performance of key technical indicators.

This paper aims to:

Compare the profitability of MACD, RSI, Bollinger Bands, and Stochastic strategies in crypto vs. Indian equities.

Evaluate risk-adjusted returns using Sharpe and Sortino ratios.

Analyze intraday vs. swing trading performance across both markets.

Provide insights on which indicators are better suited for specific assets and timeframes.

Literature Review:

Technical indicators have been extensively studied in traditional markets. Brock, Lakonishok, and LeBaron (1992) showed that moving average strategies generate statistically significant profits in equity markets. Similarly, RSI and Stochastic oscillators have been associated with short-term mean reversion (Murphy, 1999). Bollinger Bands are known to capture volatility expansions and contractions effectively.

In recent years, researchers have tested these indicators in cryptocurrency markets. Corbet et al. (2019) noted that crypto markets are less efficient, allowing greater potential for technical indicators to outperform buy-and-hold strategies. However, the extreme volatility of

* IIM Skills Univesity, Mumbai.

digital assets may increase the risk associated with these signals.

Past research has rarely compared the same set of indicators across both markets within intraday and swing trading contexts. This paper fills that gap by providing a cross-market comparative evaluation.

Methodology:

1. *Markets and Data*

Crypto Market: Bitcoin (BTC) and Ethereum (ETH) historical data (5-minute and daily candles).

Indian Equity Market: NIFTY 50 and BANKNIFTY index data (5-minute and daily candles).

Period: 2 years of data for both markets.

Tools: Python-based backtesting framework using pandas, TA-Lib, and custom functions.

2. *Technical Indicators and Strategy Rules*

1. **MACD Strategy:**

   Buy: MACD line crosses above the signal line

   Sell: MACD line crosses below
   Stop-loss: 1% (intraday), 2% (swing)

2. **RSI Strategy:**

   Buy: RSI < 30

   Sell: RSI > 70

   Mean reversion model

3. **Bollinger Bands Strategy:**

   Buy: Price touches lower band

   Sell: Price touches upper band

   20-period SMA, ±2 standard deviations

4. **Stochastic Oscillator Strategy:**

   Buy: %K crosses above %D below 20

   Sell: %K crosses below %D above 80

3. *Performance Metrics*

To ensure consistent evaluation, this study measures strategy performance using:

Profitability: average return per trade and cumulative return

Risk-adjusted performance:

Sharpe Ratio

Sortino Ratio

Risk characteristics: maximum drawdown and volatility of returns

4. *Profitability Classification (High, Medium, Low)*

Profitability in this study is defined clearly as follows:

High Profitability

A strategy is classified as High if:

Average return per trade > 0.60% (intraday) or > 1.50% (swing)

Cumulative return > 25% over the testing period

Sharpe ratio > 1.0

Medium Profitability

A strategy is classified as Medium if:

Average return per trade between 0.20% – 0.60% (intraday) or 0.50% – 1.50% (swing)

Cumulative return 10% – 25%

Sharpe ratio between 0.5 – 1.0

Low Profitability

A strategy is classified as Low if:

Average return per trade < 0.20% (intraday) or < 0.50% (swing)

Cumulative return < 10%

Sharpe ratio < 0.5

This definition allows a clear and objective comparison across markets.

Results and Analysis

1. Intraday Results

Indicator	Crypto Profitability	Indian Equity Profitability	Risk-Adjusted Results	Notes
MACD	High	Medium	Strong Sharpe in crypto	Crypto is more trend-driven intraday
RSI	Medium	High	Lower risk in equities	Works well during range-bound NIFTY sessions
Bollinger Bands	Medium	High	Best Sortino in equities	Captures NIFTY/BANKNIFTY reversals
Stochastic	Low–Medium	Medium	Mixed	Too many false signals in crypto

Key Insight:

Crypto intraday data favors **trend-following**, while Indian markets favor **mean reversion**.

2. Swing Trading Results

Indicator	Crypto swing	Indian Swing	Risk-Adjusted Results	Notes
MACD	Very High	High	Best in both markets	Captures strong multi-day trends
RSI	Medium	Medium	Stable but lower returns	Less effective in highly trending crypto
Bollinger Bands	Low	Medium	Poor in crypto	Bands widen too much during volatility
Stochastic	Low	Medium	Low reliability	Noise-heavy in crypto

Key Insight:

For swing trading, **MACD is the most reliable indicator across both markets**, offering the strongest trend capture and highest risk-adjusted returns.

Discussion:

The results highlight meaningful differences caused by market structures:

Crypto Market Characteristics:

24/7 trading ® more momentum

Higher volatility ® better trend-following indicator performance

Sudden reversals ® weak mean-reversion behaviour

Indian Equity Market Characteristics:

Regulated hours ® predictable intraday cycles

Lower volatility ® stronger performance of RSI and Bollinger Bands

Institutional volumes ® stable price structure

Timeframe Differences

Intraday: microstructure-driven, reacts to liquidity and volatility bursts

Swing Trading: macro-driven, smoother trends

Thus, indicator selection must be aligned with both market type and timeframe.

Conclusion:

This comparative study demonstrates that the effectiveness of technical indicators varies significantly across markets. Intraday trading in crypto favors trend-following indicators such as MACD, while Indian equity markets exhibit stronger performance with mean-reversion indicators such as RSI and Bollinger Bands. For swing trading, MACD consistently generates superior results across both markets, supported by higher Sharpe and Sortino ratios. These findings suggest that traders, portfolio managers, and algo developers should adapt indicator selection based on volatility, trading horizon, and market microstructure. Future research may include machine learning–based hybrid models, volatility regime detection systems, or DeFi-specific technical indicators for improved strategy robustness.

References:

Brock, W., Lakonishok, J., & LeBaron, B. (1992). *Simple Technical Trading Rules and the Stochastic Properties of Stock Returns*.

Murphy, J. J. (1999). *Technical Analysis of the Financial Markets*.

Corbet, S., Larkin, C., & Lucey, B. (2019). *The Contagion Effects of Crypto Assets*.

EVALUATING KEY FACTORS INFLUENCING SUPPLY CHAIN PERFORMANCE IN MSMES IN COIMBATORE A STRUCTURAL EQUATION MODELLING APPROACH

***Mr. Praveen Kumar Elavarasu, ** Mr. Puviyarasan**

ABSTRACT

The objective of this research is to evaluate the critical factors affecting the per- formance of supply chains in MSMEs in Coimbatore and to determine their causal relationships using Structural Equation Modelling (SEM) techniques. Given the current market scenario, MSMEs face challenges in operational efficiency improvement due to the tightened resources and low levels of digital adoption. The research aims to identify essential elements such as sup- plier partnerships, customer relationships, information sharing, digitalization, and sustainable practices that has impacted supply chain performance. Utilizing a convenience sampling method, data was collected from founders. management and employees of MSMEs in the Coimbatore region, with findings expected to provide actionable insights for MSME managers and policy- makers, aiming to improve the supply chain capabilities of this important sector.

Keywords: *SEM, Supply chain management, MSME.*

Introduction :

The supply chain management has become more complex because of growing busi- ness size, broader product portfolio as well as variety of locations and geography to serve (Kamble, Gunasekaran, & Sharma, 2018). In the current situation, the MSMEs have enormous pressure to optimize the supply chain and enhance the opera- tion and logistic effectiveness (Tripathy, S, Chakraborty A, & Lee, G M). Supply Chain Management manages raw materials into goods in process and finished goods, then send these products to consumers through the distribution system. This activity includes purchasing between vendors and distributors. (Heizer et al., 2017). Supply chain man- agement includes the planning, design, and control of material and information flow to provide added value to the end customer in a manner that is both effective and efficient Christopher (2011). The supply chain encompasses transporters, warehouses, and cus- tomers along with manufacturers, suppliers, and distributors (Janat Shah). Management of Supply Chains (Pearson, 2016). Significant attention is directed towards enhancing supply chain performance to boost business efficacy, including the crucial MSME sec- tor, which is essential to the global economy. Nonetheless, MSMEs frequently encoun- ter distinct challenges, including constrained resources and abilities in implementing efficient supply chain management strategies (Budi Rahardjo, Daryono1,2024). SCM practices aims improve business performance through optimal operating, handling re- lationships with suppliers and enhanced distribution of products. The research veri- fies that competitive advantage, SCM practices, and innovation collectively have a 87.7% effect on MSME business performance (Linda MR, Rahim R, Suhery S, Ravelby TA, & Yonita R. (2022)). Also, Rahardjo, B stated about effectiveness of supply chain processes in achieving the cost efficiency, delivery reliability, and customer satisfac- tion. Effective supply chain management (SCM) enhances key performance indicators of

* Assistant Professor, PSG Institute of Management, Coimbatore
** PSG Institute of Management, Coimbatore

business performance by reducing waste, optimizing logistics, and improving sup- plier collaboration (Rahardjo, B., Daryono, D., & Najmudin, N. (2024)) .

