



Remsons Group
management research centre
MANAGEMENT RESEARCH



Durgadevi Saraf
institute of management studies
WE CREATE LEADERS



Durgadevi Saraf
global business school
LEARN AND INSPIRE

Conference Proceeding of

12th Remsons

International Research Conference

on

Implications of Artificial Intelligence in Contemporary Businesses



29 August 2026

Volume 12, August 2026 | ISBN 978-93-5196-952-5

DSMS

DSGS

Conference Proceeding of
12th Remsons International Research Conference
On
Implications of Artificial Intelligence in
Contemporary Businesses

29 AUGUST, 2026

Editorial Board

Chief Editor

Dr. Sumana Chaudhuri

Editorial Committee

Dr. Sunita Pujar

Ms. Pooja Goswami

Dr. Chandrashekhar Kaushik

The Editorial Board assumes no responsibility for the contributors' statements of facts or opinions expressed in this publication

Published by

Knowledge Resource Centre

**Durgadevi Saraf Institute of Management Studies
RSET Campus, S V Road, Malad (West),
Mumbai – 400 064, Maharashtra, India**

PH: 22 4520 7711 Extn – 2351/2352/ 2340

Email : sunita.pujar@dsims.org.in

Chief Patron

Shri Ashok Saraf

President RSET, Chairman DSIMS & DSGS



Chief Patron of the Conference Shri Ashok Saraf, President RSET and Chairman DSIMS & DSGS, apprised the audience about the origin of Remsons Centre for Management Research (RCMR). He said that RCMR had been established with the magnanimous donation by late Remsons Group Chairman Shri Vishwaprakashji Harlalka, who had a vision to establish a Management Research Centre. He thanked Shri Krishna Kejriwal, Chairman and Managing Director Remsons Industries Ltd, for his continued support towards RCMR. He said that RSET, a pioneer in the educational activities for the last 70 years, catering education to different sections of the society. He highlighted RSET's role in shaping more than 60,000 students so far. He informed that RSET is now in the process of establishing Skill Tech University at Malad Campus.

He appreciated the effort of the conference organisers for choosing this apt theme, ***"Implications of Artificial Intelligence in Contemporary Businesses"*** which is both timely and significant. Artificial Intelligence is no longer a distant technological concept. It has become an important force shaping the way organisations operate, compete, innovate, make decisions, serve customers, and develop their people. He also said that AI is transforming almost every dimension of business—from marketing and finance to human resources, operations, supply chains, customer experience, analytics, and strategic decision-making. He reminded us that *AI should augment human potential, not diminish human responsibility*. The future will belong to organizations that can combine technological capability with empathy, ethical leadership, creativity and sound judgement. He expressed his confidence that the deliberations at this conference will generate valuable insights and contribute to a deeper understanding of how Artificial Intelligence can be harnessed for sustainable and responsible business growth.

He congratulated all the researchers who have submitted their work and encouraged them to view this conference not merely as an opportunity to present a paper, but as an opportunity to learn, question, collaborate and build relationships that may continue long after the conference concludes. He wished the Conference every success and can usher new hope, new ideas, new perspectives and new collaborations.

Excerpts of Inaugural Speech

By

Chief Guest

Mr. Rohit Darji

**Company Secretary & Compliance Officer and GM – Legal & Finance,
Remsons Industries Ltd.**



Chief Guest Shri Rohit Darji, Company Secretary & Compliance Officer and GM – Legal & Finance, Remsons Industries Ltd. delivered an insightful inaugural speech.

Report of Remsons Centre for Management Research (RCMR)

Dr. Sumana Chaudhuri
Chief Convener, RIRC 2026



Presenting the Report of the **Remsons Centre for Management Research (RCMR) for 2025–26**, Dr. Sumana Chaudhuri highlighted the significant research contributions of the Institute's faculty members. Under the aegis of RCMR, faculty members have published several research articles in journals of national and international repute, including journals indexed in **Scopus**, **and ABDC**, with high H-index and impact factors.

Dr. Chaudhuri further informed that, since January 2026, the Institute's faculty members have published **six research papers**, of which **three research papers have been authored by Dr. Sumana Chaudhuri herself**, published in high-impact, Scopus-indexed international journals.

She also informed that RCMR has published **Volume 8, Issue 1** of its ISSN-indexed journal, *The Management Quest*, comprising **six peer-reviewed research papers**.

Excerpts of Keynote Speech

By Guest of Honor

Mr. Rajarama Rao Bannengala

Founder and MD, ProPMO Services Pvt. Ltd.



The **Guest of Honour, Mr. Rajarama Rao Bannengala, Founder and Managing Director, ProPMO Services Pvt. Ltd.**, delivered the keynote address on *“Beyond Working Smart: The AI Wave and the Future of Business, Work and Human Capability.”*

In his address, Mr. Bannengala highlighted that **Artificial Intelligence (AI) is no longer merely an emerging technology but has become a significant force shaping contemporary business and professional life.** Drawing parallels with successive industrial revolutions, he explained that the AI wave represents a transformative shift in the way organisations create value, make decisions, compete in the marketplace, and harness human capabilities.

The keynote explored the evolving relationship between **businesses, professionals, and intelligent systems**, with particular emphasis on how AI is reshaping competitive advantage, organisational structures, workforce expectations, and the very meaning of “working smart.” He emphasised the need for organisations to adapt their leadership approaches, workplace practices, and academic frameworks to effectively and responsibly navigate this transformation.

Mr. Bannengala concluded by offering a **pragmatic and positive perspective on responsible AI adoption**, highlighting its potential to foster a more productive, adaptable, and purposeful future for organisations and society.

From Editor's Desk

Dr. Sumana Chaudhuri

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the 21st century, reshaping how businesses operate, compete, and create value. From predictive analytics and intelligent automation to generative AI and advanced decision-support systems, organizations across industries are increasingly integrating AI into their strategic and operational frameworks.

As businesses continue to embrace digital transformation, AI is influencing areas such as **marketing strategies, financial decision-making, supply chain optimization, human resource management, and customer experience.**

Recent advancements in **machine learning, big data analytics, and cloud computing** have accelerated AI adoption across sectors including **finance, healthcare, manufacturing, retail, logistics, and education.** While these developments create unprecedented opportunities for innovation, productivity, and efficiency, they also raise important concerns regarding:

- Ethical use of AI
- Workforce transformation
- Data privacy and governance
- Regulatory frameworks

Under the aegis of Remsons Centre for Management Research (RCMR), DSIMS and DSGS organised the 12th Remsons International Research Conference (RIRC) on 29 August 2026. The conference was inaugurated by Shri Krishna Kejriwal, Chairman and Managing Director, Remsons Industries limited and delivered his insightful inaugural speech. Keynote Speaker Mr. Rajarama Rao Bannengala, Founder and Managing Director, Pro PMO Services Pvt. Ltd., illuminated the audience with his thought-provoking speech.

The objective of this conference is to bring academicians, research scholars and practicing professionals to deliberate and present their perspectives on the broader implications of AI in contemporary businesses and to explore sustainable strategies for responsible AI adoption.

The 12th Remsons International Research Conference received good responses from academia and industry in terms of research paper contributions. RCMR received 25 research papers. After initial screening, based on merit, around 15 selected research papers by academicians, like Professors and Deans of various Management Institutes, research scholars and MBA students and by industry professionals had been presented in the Conference.

As a Session Chair, Prof. Dr. Krupa A Rai discussed the future research direction in the field of business and management.

Co-Convener Dr. C Kaushik has beautifully summarized the proceedings of the research papers presented at the Conference.

Based on a fair evaluation by the Session Chair and blind reviewers, two papers each from both the Professional and Student Tracks were chosen as the Best Paper Awardees.

Conference Co-Convener Dr. Sunita Pujar and Ms. Pooja Goswami offered the vote of thanks respectively in the plenary session and in the afternoon session.