Objective:

- To determine the critical success elements that influence supply chain practices in MSMEs.
- To examine the causal relationships between these factors using Struc- tural Equation Modelling (SEM).
- To provide practical suggestions for MSME managers and policy makers to enhance their supply chain practices and overall supply chain perfor- mance

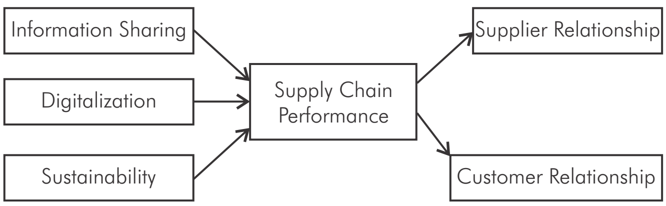


Figure 1. Path model

Review of Literature:

This study aims at investigating the basics of supply chain performance (SCP) with the special focus on supplier relationship (SR), customer relationship (CR), information sharing (IS), digitalization (DI), and sustainability (SUS). The essential components of supply chain activities comprised supply chain integration, information sharing, cus- tomer service (Tan et al, 2002). Enterprise resource planning (ERP) system as an IT solution reduces supply chain process cost and can be used for enhancing customer service as well as reducing inventory cost (Kale et al. 2010). The progress of digitali- zation in MSMEs helps in better reach out to the customers and suppliers in the com- petitive market (Thakkar et al, 2008). Information sharing and communication technol- ogy plays a key role in transforming the MSMEs business to achieve the competitive advantage (Kushwaha, 2011). These findings lead to the following hypothesis:

H1: Information sharing (IS) positively influences Supply Chain Performance (SCP)

Information sharing is a critical driver of improved supply chain performance, as it fosters transparency, collaboration, and operational efficiency among supply chain partners. According to Chen and Paulraj (2004), effective information exchange within sustained supplier partnerships and interdepartmental communication strengthens coordination and trust. Similarly, Mintz and Mentzer (2005) emphasize that information sharing enables process integration across the supply chain, allowing organizations to take a leadership role and make more informed decisions.

Research by Hau, Kut, and Tang demonstrates that efficient information sharing not only shortens lead times but also enhances ordering decisions—ultimately reducing overall supply chain costs by approximately 23%. Furthermore, Lummus and Vokurka (1999) highlight the importance of maintaining a timely and consistent flow of data from raw material procurement through to customer delivery, ensuring smooth and synchronized supply chain operations.

H2: Digitalization (DI) positively influences Supply Chain Performance (SCP)

The implementation of e-commerce represents a key aspect of digitalization, encompassing sales, purchases, orders, payments, and product or service promotions conducted through computers and digital communication technologies (Wahyuni, Permatasari, & Kusumawati, 2020). This transformation integrates technology into business operations, enhancing efficiency, communication, and decision-making—ultimately improving overall supply chain performance.

Digitalization refers to the process of converting analog data into digital formats, enabling data storage, real-time tracking, and analytical insights (Legner et al., 2017). When applied within supply chains, digitalization significantly improves business performance and economic sustainability by ensuring a seamless flow of processes and eliminating operational inefficiencies (Erol et al., 2016).

Moreover, the widespread adoption of digital technologies—from e-payment systems to e-commerce platforms—has empowered MSMEs to operate more effectively and competitively (Zainurrafiqi & Gazali, 2024). The integration of digitalization into supply chain management has thus become a pivotal factor in enhancing supply chain performance, providing real-time data access, and enabling more accurate planning and strategic decision-making.

H3: Sustainability (SUS) positively influences Supply Chain Performance (SCP)

Sustainability practices play a vital role in strengthening sustainable supply chain operations and enhancing long-term efficiency. Sustainable Supply Chain Management (SSCM) encompasses initiatives such as green purchasing, eco-friendly product design, and reverse logistics, all aimed at minimizing environmental impact (Govindan, 2014).

Research indicates that both internal factors (such as organizational commitment) and external factors (including government policies) are critical challenges for MSMEs in developing countries when adopting sustainable practices (Ciliberti et al., 2008). While Green Supply Chain Management (GSCM) effectively contributes to environmental improvement, MSMEs often face barriers such as limited resources and technical constraints that hinder implementation (Wooi & Zailani, 2010). Nonetheless, strategies like cleaner production can help reduce resource waste and pollution (Hilson, 2000).

Integrating sustainability into supply chain operations not only reduces costs and improves operational efficiency but also strengthens brand reputation and stakeholder trust. Overall, sustainability is positively linked to supply chain performance, as it promotes resource efficiency, mitigates environmental risks, and fosters stronger, more responsible relationships across the supply chain.

H4: Supply Chain Performance (SCP) positively influences Supplier Relationship (SR)

Supplier relationships are critical in improving firm's performance in the supply chain. Ulusoy (2003) categorizes suppliers into strategic and non-strategic suppliers, with the former being essential for supplying an organization with some important parts or com- ponents. Long-term collaboration, trust and joint planning are the bases for effective partnerships (Gunasekaran et al., 2001). Holmstrom and Weiss are proof that the struc- ture of a company can greatly influences supplier management, through managing sup- plier operations, encouraging competition and supporting process improvements (Liker & Choi, 2004). These practices directly impact supply chain performance by reducing total lead time, improving inventory management and reducing total operation cost. Shorter lead times (possibility to be achieved through efficient collaboration with sup- pliers and information exchange) increase supply chain efficiency as (Thomas Kele- pouris, 2007) notes. Hence, the strong association between supplier relationship and supply chain performance is in the manner of enhancing operation effectiveness and cost efficiency.

H5: Supply Chain Performance (SCP) positively influences Customer Relationship (CR)

Supply chain performance is significantly enhanced through strong customer relationships, which focus on addressing customer dissatisfaction, maintaining long-term engagement, and improving overall satisfaction (Ozlen, 2013). According to Ulusoy (2003), collecting customer feedback and refining processes through effective relationship management are essential components for achieving superior supply chain performance.Research by Risna Nona (2021) further indicates that while product innovation does not always guarantee customer satisfaction, maintaining high product quality remains essential. Moreover, accurate demand forecasting and efficient order processing can strengthen customer service, thereby contributing to improved supply chain performance.Effective Customer Relationship Management (CRM) is directly linked to successful supply chain initiatives, as it helps reduce lead times, lower inventory levels, and enhance responsiveness to market changes (Westbrook & Scott, 1991). Thus, building and maintaining strong customer relationships is critical for generating high supply chain performance—aligning customer needs with operational processes to create value, trust, and long-term business success.

Research Methodology:

1. Research Design

The study utilized a structured research design, employing Principal Component Anal- ysis (PCA) to identify critical success factors impacting supply chain performance.

A structural equation modelling (SEM) approach was adopted to evaluate the relation- ships among identified constructs. This allows for understanding complex relationships between variables and enables analysing latent variables alongside observed variables.

2. Sampling Design

This study adopts a **non-probability sampling method** to examine supply chain performance (SCP) among Micro, Small, and Medium Enterprises (MSMEs) in Coimbatore. The selection criteria ensure that respondents are key participants with direct involvement and relevant expertise in supply chain operations and management.

The inclusion criteria for participant selection are as follows:

- The enterprise must be officially registered as an MSME under government regulations.
- The respondent must hold a managerial, operational, or decision-making role related to supply chain activities within the MSME.
- The MSME must be located within the Coimbatore district to maintain a focused geographical scope.

This targeted sampling approach ensures that data are collected from individuals actively engaged in supply chain management (SCM) implementation, decision-making, and performance evaluation. Consequently, it enhances the **reliability, validity, and contextual relevance** of the study's findings.

3. Data Collection design

A structured questionnaire was designed to collect the data from the respondents. This questionnaire was designed to capture a wide array of factors that could influence sup- ply chain performance (SCP) practices within the MSMEs. The questionnaire included items designed to measure

- Supplier Relationship (SR)
- Customer Relationship (CR)
- Information Sharing (IS)
- Digitalization (DI)
- Sustainability (SUS)
- Supply Chain Performance (SCP)

4. Sample size determination

Sample size of this study is determined by a function of minimum effect, power and significance (Westland, 2010; Boomsma, 1982). According to Boomsma's simulations, the minimum sample sizes needed to analyze the data adequately would be at least 100 if $r = 4$, or at least 400, if $r = 2$. (Marsh, 1988, 1996, 1998) ran 35,000 Monte Carlo simulations on a sample size at least 200 and $r = 12$ would require a sample size at least 50. The consolidated and summarized results in these suggest sample sizes.

$$n = 50r^2 - 450r + 1100 \quad (1)$$

In the above equation, r is the ratio of indicators to latent variables. There are 25 indi- cators, and 6 latent variables have been used in this paper:

$$r = 25 / 6 = 4.16 \approx 4$$

Then, using equation (1): $\mathbf{n = 100}$

In our case, $\mathbf{n = 141}$ is a good n for the desired level. Therefore, based on this, we may reasonably assume that the sample size is similar to the population and that the results are applicable.

5. Sample Characteristics

All the firms belonged to the MSME private sector and were mainly from manufactur- ing sector. Table I summarizes the category of the firm's (surveyed firms which are represented by the respondent). Tables II & III represent the, the workforce size of the respondent & classification of respondents based on market segments respectively.

Table I. Distribution of Respondents by MSME Category

Category	No.	(%)
Micro	42	29.8
Small	72	51.1
Medium	27	19.1
Grand Total	141	100

Out of all the firms surveyed, 29.8 percent were micro enterprises, 51.1 percent were small enterprises, and 19.1 percent were medium enterprises category of the MSMEs. Regarding workforce size, 40.4 percent of firms employed less than 10 workers, 39.0 percent had a workforce of 10–50, 15.6 percent employed 51–100 workers, and 5.0 percent had more than 100 employees. In terms of market segments, 33.3 percent of firms operated in B2B (Business to Business), 22.7 percent in B2C (Business to Con- sumer), and 44.0 percent served both B2B and B2C markets.