The Conference was a grand success, attracting authors, Ph.D scholars, paper presenters, and participants from Mumbai as well as other reputed Management Institutions and Universities, as well as industries across India. It has enabled academicians, researchers, and practising managers to share their research findings, issues, concerns, doubts, and insights for the future vis-à-vis specific domains of knowledge and practice. We hope that the conference has not only provided a great intellectual and social interactive platform to the participants but also has given new perspectives from concrete facts. As a Chief Convener, I am deeply privileged to present the Conference Proceedings 2026 and hope that this compendium of research papers will be found useful by researchers, industry practitioners, and policymakers.

REMSONS
12th INTERNATIONAL RESEARCH CONFERENCE ON

**“Implications of Artificial Intelligence in
Contemporary Businesses’**

29th August 2026

Paper Track

Session - I

11.40 AM to 1.30 PM

Session Chair – Dr. Krupa Rai

Venue: Room No. 623, 6th Floor

SN	TIME	AUTHOR	TITLE
1	11.40 am – 11.48 am	Ms Riya Raut & Dr Shital Patil	Artificial Intelligence and Automation in Auditing Practices: Evidence from Audit and Finance Professionals
2	11.50 am – 11.58 am	Ms Sunita Kharate, Ms Ritu Mishra & Dr Krishika Chandwani	Impact of AI and Automation on Jobs
3	12.00 noon – 12.08 pm	Ms Kinjal Shah & Mr Mahendra Daima	Role of Artificial Intelligence in Enhancing Delivery Efficiency in Quick Commerce Platforms
4	12.10 pm – 12.18 pm	Mr Vikram Joshi & Dr Kitty Rana	Impact of Buyback Announcement on Share Prices of Companies
5	12.20 pm – 12.28 pm	Mr Shubham Chaurasiya, Mr Maroof Khan, Mr Anuj Pandey, Dr Yesha Mehta, Dr Charu Upadhyaya & Dr Vishal Sandanshive	The Algorithmic Impulse: AI-Driven Personalisation, Perceived Relevance, and Impulse Buying in Contemporary Indian E- Commerce — A Mediated Path Analysis with Age Moderation
6	12.30 pm – 12.38 pm	Mr Ganesh Shenoy & Mr Mahesh Manohar Bhanushali	Logistics Cost Performance in International Supply Chains: A Literature Synthesis for India’s Energy Equipment Manufacturing Sector
7	12.40 pm – 12.48 pm	Ms Kashish Jain, Mr Suman Jha & Dr. Kitty Rana	AI-Driven FinTech Adoption among Small Retailers: A Study of Behavioural Marketing and Financial Product Usage in Mumbai

SN	TIME	AUTHOR	TITLE
8	12.50 pm – 12.58 pm	Mr Rahul Parchure & Dr Bernadette D'Silva	The Role of AI and Chatbots in Guest Services and their Influence on Employee Attrition in 5-Star Hotels in Mumbai
9	01.00 pm – 01.08 pm	Ms Nivida Ghorpade & Dr Chhaya Mane	Marketing the Future: Leveraging AI Chatbots to Enhance User Engagement and Service Discovery in Management Libraries
10	01.10 pm – 01.18 pm	Mr Mahendra Daima & Ms Kinjal Shah	Determinants Affecting Consumer Trust in Communication with AI Chatbots in Quick-Commerce Platforms: The Moderating Effect of Privacy Concerns - A Study of Maharashtra
11	01.20 pm – 01.28 pm	Dr Ar. Mildred Jose	'Platform Urbanism': Evaluating Algorithms within Smart Cities

Lunch Break – 1.30. PM to 2.30 PM

Session - II

2.30 PM to 3.10 PM

SN	TIME	AUTHOR	TITLE
12	02.30 pm – 02.38 pm	Mr Harsh Thakrar & Dr Raghukumari P. S.	Intraday Implied Volatility and Expiry-Day Surveillance in India (Online)
13	02.40 pm– 02.48 pm	Ms Khushabu Sanjay Gajabi & Ms Shikha Sharda	AI-Powered Personalization in Fashion Retail: Applications for Customer Satisfaction and Business Performance
14	02.50 pm – 02.58 pm	Mr Somesh Kumar Banerji	How Lego Stopped Thinking Outside the Box and Innovated Inside the Brick
15	03.00 pm – 03.08 pm	Ms Kinjal Shah & Mr Mahendra Daima	AI Adoption and Consumer Purchase Intention in Online Grocery Platforms: A Study of the Mumbai Suburban Region

3.10 PM – 4.00 PM

Observation, Comments and Summarisation of Research Presentations

Prize Distribution*****

Index

SN	Author/s	Title	Pages
1	Ms Riya Raut & Dr Shital Patil	Artificial Intelligence and Automation in Auditing Practices: Evidence from Audit and Finance Professionals	1-10
2	Ms Sunita Kharate, Ms Ritu Mishra & Dr Krishika Chandwani	Impact of AI and Automation on Jobs	11-28
3	Ms Kashish Jain, Mr Suman Jha & Dr. Kitty Rana	AI-Driven FinTech Adoption among Small Retailers: A Study of Behavioural Marketing and Financial Product Usage in Mumbai	29-38
4	Mr Rahul Parchure & Dr Bernadette D'Silva	The Role of AI and Chatbots in Guest Services and their Influence on Employee Attrition in 5-Star Hotels in Mumbai	39-46
5	Ms Ar. Mildred Jose	'Platform Urbanism': Evaluating Algorithms within Smart Cities	47-56
6	Ms Nivida Ghorpade & Ms Chhaya Mane	Marketing the Future: Leveraging AI Chatbots to Enhance User Engagement and Service Discovery in Management Libraries	57-61
7	Mr Shubham Chaurasiya, Mr Maroof Khan, Mr Anuj Pandey, Dr Yesha Mehta, Dr Charu Upadhyaya & Dr Vishal Sandanshive	The Algorithmic Impulse: AI-Driven Personalisation, Perceived Relevance, and Impulse Buying in Contemporary Indian E-Commerce — A Mediated Path Analysis with Age Moderation	62-76
8	Mr Ganesh Shenoy & Mr Mahesh Manohar Bhanushali	Logistics Cost Performance in International Supply Chains: A Literature Synthesis for India's Energy Equipment Manufacturing Sector	77-86
9	Ms Khushabu Gajabi & Ms Shikha Sharda	AI-Powered Personalization in Fashion Retail: Applications for Customer Satisfaction and Business Performance	87-98
10	Ms Kinjal Shah & Mr Mahendra Daima	AI Adoption and Consumer Purchase Intention in Online Grocery Platforms: A Study of the Mumbai Suburban Region	99-109
11	Mr Vikram Joshi & Dr Kitty Rana	Impact of Buyback Announcement on Share Prices of Companies	109-119
12	Mr Mahendra Daima & Ms Kinjal Shah	Determinants Affecting Consumer Trust in Communication with AI Chatbots in Quick-Commerce Platforms: The Moderating Effect of Privacy Concerns - A Study of Maharashtra	120-126
13	Mr Harsh Thakrar	Intraday Implied Volatility and Expiry-Day Surveillance in India	127-128

Artificial Intelligence and Automation in Auditing Practices: Evidence from Audit and Finance Professionals

Riya Raut

Senior Auditor Analyst, BDO, India

Shital Patil

Assistant Professor, Durgadevi Saraf Institute of Management of Studies, Mumbai

ABSTRACT

The rapid advancement of Artificial Intelligence (AI) and automation has significantly influenced accounting and auditing practices worldwide. AI-driven technologies such as machine learning, robotic process automation, natural language processing, and predictive analytics are increasingly assisting auditors in improving operational efficiency, strengthening fraud detection, and enhancing financial reporting accuracy. Although developed economies have witnessed considerable integration of AI within audit functions, its adoption in India is still evolving, with organizations gradually embracing digital audit technologies. The present study examines the impact of Artificial Intelligence and automation on auditing practices from the perspective of professionals working in auditing, accounting, and finance. Primary data were collected from 87 respondents using a structured questionnaire. The study follows a descriptive research design supported by secondary data collected from peer-reviewed journals, professional reports, and regulatory publications. The findings aim to understand the current level of AI adoption, perceived benefits, implementation challenges, ethical concerns, and future prospects of AI in auditing. The study concludes that AI has become an important enabler of modern auditing by improving efficiency and decision-making; however, organizations continue to face challenges relating to implementation cost, data privacy, regulatory compliance, and skill development. The chi-square test reveals statistically significant association between AI adoption and perceived effectiveness of AI in auditing, leading to rejection of null hypothesis. This study concludes that AI is likely to augment rather than replace auditors and signifies the technological investment, professional training and supportive regulatory framework can facilitate responsible AI adoption in audit profession.