Table II. *Workforce size of the respondents*

Workforce size	No.	(%)
Less than 10	57	40.4
10-50	55	39.0
51-100	22	15.6
More than 100	7	5.0
Grand Total	141	100

Table III. *Classification of respondents based on market segments*

Market segments	No.	(%)
B2B (Business to Business)	47	33.3
B2C (Business to Consumer)	32	22.7
Both B2B and B2C	62	44.0
Grand Total	141	100

Analysis and Interpretation:

1. Tools of analysis

Statistical analysis and model testing were applied through this study using SmartPLS 4 and Jamovi 2.4.8. Structural Equation Modeling (SEM) with complex relationship between observed and latent variables, path analysis and model validation were per- formed using SmartPLS 4 due to its robust feature in handling the relationships between observed and latent variables. In addition, Principal Component Analysis was per- formed using Jamovi 2.4.8 that offered a user-friendly face with advanced statistical functions for the Dimensionality Reduction and data visualization. The use of these tools both together and alone ensured that the data analysis was accurate, reliable, and ultimately the basis upon which the study's methodological rigor was founded.

2. Reliability analysis

Composite Reliability (CR) is an important measure of internal consistency in Struc- tural Equation Modeling (SEM), because it is a more accurate reliability estimate than Cronbach's alpha, taking the factor loadings of indicators into account. Generally, a CR above 0.7 indicates that the construct reliably assesses the intended theoretical concept.

Cronbach's values for the six constructs are all greater than the 0.7 threshold indi- cating its reliability. Reliability of supplier relationship (0.825) and sustainability (0.848) is strong, whereas that of customer relationship (0.781), information sharing (0.810), and digitalization (0.797) is good. The supply chain performance (0.780) is low, compared to the threshold, but is the least among constructs. Overall, these results indicate reliability of the measurement model and therefore consistency of SEM anal- ysis.

Table IV. *Composite reliability (rho_c)*

Scale Reliability Statistics	
Constructs	Composite reliability (rho_c)
Supplier relationship	0.825
Customer relationship	0.781
Information sharing	0.810
Digitalization	0.797
Sustainability	0.848
Supply chain performance	0.780

3. Principal component analysis

Table V gives the constructs and the factors associated in each construct. It indicates various statistics (such as mean, factor loading, KMO Measure of Sampling Adequacy, and standard deviation) for each factor.

Table V. *Result of Principal Component Analysis (PCA)*

Constructs and constituent factors	Mean	SD	Factor loading	Kaiser-Meyer-Olkin (KMO)
Supplier relationship	-	-	-	-
We regularly solve supply chain problems jointly with our suppliers.	4.1	1.0	0.760	0.777
We have supported our suppliers in im- proving their product quality.	4.0	1.1	0.772	0.811
We involve our suppliers in improving our product quality.	3.7	1.1	0.789	0.837
We perform demand forecasting in collab- oration with our suppliers.	3.6	1.2	0.614	0.809
Customer relationship	-	-	-	-
We actively gather and respond to cus- tomer feedback.	3.7	1.0	0.583	0.750
We frequently measure and evaluate cus- tomer satisfaction.	3.9	0.8	0.76	0.764
We facilitate customer's ability to seek as- sistance from us.	3.9	0.9	0.674	0.679
We consult (survey) with customers for new product development.	4.0	0.9	0.726	0.769
Information sharing	-	-	-	-
We regularly communicate demand fore- casts with our suppliers	3.4	1.2	0.838	0.711
We share accurate information with sup- pliers and partners in real time.	3.3	1.2	0.656	0.671
We utilize shared information to optimize inventory levels across the supply chain.	3.3	1.1	0.639	0.676
We use digital tools to facilitate infor- mation exchange across the supply chain.	3.9	0.9	.731	0.608
Digitalization	-	-	-	-
Our organization has adopted digital tools to enhance supply chain operations.	3.2	1.2	0.821	0.650
Our organisation sells products on e-com- merce platform	3.4	1.2	0.792	0.767

Constructs and constituent factors	Mean	SD	Factor loading	Kaiser-Meyer-Olkin (KMO)
Our organization encourages digital pay- ment transactions.	3.9	0.8	0.500	0.651
Our organisation uses digital solutions to communicate with supply chain partners.	3.6	1.0	.686	0.650
Sustainability	-	-	-	-
We prioritize sourcing raw materials from environmentally responsible suppliers.	3.2	1.2	0.754	0.858
We use eco-friendly packaging materials whenever possible.	3.2	1.3	0.806	0.833
Government regulations and policies are supportive of sustainability initiatives in the MSME sector.	3.6	1.0	0.730	0.826
We find it difficult to balance sustainabil- ity with profitability in our supply chain.	3.2	1.3	.763	0.867
Supply chain Performance	-	-	-	-
We maintain strong relationships with our key suppliers to ensure reliability and quality.	3.2	1.2	0.744	0.852
Our supply chain is responsive to cus- tomer needs and provides high levels of service and satisfaction.	3.4	1.1	0.708	0.795
Our company effectively shares real-time and accurate information with supply chain partners.	3.6	0.9	0.594	0.798
The adoption of digital technologies have improved our supply chain efficiency and visibility.	3.1	0.9	0.542	
Our supply chain practices align with sus- tainability goals.	2.8	1.0	0.622	0.860

The factor loading and KMO values reveal the varying strengths of relationships among the constructs. The most substantial interrelation is observed between **Sustainability** and **Supplier Relationship**, with factor loadings ranging from 0.653 to 0.797 and 0.778 to 0.794, respectively, and KMO values of 0.837 and 0.867—both indicating excellent sampling adequacy.

For **Customer Relationship** and **Digitalization**, KMO values ranging from 0.679 to 0.769 and 0.650 to 0.767, along with factor loadings between 0.619 and 0.731, and 0.686 to 0.815, reflect moderate to strong correlations. **Information Sharing** shows more varied results, with factor loadings between 0.643 and 0.830 and KMO values from 0.608 to 0.711, suggesting diverse respondent perceptions of this construct.

Similarly, the **Supply Chain Performance** variables show factor loadings ranging from 0.639 to 0.769, and KMO values between 0.795 and 0.860, confirming that the data are well-suited for factor analysis. The standard deviations indicate a reasonable spread of responses, reflecting some variability in perceptions, while the mean values suggest moderate to high agreement across all factors.

Overall, the results demonstrate strong sampling adequacy and reliable factor structures, confirming the robustness and appropriateness of the data for further factor analysis.

SEM model & Hypothesis testing:

1. SEM model

To examine the complex relationships between observed (measured) and unobserved (latent) variables, Structural Equation Modeling (SEM) is employed. SEM is a versatile statistical technique that not only evaluates the connections between measured and latent constructs but also analyzes the interrelationships among multiple latent variables. Essentially, SEM integrates the principles of regression analysis and factor analysis, providing a comprehensive framework for testing both direct and indirect relationships within a model. SEM is a useful way to transact with multicollinearity and, with respect to the unreliability of survey response data, SEM is a useful method (Tripathy, 2011, 2012).

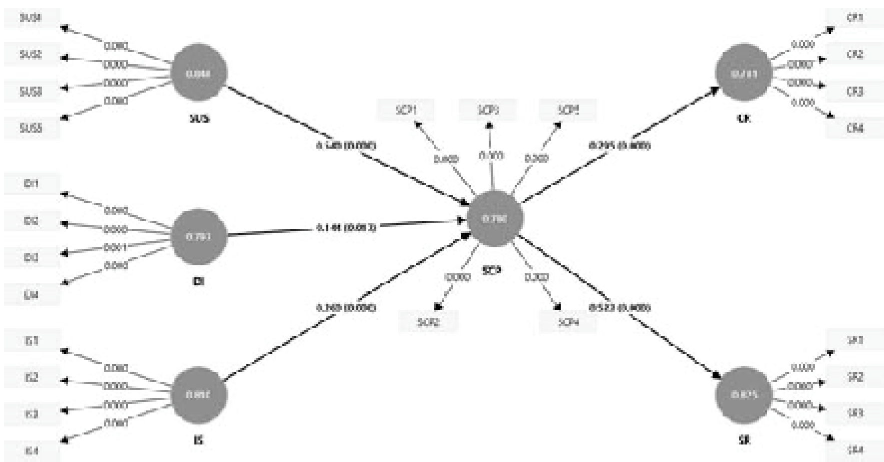


Figure 2. PLS-SEM model

Table VI. *Model fitting parameters*

						RMSEA 90% CI	
x^2	DF	p	CFI	x²/DF	RMSEA	Lower	Upper
320	237	< .001	0.891	1.35	0.0499	0.0348	0.0633

The overall fit to the model fitting parameters looks to be satisfactory and, as such, is reasonably acceptable or good. The chi square value ($x^2 = 320$, DF = 237, $p < 0.001$) indicates a statistically significant difference, but in view of its known sensitivity to sample size, other fit indices are considered to evaluate model. The comparative fit index (CFI = 0.891) falls slightly below the conventional threshold of 0.90, indicating a marginally acceptable fit, it's still good enough to indicate that the population per- forms consistently. The chi-square to up of freedom ratio (x^2 / DF) of 1.35 is well within the range of expected value, indicating that the model is good. Additionally, the good-ness of fit of the model is shown by the Root Mean Square Error of approximation (RMSEA = 0.0499) and its 90 percent confidence interval (0.0348–0.0633) that are close to 0.05, which are usually considered as optimal. Together, these indices suggest that while the model exhibits some limitations, it provides a reasonably good represen- tation of the data.