Keywords: artificial intelligence, auditing, automation, fraud detection, financial reporting

1. INTRODUCTION

1.1 Introduction to Artificial Intelligence in Auditing

Over the last decade, rapid technological advancements have brought significant changes to the auditing profession. Auditing, which traditionally depended on manual verification, sampling techniques, and the professional judgment of auditors, is gradually evolving into a more technology-enabled function. Among these technological developments, Artificial Intelligence (AI) has emerged as one of the most influential innovations, offering new ways to improve the efficiency, accuracy, and effectiveness of audit processes.

AI-powered technologies such as Machine Learning (ML), Robotic Process Automation (RPA), Natural Language Processing (NLP), and predictive analytics are increasingly being integrated into audit practices (2017). These tools enable auditors to process and analyse large volumes of financial data in a relatively short period, identify unusual patterns, automate repetitive tasks, and support more informed decision-making. As a result, organizations are experiencing improvements in audit quality, operational efficiency, fraud detection, and financial reporting.

1.2 Global Adoption of AI in Auditing:

Globally, leading audit firms have been early adopters of AI and related digital technologies. They use these tools for continuous auditing, risk assessment, anomaly detection, automated documentation, and compliance monitoring (2023). Rather than replacing human auditors, AI is helping professionals focus on higher-value activities such as critical analysis, professional judgment, strategic decision-making, and advisory services (December 2025). This shift reflects the changing nature of the auditing profession, where technology complements rather than substitutes human expertise.

1.3 AI adoption in the Indian Auditing Environment:

In India, the adoption of AI in auditing has also gained momentum in recent years. Initiatives promoting digital transformation, greater transparency, and technology-driven governance have encouraged organizations to modernize their audit functions. Sectors such as banking, financial services, information technology, manufacturing, and public enterprises are increasingly investing in AI-enabled audit solutions to strengthen internal controls, improve compliance, and enhance financial reporting (2023) (2023).

1.4 Challenges in AI Adoption:

Despite these developments, the adoption of AI is not uniform across organizations. Large organizations often have the financial and technological resources required to implement sophisticated AI-based audit systems, whereas small and medium-sized organizations continue to face several challenges (December 2025) (Kostic, 2026). High implementation costs, limited technological infrastructure, data privacy concerns, cybersecurity risks, regulatory uncertainties, and a shortage of skilled professionals remain significant barriers to successful AI adoption (Deloitte: Sniderman, 2024) (Lidiana, 2024). In addition, concerns relating to algorithmic transparency, ethical accountability, and overreliance on automated systems continue to attract attention from both researchers and practitioners. (Kokina, Blanchette, Davenport, & Pachamanova)

1.5 Changing Role of Auditors:

The changing role of auditors is another important aspect highlighted in the existing literature. While AI has automated many routine and repetitive audit activities, professional scepticism, ethical reasoning, critical thinking, and sound judgment remain essential components of the audit process (Steve G. Sutton, 2016). Consequently, understanding how audit and finance professionals perceive the opportunities and challenges associated with AI has become increasingly important for organizations planning future investments in digital audit technologies (Kokina, Blanchette, Davenport, & Pachamanova).