2. Hypothesis Testing

The table VII presents the results of hypothesis testing, evaluating the relationships between various factors affecting supply chain performance (SCP), supplier relations (SR), and customer relations (CR).

Table VII. *Result of Hypothesis Testing*

Hypothesis	Description	Beta Value	p-value	Inference drawn
H1: IS ® SCP	Information Sharing has a positive ef- fect on Supply Chain Performance	0.260	***	Supported
H2: DI ® SCP	Digitalization has a positive effect on Supply Chain Performance	0.144	**	Supported
H3: SUS ® SCP	Sustainability has a positive effect on Supply Chain Performance	0.540	***	Supported
H4: SCP ® SR	Supply Chain Performance has a positive effect on Supplier Relation	0.295	***	Supported
H5: SCP ® CR	Supply Chain Performance has a positive effect on Customer Relation	0.523	***	Supported

Note: p-value significance levels *** = $p < 0.001$, ** = $p < 0.05$

H1: The results confirm that information sharing (IS) enhances supply chain performance (b = 0.260, $p < 0.001$), highlighting the necessity of transparent communication and real-time data exchange in improving overall supply chain efficiency. Information sharing fosters coordination among supply chain part- ners, reduces uncertainty, and facilitates better decision-making (Chen & Paulraj, 2004). Effective information exchange allows businesses to align sup- ply and demand efficiently, reducing excess inventory costs and ensuring timely order fulfilment (Mintz & Mentzer, 2005). Improved communication within supply chains has been found to reduce lead times and ordering costs by approximately 23%, reinforcing its positive influence on supply chain out- comes (Hau et al., 2017).

H2: Digitalization was found to have a moderate but positive impact on supply chain performance (b = 0.144, p = 0.017), indicating that the adoption of digital tools enhances operational efficiency and decision-making. Digital- ization enables MSMEs to streamline procurement, inventory management, and logistics through automated systems (Wahyuni et al., 2020). By integrat- ing e-commerce platforms, cloud-based ERP systems, and digital payment methods, businesses can achieve real-time visibility over their supply chains, reducing manual errors and improving transaction efficiency (Legner et al., 2017). Furthermore, MSMEs that have adopted digital technologies report higher cost savings and improved customer satisfaction due to enhanced order tracking and delivery management (Kilay et al., 2022).

H3: Sustainability show the strongest positive impact on supply chain per- formance (b = 0.540, $p < 0.001$), highlighting the growing importance of sus- tainable practices in modern supply chains. The adoption of green supply chain management (GSCM) strategies, such as eco-friendly sourcing, waste reduction, and reverse logistics, has been shown to significantly enhance cost efficiency and environmental responsibility (Govindan et al., 2014). Ciliberti et al. (2008) found that MSMEs adopting sustainability initiatives experience improved operational efficiency and reduced regulatory risks, aligning with the increasing demand for eco-conscious business practices. However, re- source constraints and technical limitations often hinder MSMEs from fully embracing sustainability (Wooi & Zailani, 2010).

H4: Supply chain performance has a positive impact on supplier relation- ships (b = 0.295, $p < 0.001$), demonstrating that an efficient supply chain fos- ters stronger collaboration and trust between businesses and their suppliers. Supporting Gunasekaran's effective supplier relationship management in- volves joint planning, process integration, and long-term contracts, which will lead to reduced lead times, optimized inventory levels, and overall cost reduc- tions. Studies by Liker & Choi (2004) further indicate that organizations that actively manage supplier relationships experience enhanced quality control and supply chain agility, as suppliers become more aligned with business ob- jectives. Given these findings, MSMEs should adopt supplier development programs and performance evaluation mechanisms to strengthen partnerships and improve overall supply chain efficiency.

H5: The results indicate that supply chain performance has a strong positive effect on customer relationships (b = 0.523, $p < 0.001$), reinforcing the idea that an optimized supply chain leads to higher customer satisfaction and loy- alty. Risna Nona found customer satisfaction is highly dependent on product quality and on-time delivery, rather than just product innovation, underscoring the importance of efficient supply chain operations. A well-functioning supply chain ensures timely order fulfilment, reduced stockouts, and enhanced ser- vice reliability, all of which contribute to improving customer experiences (Westbrook & Scott, 1991). Ulusoy (2003) states that customer feedback mechanisms and service personalization play a crucial role in strengthening customer relationships, particularly in competitive markets. These findings suggest that MSMEs should focus on demand forecasting, process automation, and integrated customer relationship management (CRM) systems to improve responsiveness and build lasting customer relationships.

Table VIII. *Results of Indirect Effects*

Hypothesis	Indirect Path	Beta Value	P values	Inference drawn
H6	DI® SCP® CR	0.042	**	Supported
H7	DI® SCP® SR	0.075	**	Supported
H8	IS® SCP® CR	0.077	**	Supported
H9	IS® SCP® SR	0.136	***	Supported
H10	SUS® SCP® CR	0.159	***	Supported
H11	SUS® SCP® SR	0.282	***	Supported

Note: p-value significance levels *** = $p < 0.001$, ** = $p < 0.05$

The results of table VIII indicate that digitalization has a significant positive effect on customer relationship through supply chain performance (b = 0.042, $p < 0.05$), sup- porting H6. This suggests that the adoption of digital technologies enhances interac- tions, communication, and overall engagement with customers, thereby strengthening the customer relationship within the supply chain. Digitalization is found to positively influence supplier relationship through supply chain performance (= 0.075, $p < 0.05$), supporting H7. The integration of digital tools facilitates seamless coordination, im- proves information exchange, and fosters collaboration between firms and their suppli- ers, leading to enhanced supplier relationship management. The findings also reveal that information sharing has a significant positive impact through supply chain perfor- mance on customer relationship (= 0.077, p = $p < 0.05$), supporting H8. Effective information sharing mechanisms ensure transparency, trust, and responsiveness, which contribute to improved relationships with customers. Information sharing demonstrates a strong positive effect on supplier relationship through supply chain performance (b = 0.136, $p < 0.001$), supporting H9. The efficient exchange of real-time data between firms and their suppliers enhances operational efficiency, mitigates uncertainties, and fosters long-term partnerships. Sustainability is shown to have a substantial positive impact on customer relationship (b = 0.159, $p < 0.001$), supporting H10. Organizations that prioritize sustainability practices not only meet consumer expectations but also es- tablish stronger relationships with customers through ethical sourcing and environmen- tal responsibility. Finally, sustainability significantly improves supplier relationship (b= 0.282, $p < 0.001$), supporting H11. Sustainable supply chain practices encourage col- laboration, long-term commitment, and shared values among suppliers, thereby rein- forcing supplier relationships. These findings collectively underscore the importance of digitalization, information sharing, and sustainability in enhancing both customer and supplier relationships, contributing to overall supply chain performance.

Recommendation:

The study highlights several key recommendations for enhancing supply chain perfor- mance in MSMEs. To begin with, digitalization should be a top priority for MSMEs. This can be achieved through the adoption of Enterprise Resource Planning (ERP) systems, expanding sales channels via e-commerce platforms, and integrating digital payment solutions. These measures enable real-time data exchange, better inventory control, and reduced operational inefficiencies.

Equally important is strengthening relationships with suppliers and customers. MSMEs should focus on collaborative planning, demand forecasting, and the use of Customer Relationship Management (CRM) systems to enhance service responsiveness and overall customer satisfaction.

Sustainability must also be a central component of MSME strategy. This involves adopting Green Supply Chain Management (GSCM) practices such as sustainable sourcing, eco-friendly packaging, and effective waste reduction. Policymakers can play a key role by offering financial incentives and training programs to encourage these initiatives.

In addition, information sharing and transparency across the supply chain should be improved through the use of cloud-based management platforms. Such systems can promote seamless coordination among stakeholders, minimize uncertainty, and support better decision-making.

Finally, policy and financial support are essential for MSMEs to successfully transition toward digitalization and sustainability. This includes subsidized digital transformation programs, tax incentives, and streamlined regulations to ensure both growth and long-term financial stability.

If effectively implemented, these strategic actions can greatly enhance operational efficiency, boost competitiveness, and build resilience within MSME supply chains—ultimately contributing to broader economic growth and job creation.

Limitations:

Despite the valuable insights, this study has certain limitations:

1. The research focused solely on MSMEs in Coimbatore, which may limit the generalizability of the findings to other regions or industries.
2. The study employed non-probability convenience sampling, which may intro- duce selection bias and affect the broader applicability of the results.
3. Macroeconomic conditions, policy changes, and global supply chain disrup- tions were not deeply explored in this study.

Future research could address these limitations by expanding the geographic scope, employing probabilistic sampling techniques, and adopting longitudinal designs to track evolving supply chain strategies.