Against this backdrop, the present study examines the impact of Artificial Intelligence and automation on auditing practices in India. Using responses collected from professionals working in auditing, accounting, finance, and related fields, the study explores the current level of AI adoption, the perceived benefits of AI-enabled auditing, its role in fraud detection and financial reporting, the major challenges encountered during implementation, and the future prospects of AI within the auditing profession. The findings are expected to provide useful insights for practitioners, organizations, policymakers, and researchers seeking to understand the evolving relationship between Artificial Intelligence and modern auditing practices.

2. REVIEW OF LITERATURE

The application of Artificial Intelligence (AI) and automation in auditing has evolved considerably over the past decade, transforming conventional audit procedures into technology-enabled, data-driven assurance processes. Earlier studies primarily focused on the potential of AI to improve audit quality

and efficiency, whereas more recent research has examined implementation challenges, ethical implications, governance issues, and the changing role of auditors.

(Issa, Sun, & Vasarhelyi, 2016) Their study highlighted that AI could significantly improve audit quality through continuous auditing, intelligent data analysis, and automated examination of large volumes of financial information. The authors argued that AI has the potential to enhance auditors' analytical capabilities while reducing dependence on traditional sampling methods.

(Steve G. Sutton, 2016) Examined the evolving role of Artificial Intelligence in accounting and auditing. They concluded that AI should be viewed as a complementary technology that supports professional judgment rather than replacing auditors. Their study emphasized that human expertise remains indispensable in interpreting audit evidence, exercising professional scepticism, and making ethical decisions.

(Appelbaum, Kogan, & Vasarhelyi, 2017) Further strengthened the literature by demonstrating that Big Data analytics and Artificial Intelligence enable auditors to evaluate complete datasets instead of relying solely on sample-based testing. Their research suggested that AI contributes to higher audit quality, improved risk assessment, and more informed decision-making through advanced analytical techniques.

(Kokina & Davenport, 2017) Observed that automation reduces repetitive audit procedures and allows auditors to focus on higher-value analytical and advisory activities. Their findings indicated that AI enhances productivity while simultaneously redefining the professional responsibilities of auditors.

(Vasarhelyi, 2018) Extended previous research by examining the use of smart technologies in auditing. Their study demonstrated that machine learning and predictive analytics substantially improve fraud detection, anomaly identification, and audit effectiveness. The authors concluded that AI-enabled technologies provide auditors with greater analytical capabilities and contribute to more reliable audit outcomes.

As Artificial Intelligence became more widely adopted across industries, professional accounting bodies began examining its practical implications. The Institute of Chartered Accountants of India (2023), through its "Technical Guide on Technology Enabled Auditing", emphasized that AI, data analytics, and digital audit tools should be integrated into audit methodologies to improve audit quality, compliance, and transparency. Similarly, the International Federation of Accountants (2023) highlighted the importance of digital competencies, ethical governance, and continuous professional development to ensure responsible adoption of emerging technologies within the accounting profession.

Recent industry reports have also confirmed the increasing importance of AI in auditing. (PwC, 2023) In its 'Global Digital Trust Insights Survey', it reported that organizations implementing AI experienced improvements in operational efficiency, compliance monitoring, and risk management. Ernst & Young (2023) similarly observed that AI enhances audit planning, documentation, anomaly detection, and financial reporting by automating repetitive audit activities while supporting professional decision-making.

The review article (Sebele, 2023) examined ongoing debates regarding AI adoption in external auditing. The study concluded that although AI significantly improves audit quality and efficiency, concerns remain regarding transparency, legal admissibility of AI-generated evidence, compliance with international auditing standards, and stakeholder confidence. The authors recommended strengthening digital education and interdisciplinary collaboration between accounting professionals and technology specialists.

Further evidence was presented by (Lidiana, 2026), who reported that AI adoption contributes to higher audit quality, greater efficiency, continuous auditing, and improved decision-making. Nevertheless, the study identified high implementation costs, customisation requirements, and organizational readiness as important challenges that influence successful AI adoption.

(Deloitte: Sniderman, 2024) Similarly, growing AI adoption across finance and audit functions. The report highlighted improvements in operational efficiency, decision-making, and risk management, while identifying shortages of skilled professionals and organisational readiness as ongoing barriers to implementation.

(Kokina, Blanchette, Davenport, & Pachamanova, December 2025), who investigated Artificial Intelligence adoption within audit firms. Their field-based research found that automation, natural language processing, and machine learning are increasingly integrated into auditing practices. In contrast, more advanced AI applications remain at an early stage of implementation. The study identified transparency, algorithmic bias, regulatory uncertainty, data privacy, and return on investment as the principal challenges affecting AI adoption. The authors concluded that AI should augment rather than replace auditors and emphasised continuous investment in technology, workforce development, and explainable AI systems.

(Thejus Jackson Adhikarathil, 2026) Examined the transformation of financial auditing through automation and analytics. Their findings revealed that machine learning, robotic process automation, and intelligent analytics improve audit precision, reduce human error, and facilitate real-time assurance. However, the study stressed that sustainable audit quality requires integrating AI-generated insights with human professional judgment to maintain accountability and ethical decision-making.

(Kostic, 2026) Studied in, 'Transforming Cybersecurity Audit Practices with Agility and Artificial Intelligence', highlighted AI's ability to improve audit precision, cybersecurity assurance, and analytical efficiency. The study also discussed emerging concerns relating to data privacy, algorithmic bias, auditor accountability, and governance. To address these issues, the author proposed a hybrid auditing framework in which Artificial Intelligence complements, rather than replaces, professional expertise.

Overall, the literature demonstrates a clear progression in the understanding of Artificial Intelligence within auditing. Earlier studies established AI's potential to improve audit quality and efficiency, while subsequent research focused on fraud detection, continuous auditing, and intelligent automation. More recent studies and professional reports emphasize responsible implementation, ethical governance, regulatory compliance, workforce reskilling, and the collaborative relationship between Artificial Intelligence and professional auditors. Despite significant technological advances, the consensus across the literature is that AI is most effective when it enhances human judgment rather than replacing it, thereby enabling auditors to deliver more efficient, accurate, and value-added audit services.

3. SUGGESTED RESEARCH GAP

Existing studies primarily focus on the technological capabilities, implementation challenges, and theoretical aspects of Artificial Intelligence in auditing. However, limited empirical research has examined professionals' perceptions of AI adoption in the Indian auditing context. In particular, studies integrating AI adoption, audit efficiency, fraud detection, financial reporting, implementation challenges, and prospects using primary survey data remain scarce. The present study addresses this gap by examining professionals' perceptions of the impact of Artificial Intelligence and automation on auditing practices in India.

4. RESEARCH OBJECTIVES

The study was undertaken with the following objectives:

- To assess the extent of Artificial Intelligence adoption in auditing practices.
- To evaluate the perceived benefits of AI-enabled auditing.
- To examine professionals' perceptions regarding the role of AI in fraud detection and financial reporting.
- To identify the challenges and barriers associated with implementing AI-driven audit tools.
- To explore professionals' perceptions of the future role of Artificial Intelligence in the auditing profession.

5. RESEARCH METHODOLOGY

The study adopted a descriptive research design to examine professionals' perceptions of Artificial Intelligence and automation in auditing. Primary data were collected through a structured Google Forms questionnaire from 87 professionals working in auditing, accounting, finance, and related fields using convenience sampling. Secondary data were sourced from peer-reviewed journals, books, and reports published by professional and regulatory bodies. The data were analysed using descriptive statistics (frequency and percentage analysis) and the Chi-square test to examine the research hypothesis.

- **Null Hypothesis (H_0)**

There is no significant association between the level of Artificial Intelligence adoption and the perceived effectiveness of AI in improving auditing practices.

6. RESULTS AND DISCUSSION

6.1 Demographic Profile of Respondents

The study is based on 87 responses collected from professionals working in auditing, accounting, finance, banking, taxation, and related fields. The respondents represented a diverse range of professional backgrounds and organizations with varying levels of Artificial Intelligence adoption in their audit functions. This diversity provided a balanced understanding of professionals' experiences and perceptions regarding AI-enabled auditing.