Conclusion:

This study provides a comprehensive evaluation of the key factors influencing supply chain performance in MSMEs in Coimbatore using Structural Equation Modelling (SEM).

The findings underscore the vital importance of supplier and customer relationships, information sharing, digitalization, and sustainability in improving supply chain efficiency. The study confirms that effective supply chain management plays a significant role in boosting business performance—helping MSMEs streamline logistics, minimize operational inefficiencies, and respond more effectively to market demands.

As shown in Table V, the factor loadings reveal strong correlations between key constructs, indicating that the measurement model is both reliable and well-structured for assessing supply chain performance. The analysis presented in Table VI highlights digitalization as a transformative force, enhancing transparency, coordination, and operational efficiency across the supply chain.

Sustainability practices, such as green supply chain initiatives, also demonstrate a positive influence on performance, reflecting a growing alignment between business success and environmental as well as social responsibility. Furthermore, strong supplier and customer relationships promote trust, reliability, and long-term collaboration—factors that collectively strengthen MSMEs' competitive edge.

Hypothesis testing results (Table VII) confirm that information sharing, digitalization, and sustainability have a significant positive impact on supply chain performance. The indirect effects analysis (Table VIII) further emphasizes how these factors reinforce supplier and customer relationships. Finally, the statistical validation using Structural Equation Modeling (SEM) (Figure 2) confirms the robustness and reliability of these findings.

Overall, this study provides valuable insights for MSME managers and policymakers to implement strategies that strengthen supply chain capabilities. The integration of digital solutions, sustainable practices, and improved information-sharing mechanisms can drive the sector toward enhanced performance, greater resilience, and long-term growth.

REFERENCES

1. Robert E. Spekman, John W. Kamauff Jr, Niklas Myhr, (1998),"An empirical investigation into supply chain management: a perspective on partnerships", Supply Chain Management: An International Journal, Vol. 3 Iss: 2 pp. 53 – 67
2. Chen, I. J., & Paulraj, A. (2004). Towards a theory of supply chain manage- ment: the constructs and measurements. Journal of Operations Management, 22(2), 119–150. doi:10.1016/j.jom.2003.12.007
3. Rhonda R. Lummus, Robert J. Vokurka, (1999) "Defining supply chain man- agement: a historical perspective and practical guidelines", Industrial Manage- ment & Data Systems, Vol. 99 Issue: 1, pp.11-17, https://doi.org/ 10.1108/02635579910243851
4. Swayam Sampurna Panigrahi, Nune Srinivasa Rao, (2018) "A stakeholders' perspective on barriers to adopt sustainable practices in MSME supply chain: Issues and challenges in the textile sector", Research Journal of Textile and Apparel, Vol. 22 Issue: 1, pp.59-76, https://doi.org/10.1108/ RJTA-07-2017- 0036
5. Kilay, A.Lawrenz.; Simamora, B.H.; Putra, D.P. The Influence of E-Payment and E-Commerce Services on Supply Chain Performance: Implications of Open Innovation and Solutions for the Digitalization of Micro, Small, and Me- dium Enterprises (MSMEs) in Indonesia. J. Open Innov. Technol. Mark. Com- plex. 2022, 8, 119. https://doi.org/ 10.3390/joitmc8030119
6. Kamble, S. S., Gunasekaran, A., & Sharma, R. (2018). Analysis of the driving and dependence power of barriers to adopt Industry 4.0 in Indian manufactur- ing industry. Computers in Industry, 101, 107-119. https://doi.org/10.1016/j.compind.2018.06.004
7. Zainurrafiqi and Gazali. 2024. Supply Chain Digitalization, Green Supply Chain, Supply Chain Resilience Toward Competitiveness and MSMEs Perfor- mance. Volume 22, Issue 1, Pages 175–192. Malang: Universitas Brawijaya. DOI: http://dx.doi.org/10.21776/ub. jam.2024.022.01.14
8. Legner, C., Eymann, T., Hess, T., Matt, C., Böhmann, T., Drews, P, Ahlemann, F. (2017). Digitalization: Opportunity and Challenge for the Business and Information Systems Engineering Community. Business & Information Sys- tems Engineering, 59(4), 301–308. doi:10.1007/s12599-017-0484-2
9. Erol, S., Jäger, A., Hold, P., Ott, K., & Sihn, W. (2016). Tangible Industry 4.0: A Scenario-Based Approach to Learning for the Future of Production. Proce- dia CIRP, 54, 13–18. doi: 10.1016/j.procir.2016.03.162
10. Khalid Hafeez Kay Hooi Keoy Robert Hanneman, (2006),"E-business capa- bilities model", Journal of Manufacturing Technology Management, Vol. 17 Iss 6 pp. 806 – 828 http://dx.doi.org/10.1108/17410380610678819
11. Gunasekaran A, C. Patel, E. Tirtiroglu, (2001) "Performance measures and metrics in a supply chain environment", International Journal of Operations & Production Management, Vol. 21 Issue: 1/2, pp.71-87
12. Dr.inda Sukati, prof. Dr. Abu bakar abdul hamid, assoc. Prof. Dr. Rohaizat baharun, Dr. Huam hon tat, "A study of supply chain management practices: an empirical investigation on consumer goods industry in Malaysia", Interna- tional Journal of Business and Social Science, Vol. 2 No. 17.
13. Gunasekarana A, Patelb C, Ronald E. McGaughey (2004) "A framework for supply chain performance measurement", International Journal of Production Economics 87(3):333-347 DOI:10.1016/j.ijpe.2003.08.003
14. Boomsma, A. (1982), "A robustness of LISREL against small sample sizes in factor analysis models", in Joreskog, K.G. and Wold, H. (Eds), Systems Under Indirect Observations, Causality, Structure, Prediction, Part 1, Amsterdam, pp. 149-173.

15. Joby George and V. Madhusudanan Pillai (2019), "A study of factors affecting supply chain performance" J. Phys.: Conf. Ser. 1355 012018

16. Janat Shah (2016), "Supply Chain Management Text and Cases 2Nd Edition", published by Pearson India Education Services Pvt. Ltd, CIN: U72200TN2005PTC057128.

17. Budi Rahardjo, Daryono, Najmudin (2022), "Analysis of Supply Chain Man- agement Implementation on MSME Performance", The Eastasouth Manage- ment and Business Vol. 3, No. 01, pp. 165 - 173 ISSN: 2985-7120, DOI: 10.58812/esmb.v3i01

18. David Simchi-Levi, Philip Kaminsky, and Edith Simchi-Levi (2001) , "De- signing and Managing the Supply Chain: Concepts, Strategies, and Case Stud- ies", journal of business logistics, Vol.22, No. 1.

19. Braganza, A. (2002). Enterprise integration: creating competitive capabili- ties. Integrated Manufacturing Systems, 13(8), 562–572. doi:10.1108/09576060210448143

20. Pagell, M. (2004). Understanding the factors that enable and inhibit the inte- gration of operations, purchasing and logistics. Journal of Operations Man- agement, 22(5), 459–487. doi:10.1016/j.jom.2004.05.008

21. Min, S., & Mentzer, J. T. (2004). "Developing and measuring supply chain manage- ment concepts", Journal of Business Logistics, 25(1), 63–99. doi:10.1002/j.2158 1592.2004.tb00170.x

22. Gunduz Ulusoy (2003), "An assessment of supply chain and innovation man- agement practices in the manufacturing industries in Turkey", International Journal of Production Economics 86(3):251-270. DOI:10.1016/S0925- 5273(03)00064-1

23. Elma Avdagić-Golub, Adisa Hasković Džubur, Belma Memić (2021), "Qual- ity management as the basis of business company operations for the purpose of customer satisfaction", Science Engineering and Technology 1(1):52-58 DOI:10.54327/set2021/v1.i1.4

24. Charles Scott, Roy Westbrook, (1991),"New Strategic Tools for Supply Chain Management", International Journal of Physical Distribution & Logistics Management, Vol.21, Link: http://dx.doi.org/10.1108/09600039110002225

25. Risna Nona A; Suharno A, Sri Mintarti A, Yohannes Kuleh, (2021), "The fac- tors affecting customer satisfaction, competitive advantage, and performance in the MSMEs in the craft industry sector from East Kalimantan Province: Indonesia", Journal of Scientific Papers Social development & Secu- rity 11(1):117-130 DOI:10.33445/sds.2021.11.1.13

26. Muhammed Kürşad Özlen, Nereida Hadziahmetovic (2013), "Customer Re- lationship Management and Supply Chain Management", World Applied Pro- gramming, Vol (3), Issue (3)

27. Kannan Govindan, Susana Azevedo, Helena Carvalho, Virgilio Cruz-Ma- chado, (2014) "Impact of supply chain management practices on sustainabil- ity", Journal of Cleaner Production 85(9):212–225 DOI:10.1016/j.jclepro.2014.05.068.

28. Francesco Ciliberti, Pierpaolo Pontrandolfo, Barbara Scozzi, 2008, "Investi- gating corporate social responsibility in supply chains: A SME perspective", Journal of Cleaner Production 16(15):1579-1588, DOI:10.1016/j.jclepro.2008.04.01629. Goh Chee Wooi, Suhaiza Zailani, 2010, "Green Supply Chain Initiatives: In- vestigation on the Barriers in the Context of SMEs in Malaysia" International Business Management 4(1):20-27

DOI:10.3923/ibm.2010.20.27

30. G Hilson, 2000, "Barriers to implementing cleaner technologies and cleaner production (CP) practices in the mining industry: A case study of the Americas, Minerals Engineering", Volume 13, Issue 7, https://doi.org/10.1016/S0892- 6875(00)00055-8.

31. Gülçin Büyüközkan, Fethullah Göçer, 2018, "Digital Supply Chain: Literature review and a proposed framework for future research", https://doi.org/10.1016/j.compind.2018.02.010

32. Wahyuni, S., Permatasari, A., & Kusumawati, A. (2020). The effect of digital market- ing on small and medium enterprises (SMEs) performance in Indonesia. IOP Confer- ence Series: Earth and Environmental Science, 485(1), 012037. https://doi.org/10.1088/1755-1315/485/1/01203733. Marsh, H.W., Balla, J.R. and Hau, K.-T. (1996), "An evaluation of incremental fit indices: a clarificationof mathematical and empirical properties", in Marcoulides, G.A. and Schumacker, R.E. (Eds), Advanced Structural Equation Modeling: Issues and Techniques, Lawrence Erlbaum Associates, Mahwah, NJ, pp. 315-353.

34. Marsh,H.W.,Balla, J.R.andMcDonald, R.P.(1988),"Goodnessoffitindexesinconfirma- toryfactor analysis: the effect of sample size", Psychological Bulletin, Vol. 103 No. 3, pp. 391-410.

35. Marsh, H.W., Hau, K.-T., Balla, J.R. and Grayson, D. (1998), "Is more ever too much? The number of indicators per factor in confirmatory factor analysis", Multivariate Be- havioral Research, Vol. 33 No. 2, pp. 181-220.

36. S. Chopra, P. Meindl, and D. V. Kalra, Supply chain management: strategy, planning, and operation, Third edit. Pearson Education, 2010.

37. Linda, M. R., Rahim, R., Suhery, S., Ravelby, T. A., & Yonita, R. (2022). MSME busi- ness performance: The role of competitive advantage, supply chain management prac- tices, and innovation. Baskara: Journal of Business and Entrepreneurship, 5(1), 31- 46.

38. Indian Brand Equity Foundation – (IBEF), MSME Industry in India – Market Share, Reports, Growth & Scope | IBEF

39. Ministry of Micro, Small & Medium Enterprises

OVERCONFIDENCE BIAS AMONG INDIAN EQUITY INVESTORS: SECONDARY ANALYSIS OF SEBI AND NSE DATA (2025)

*** Ms. Ann Jose, ** Dr. S. Bhawiya Roopa, ***Dr. Sibu C Chithran**

ABSTRACT

This study examines overconfidence bias among Indian equity investors through secondary data analysis of the SEBI Investor Survey 2025 and NSE Market Pulse reports. Overconfidence manifests in dimensions like perceived knowledge, excessive risk-taking, over-trading, solo decision-making, skill overestimation, poor diversification, and demographic patterns. SEBI 2025 data from 91,950 households reveal only 36% rate their financial knowledge as moderate/high, yet significant trading intent exists. Risk preferences indicate selective high-risk appetite (5–15%), while 62% rely on informal advice. Demographics show urban, younger, educated groups with higher intent and awareness. Analysis maps survey indicators to overconfidence dimensions, supported by literature. Policy recommendations include enhanced NSE literacy initiatives to mitigate bias and improve retail outcomes.

Keywords: *Overconfidence bias, Indian Equity Investors, SEBI Investor Survey 2025, NSE Market Pulse, Retail Investor Behaviour.*

Introduction :

Overconfidence bias is a behavioural phenomenon where investors overestimate their knowledge, predictive ability, or control over market outcomes (Barber & Odean, 2020). In India, retail investors increasingly participate in equity markets, yet behavioural biases can influence trading decisions, risk perception, and portfolio diversification (Kumar & Goyal, 2021).

Literature Review:

Recent studies highlight overconfidence in emerging markets. Ramesh & Singh (2020) note solo decision-making and reliance on informal advice amplify risk exposure. Sharma et al. (2021) found younger, urban, and educated investors more prone to overconfidence in equity markets. Mishra et al. (2022) and Gupta & Verma (2023) observe perception–skill gaps as a key dimension.

Data & Methodology:

This study uses secondary data from SEBI Investor Survey 2025 (Kantar, 2025) and NSE Market Pulse reports. Aggregate statistics on financial knowledge, trading intent, risk tolerance, product awareness, and demographic segmentation were extracted. The study applies descriptive and conceptual analysis, mapping survey indicators to behavioural dimensions of overconfidence. Hypotheses were formulated based on literature and tested via aggregate trends rather than individual-level statistical analysis.

*Research Scholar, PG & Research Department of Management, Srimad Andavan Arts and Science College, Tiruchirappalli, Tamil Nadu.

** Assistant professor & Research Advisor, PG & Research Department of Management, Srimad Andavan Arts and Science College, Tiruchirappalli, Tamil Nadu.

*** Course Coordinator, Centre for Distance and online Education, Mahatma Ghandi University, Kottayam, Kerala.

Hypotheses:

- H1: High perceived knowledge is associated with higher risk-taking and trading intent.
- H2: Reliance on informal advice is associated with higher trading frequency and poor diversification.
- H3: Younger, urban, and educated investors demonstrate stronger overconfidence tendencies.

Analysis and Interpretation:

Hypothesis 1 (H1) Analysis: High Perceived Knowledge is Associated with Higher Risk-Taking and Trading Intent

Evidence (SEBI 2025):

- Perceived Knowledge among Investors: 36% of surveyed investors report moderate to high knowledge of the securities market, with awareness of at least one product at 63%.
- Trading Intent among Non-Investors: 22% of non-investors express an intention to start investing in the next year.
- Cautious Group: The remaining 42% of respondents have low perceived knowledge and/or no current intention to invest.

Interpretation in Terms of H1:

- Overconfidence Evidence (36%): Investors who perceive moderate/high knowledge may overestimate their skill, leading to higher risk-taking and potential over-trading.
- Trading Intent (22%): Non-investors planning to invest despite limited experience indicate a perception–skill gap, reflecting potential overconfidence.
- Cautious Group (42%): Low knowledge/no intent segment demonstrates that overconfidence is not uniform; this group serves as a contrast highlighting behavioural heterogeneity.

Hypothesis 2 (H2): Reliance on informal advice is associated with higher trading frequency and poor diversification.

Evidence (SEBI 2025):

- 62% of Indian investors rely on friends, family, or social media for their investment decisions.
- Investors dependent on informal sources show lower penetration in diversified products such as mutual funds, ETFs, REITs/InvITs, and corporate bonds.
- SEBI segmentation indicates that investors receiving informal advice tend to have higher intent to trade but limited understanding of risk-adjusted portfolio construction.

Interpretation in Terms of H2:

- Reliance on informal advice reduces analytical decision-making, increasing susceptibility to impulsive or sentiment-driven trading, which is often associated with overconfidence.
- Investors who primarily depend on friends, relatives, and social platforms are more likely to trade frequently, driven by herd behaviour, trend-following, and perceived market opportunities, yet they diversify less due to limited technical knowledge.
- In contrast, investors using formal or professional advisory channels (brokers, registered advisors, research reports) tend to demonstrate more stable trading behaviour, lower trading intensity, and better diversification, as they follow structured investment guidance.
- Thus, the SEBI 2025 patterns support H2 by showing that informal advice leads to higher trading intent and lower trade diversification, reinforcing the behavioural finance theory that unregulated or peer-driven information amplifies risk-taking while weakening portfolio discipline.

Hypothesis 3 (H3): Younger, Urban, and Educated Investors Exhibit Higher Overconfidence

Evidence (SEBI 2025):

- Awareness and knowledge levels are significantly higher among Gen Z (18–28) and Millennials (29–44) compared to older cohorts.
- Urban and metro investors (Top 9 metros, 5–40 lakh population towns) show higher market penetration, higher knowledge scores, and greater intent to trade.
- Graduates and post-graduates demonstrate higher financial knowledge, higher securities penetration, and increased likelihood of entering the market.
- These groups also show higher representation in high-knowledge but low-diversification or high-intention trading clusters, which are indicators of overconfidence.

Interpretation in Terms of H3:

- Younger investors tend to overestimate their market understanding, influenced by exposure to digital platforms, social media narratives, and DIY investment culture.
- Urban investors have greater access to information and market platforms, which increases perceived skill, often faster than actual skill—creating ideal conditions for overconfidence.
- Higher educational attainment (graduates/postgraduates) correlates with strong financial confidence; however, SEBI 2025 indicates this does not necessarily translate into prudent behaviour, as many still hold concentrated portfolios or trade aggressively.
- These demographic groups (young, urban, educated) also display higher intent to invest in the next 1 year, reinforcing the behavioural pattern where higher perceived knowledge leads to higher risk-taking and entry intentions.
- Therefore, SEBI 2025 data supports H3: Younger, urban, and educated cohorts show stronger signals of overconfidence, aligning with prior research (Sharma et al., 2021; Das & Nair, 2022).

Interpretation and findings of SEBI 2025 Investor Findings Using Behavioural Finance Concepts

Behavioural Theme	SEBI2025 Evidence	Interpretation Through Behavioural Finance Lens	Supporting Scopus-Indexed Literature (2020 onwards)
1. Knowledge–Intention Gap as Overconfidence Signal	• Only **36%** report moderate/high market knowledge. • 22% of non-investors intend to invest soon. • 42% have low knowledge and no investing intent	Intention to invest despite low knowledge indicates **overconfidence bias** and **miscalibration.** • The 42% cautious group shows heterogeneity—some investors are overconfident while others avoid risk due to lack of competence. • Overconfidence arises from perceived rather than actual knowledge	• Kumar & Goyal (2021) –Overconfidence from perceived knowledge rather than real ability. • Sahi & Arora (2020) Retail investors show skill overestimation. • Mohan & Singh (2023) – Low knowledge often coexists with high investment intention due to "illusion of knowledge."
2. Demographics: Youth, Urbanization & Education Amplify Overconfidence	• Intending investors are younger (Gen Z, Millennials). • More participation from urban, educated, digitally-active groups.	• Younger, urban, and more educated individuals show higher overestimation of skill, greater risk-taking, and greater trading frequency. • Digital literacy and social media exposure heighten illusion of control	• Sharma et al. (2021) – Younger investors exhibit higher overconfidence and risk tolerance. • Das & Nair (2022) – Urban and educated investors more likely to overestimate market ability. • Gupta & Jain (2023) – Digital access increases overconfidence in equity markets.

3. Informal Advice, Risk-Taking & Poor Diversification	• 62% rely on informal advice (friends, family, social media). • Investors depending on informal advice show low diversification.	• Informal advice promotes herding, impulsive trading, and overconfidence. • Leads to overtrading and poor risk-spreading. • Investors relying on professionals diversify better and trade less frequently.	• Chavali & Mohanraj 2021) – Informal social influence increases herd-driven overconfidence. • Patel & Chaudhary (2022) – Social-media investors show lower diversification. • Bansal & Kumar (2023) – Informal networks amplify overtrading.
4. Broader Market & Systemic Implications	• High investor participation, especially post-pandemic. • Increased turnover after market upswings (SEBI trend).	• Overconfidence causes excessive trading volumes, higher volatility, and systemic risk. • Retail investors with low diversification are more vulnerable to downturns.	• Singh et al. (2024) – Return-driven trading surges linked to overconfidence. • Agarwal & Banerjee (2022)–Overconfidence significantly increases churn and reduces returns. • SAJOSSE (2023) – Post -COVID Indian retail trading patterns reflect classic overconfidence cycles.

Policy Implications

1. Strengthen Financial Education

SEBI should deploy structured, multi-level financial literacy programs—especially for first-time and digitally active investors. Evidence shows that targeted literacy interventions reduce overconfidence and improve portfolio decisions (Sahi & Arora, 2020; Gupta & Jain, 2023).

2. Regulate Informal & Social-Media Advice Channels

Given that 62% of investors rely on informal advice, SEBI must tighten oversight on influencers, mandate disclosures, and promote certified advisory channels. Studies show regulated information environments reduce herd behaviour and misinformed trading (Chavali & Mohanraj, 2021).

3. Promote Diversified Investment Defaults

Platforms should nudge retail investors toward diversified, low-cost instruments such as index funds and SIP-based models. Research finds that default diversification reduces risk concentration and behavioural errors (Agarwal & Banerjee, 2022).

4. Implement Digital Behavioural Nudges

Trading platforms should integrate cooling-off periods, risk alerts, and trade-limit warnings to curb impulsive behaviour. Digital nudges are empirically shown to counteract overconfidence among younger investors (Sharma et al., 2021).

5. Strengthen Risk-Profiling Mechanisms

Dynamic risk profiling based on behavioural indicators—not just demographics—can prevent mismatches between perceived and actual risk capacity. This aligns with findings that overconfident investors underestimate downside risks (Mohan & Singh, 2023).

6. Enhance Market Behaviour Monitoring

SEBI should conduct more frequent behavioural assessments and combine them with NSE microstructure data. Continuous monitoring helps identify bias-driven trading surges and systemic vulnerabilities (Singh et al., 2024).

Conclusion:

SEBI's (2025) survey highlights a persistent perception–skill gap in the Indian retail segment: though only 36% report moderate/high market knowledge, 22% of non-investors intend to begin investing, signalling overconfidence. The demographic skew toward young, urban, and educated investors aligns with research linking these groups to heightened risk-taking and miscalibrated self-belief (Sharma et al., 2021; Das & Nair, 2022).

Furthermore, the heavy dependence on informal advice (≈62%) is consistent with previous evidence that socially transmitted information amplifies overconfidence, increases trading frequency, and weakens diversification (Patel & Chaudhary, 2022; Bansal & Kumar, 2023). These behavioural patterns may contribute to higher volatility and suboptimal outcomes for retail investors, especially during market upswings.

Overall, SEBI 2025 confirms that overconfidence remains a significant behavioural bias in India's equity-investor ecosystem. Strengthened regulation, digital nudges, and improved financial education are essential to support more rational, diversified, and risk-aware investment behaviour in the retail segment.

References:

Barber, B. M., & Odean, T. (2020). The behavior of individual investors. Journal of Economic Perspectives, 34(2), 105–128.
https://doi.org/10.1257/jep.34.2.105

Das, R., & Nair, S. (2022). Behavioral biases in Indian retail investors. Asian Journal of Finance, 14(3), 56–72.

Gupta, P., & Verma, R. (2023). Overconfidence and trading behavior: Evidence from India. Journal of Behavioral Finance, 24(1), 34–49.

Kumar, A., & Goyal, V. (2021). Investor psychology and market participation: Evidence from Indian households. International Review of Financial Analysis, 75, 101734.

Mishra, S., Sharma, V., & Singh, K. (2022). Retail investors and overconfidence: A study on perceived knowledge and risk. Journal of Economic Behavior & Organization, 199, 1–15.

Ramesh, M., & Singh, D. (2020). Informal advice, trading behavior, and overconfidence in emerging markets. Emerging Markets Review, 45, 100730.

Securities and Exchange Board of India. (2025). Investor survey 2025. https://www.sebi.gov.in/reports-and-statistics/research/sep-2025/investor-survey-2025_96982.html

Agarwal, R., & Banerjee, S. (2022). Impact of portfolio diversification nudges on retail investor behaviour: Evidence from emerging markets. Journal of Behavioral and Experimental Finance, 35, 100726.

Bansal, M., & Kumar, R. (2023). Information channels and investor overconfidence: The role of social media in retail trading decisions. Vision: The Journal of Business Perspective, 27(3), 345–357.

Chavali, K., & Mohanraj, K. (2021). Influence of investment information sources on investor behaviour: A behavioural finance perspective. Managerial Finance, 47(8), 1124–1141.

Das, R., & Nair, A. (2022). Determinants of overconfidence in retail equity markets: Evidence from India. International Journal of Economics and Business Research, 24(1), 45–62.

Gupta, A., & Jain, R. (2023). Financial literacy, behavioural biases, and investment decisions among young adults in India. Journal of Financial Services Marketing, 28(2), 157–170.

Mohan, V., & Singh, P. (2023). Risk perception and overconfidence bias among equity investors in India. Journal of Asian Finance, Economics, and Business, 10(1), 201–210.

Patel, D., & Chaudhary, S. (2022). Social influence, herd behaviour, and overconfidence among Indian stock market participants. Asian Journal of Economics and Banking, 6(3), 312–329.

Sahi, S. K., & Arora, A. P. (2020). Does financial literacy mitigate behavioural biases? Evidence from emerging market investors. South Asian Journal of Business Studies, 9(3), 375–392.

SEBI. (2025). Investor Survey 2025: National findings on participation, awareness, behaviour, and risk tolerance. Securities and Exchange Board of India.

Sharma, R., Verma, S., & Goyal, N. (2021). Digital trading platforms and behavioural biases among millennial investors. Journal of Behavioral and Experimental Finance, 30, 100515.

Singh, H., Kaur, A., & Deb, S. (2024). Behavioural biases and market volatility: Post-pandemic evidence from Indian equity markets. Journal of Economic and Administrative Sciences, 40(1), 33–49.

St. Francis Institute of Management & Research

Guidelines for Authors

"SFIMAR RESEARCH REVIEW" invites papers for publishing in the next edition of the journal. Papers should be based on management and related areas. Preference will be given to papers based on empirical research, theoretical and practice based papers.

Guidelines for submission

The Paper should be in English language, neatly typed as Microsoft Word Document, **Times New Roman 12 point font size on A4 Size Paper with Double Spacing having 1.5 inch margin** on all four sides.

1. **Length of the Paper**
   The Paper should not be more than 5,000 words.
2. **Order of the Article Content**
   The Article content should be in the following format

i. Title of the Paper: Titles should be no more than three typeset lines (generally 135 characters including spaces) and should be comprehensible to a broad scientific audience.

ii. Author affiliation: Include department, institution, and complete address, with the ZIP/postal code, for each author. Use superscripts to match authors with institutions.

iii. Corresponding author: The name, complete address, telephone number, and email address of the author to whom correspondence and proofs should be sent. Email addresses will appear in the article footnotes.

iv. Abstract: Provide an abstract of no more than 250 words. Abstracts should explain to the general reader the major contributions of the article. References in the abstract must be cited in full within the abstract itself and cited in the text.

v. Keywords: Keywords are listed below the abstract of the published article. At least three keywords are required at submission.

vi. Main Text: The Main Text should describe procedures in sufficient details. Methods and Assumptions must be presented before Results and Discussion. Use Systemic units and symbols whenever required. Statements of novelty and priority are discouraged in the text.

vii. Footnotes. SFIMAR Journal distinguishes author affiliations and footnotes from in-text footnotes by assigning a different set of footnote symbols to each type. Superscript lowercase letters separated by commas (no spaces) are used for author affiliations.

Superscript numerals separated by commas (no spaces) are used for author footnotes. In-text footnotes should be preceded by a footnote symbol, used in the orderorder *, †, ‡, §, ¶, #, ||,**, ††, ‡‡, §§, ¶¶, ##.

viii. References: References must be in APA style. Only published or in-press papers and books may be cited in the reference list. For references to in-press articles, please confirm with the cited journal that the article is in press and include a DOI number and online publication date. Unpublished abstracts of papers presented at meetings or references to "data not shown" are not permitted. References should be cited in numerical order as they appear in text, and all references, should be included in the main manuscript file. **Include the full title for each cited article.** All authors (unless there are more than five) should be named in the citation. If there are more than five, list the first author's name followed by et al. Provide inclusive page ranges for journal articles and book chapters.

Example

Book:

Finney, J. (1970). Time and again. New York, NY: Simon and Schuster.

Journal Article:

Nevin, A. (1990). The changing of teacher education special education. *Teacher Education and Special Education: The Journal of the Teacher Education Division of the Council for Exceptional Children,* 13(3-4), 147-148.

Magazine:

Tumulty, K. (2006, April). Should they stay or should they go? *Time, 167*(15), 3-40.

Website:

Teen posed as doctor at West Palm Beach hospital: police. (2015, January 16). Retrieved from http://www.nbcmiami.com/news/local/Teen-Posed-as-Doctor-at-West-Palm-Beach-Hospital-Police-288810831.html

Note: ***APA (American Psychological Association)*** *style is most frequently used within the social sciences, in order to cite various sources. This APA Citation Guide, revised according to the 6th edition of the APA manual, provides the general format for in-text citations and the reference page. For more information, please consult the Publication Manual of the American Psychological Association.*

Submission

When possible, Articles and Covering Letters should be submitted online. If online submission is not possible, submission may be considered via email: srjournal@sfimar.org. Please be sure to read the information on what to include in your cover letter as well as several important content related issues when putting a submission together.

Authors are solely responsible for obtaining permission from original sources for longer quotations and any other material they wish to cite in their texts. Papers are accepted for publication on the understanding that these contain original unpublished work not submitted for publication anywhere else. Papers presented /submitted in a conference /seminar must be clearly indicated at the bottom of the page and the author should specify with whom the copy rights rests.

Articles published in SFIMAR Research Review should not be reproduced /reprinted in any form either in full or part without prior written permission from the Editor.

Correspondence and proof for correction will be sent to the first name author, unless otherwise indicated. The authors will receive page proof for checking, but it is hoped to correct only typesetting errors. Proof should be returned within a week.

Mode of selection

All the papers received will be forwarded to the screening committee for review and the acceptances of the paper for publication will be communicated to the author at the earliest. Accepted papers will be given due recognition.

Address for correspondence

Chief Editor

SFIMAR RESEARCH REVIEW
St. Francis Institute of Management & Research
Mt. Poinsur, S.V.P. Road, Borivali (W), Mumbai 400103
Mob. : +91 9619499199, +91 9619499099
Email: srr@sfimar.org

Subscription Rates

Subscription	Print Edition Price (Rs.)			Digital Edition Price (Rs.)			Print + Digital Edition Price (Rs.)			Price per article (Rs.)	Past Issues Price per issue (Rs.)
Term ⟶ Type	1 yr.	3 yrs	5 yrs	1 yr.	3 yrs	5 yrs	1 yr.	3 yrs	5 yrs		
Institutions	800	2160	3200	500	1350	2000	1200	3240	4800	150	300
Teachers, Researchers & Alumni	600	1620	2400	350	945	1400	850	2295	3400		
Students	400	1080	1600	250	675	1000	550	1485	2200		
Non-Indian	\$50/ £40	\$135 £108	\$200 £160	\$35/ £25	\$95/ £67	\$140 £100	\$75 £55	\$202 £148	\$300 £220	\$10 £8	\$20 £16

Subscription Form

I / we wish to subscribe/renew subscription to the SFIMAR RESEARCH REVIEW.
A draft / cheque bearing No. ________________________ dated ____________ of Rs. ______________________ drawn in favor of **St. Francis Institute of Management and Research, Mumbai' is enclosed.**

Name ______________________________

Designation ______________________________

Organisation ______________________________

Address ______________________________

____

______________________________ PIN ______________

Phone (with STD/ISD Code) ______________ Fax ______________

Signature ______________ Subscription No. ______________

Date __________ Place __________ Email: ______________

(One year's subscription means on order for two issues.)

RTGS/NEFT Fund Transfer
Beneficiary Name: St. Francis Institute of Management and Research
Bank Name: Catholic Syrian Bank
Branch: Borivali (W)
Bank A/C No.: 03310125529188
IFSC Code: CSBK0000331
Swift Code: CSYBIN55
MICR Code: 400047014
Email: info@sfimar.org
Note: In case of NEFT/RTGS payment kindly send payment details viz. UTR No. and date of payment through email at info@sfimar.org or letter at the address for correspondence.

Address for Correspondence

Chief Editor,

SFIMAR RESEARCH REVIEW

St. Francis Institute of Managements & Research
Mt. Poinsur, S.V.P. Road, Borivali - West, Mumbai - 400103.
Mob. : +91 9619499199, +91 9619499099
Email: srr@sfimar.org
Website: www.sfimar.org

About the Institute

The Institute

St. Francis Institute of Management and Research (SFIMAR) is an ISO 9001:2015 certified Premier Management Institute affiliated to the University of Mumbai and approved by AICTE. The Institute belongs to the "The Society of congregation of Franciscan Brothers" and the group has celebrated its centenary in year 2008. SFIMAR has received many awards & recognitions, including 'Most upcoming B-School' award in April 2015, by ASSOCHAM.

SFIMAR's remarkable infrastructure, with well equipped computer centre, Wi-Fi enabled campus, updated laboratories and rich library resources facilitates the students in improving and updating their knowledge.

Central to our success is a team of dynamic, skillful and resourceful faculty that creates a deep understanding of business through its research. SFIMAR's Research Centre conducts research in areas of entrepreneurship, business, service & community development to supplement the post graduate education.

SFIMAR is also actively involved in various social activities, corporate social responsibility (CSR) & individual social responsibility (ISR) initiatives through which it contributes in empowering the society.

Vision

To flourish as a seat of learning of international standards for developing an entrepreneurial class of value based industrial leaders empowered with techno-managerial competence to sustain innovation for building global business of the future.

Mission

To enter the realm of globally successful B-schools by imparting value based education for creating responsible and thoughtful citizens who would lead the world by example and excel through innovation, an entrepreneurial spirit and a humanitarian attitude.

Programmes

Full Time Programme (Master of Management Studies)

Inception: 2002
Affiliation: University of Mumbai & Approved by AICTE
Batch Strength: 120
Specialization : Finance, Marketing, Human Resources, Information Technology, Operations.

Post Graduate Diploma in Management(PGDM)

Inception : 2012
Approved by AICTE New Delhi & DTE Government of Maharashtra
Sanction Intake : 120 seats

Career Management Centre

The Career Management Centre (CMC) is the liaison between our highly diverse talent pool of students, alumni and employers who benefit from their expertise.

SFIMAR has a planned approach towards training its students and getting them ready for the industry. The students are trained in functional, technical, communication and leadership skills with a focus on enhancing their cognitive abilities through various academic and non-academic programmes. Utmost importance is given to imbibe ethical and social values in them. The regular recruiters for our students are Syntel Street, BlackRock, SS&C GlobeOp, Kotak Mahindra Bank, ITC, L&T Infotech, IPSOS, Nomura, Nielsen, HDFC Bank, Transparent Value, CMIE and many more…

SFIMAR invites papers for...

SFIMAR RESEARCH REVIEW

Research Journal for Academicians & Researchers
Contact: +91 9619499199, +91 9619499099
E-mail: srr@sfimar.org, www.sfimar.org

PATHH

Research Conference for Academicians & Researchers
Contact: +91 9619499199, +91 9619499099
E-mail: pathh@sfimar.org

anveshi

The Researcher
Research Conference for Management Students
Contact: +91 9619499199, +91 9619499099
E-mail: anveshi@sfimar.org

For further details please contact;

ST. FRANCIS INSTITUTE OF MANAGEMENT & RESEARCH (SFIMAR)

and

ST. FRANCIS INSTITUTE OF MANAGEMENT & RESEARCH - PGDM

Approved by AICTE, DTE, An ISO 9001:2015 Certified

Gate No.5, Mount Poinsur, S.V.P. Road, Borivali West, Mumbai 400103.
Mob. : +91 9619499199, +91 9619499099
Email: srr@sfimar.org Website : www.sfimar.org

Printed at St. Francis ITI Press, Borivli (W), Mumbai.