The varied profile of the respondents strengthened the study by capturing views from individuals exposed to different auditing environments, levels of technological adoption, and organizational practices. Consequently, the sample offered a reliable basis for examining AI adoption, its perceived benefits, implementation challenges, and future prospects within the Indian auditing profession.

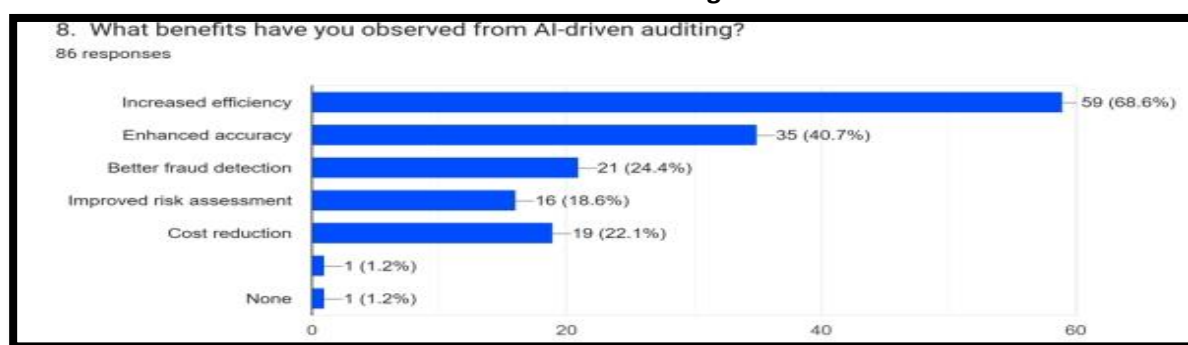
6.2 Adoption of Artificial Intelligence

Chart 1 AI Adoption in organisations



Source: Primary Data

Chart 2 Artificial Intelligence



Source: Primary Data

Interpretation: The findings indicate that AI adoption remains at a developing stage. 37.3% reported moderate implementation of AI, 34.9% reported partial implementation, while only 3.6% indicated extensive or fully automated audit systems. Hence this data indicated that adoption of AI in auditing is still in transition phase, not yet fully mature.

6.3 Perceived Benefits of AI in Auditing practices

Table 1: How has AI impacted financial reporting accuracy in your organization?	
Impact on Financial reporting	Count
No significant impact	7
Not applicable	7
Significantly improved	39
Somewhat improved	34
Grand Total	87

Table 2 on AI implementation benefits		
Benefit Observed	Frequency	% of Respondents
Increased efficiency	59	68.60%
Enhanced accuracy	35	40.70%
Better fraud detection	21	24.40%
Cost reduction	19	22.10%
Improved risk assessment	16	18.60%
None	1	1.20%

Source: Primary Data

Interpretation: The findings indicate that professionals view Artificial Intelligence as an effective tool for improving auditing practices. As shown in Table 1, 68.6% of respondents identified increased efficiency as the key benefit of AI, followed by enhanced accuracy (40.7%) and better fraud detection (24.4%). Respondents also acknowledged improvements in cost reduction and risk assessment.

Table 2 further shows that 84.8% of respondents believed AI has significantly or somewhat improved the accuracy of financial reporting. Overall, the results suggest that AI enhances audit quality by improving efficiency, accuracy, and the reliability of financial reporting, which is consistent with existing literature on AI-enabled auditing.

6.4 Professionals' Perceptions Regarding AI in Fraud Detection and Financial Reporting

Table 3. Professionals' Perceptions Regarding AI in Fraud Detection		
Variable	Dominant Response	%
AI effectiveness (Q11)	More effective	40.7
	Equally effective	39.5
Improvement in financial reporting (Q12)	Significantly improved	45.3
	Somewhat improved	39.5
AI used to analyse financial anomalies (Q14)	Yes	31.4
Planning implementation (Q14)		16.3

Source: Primary Data

Interpretation: The findings indicate that professionals hold a positive perception of Artificial Intelligence in fraud detection and financial reporting. Around 80.2% of respondents considered AI to be either more effective or equally effective than traditional auditing methods in detecting fraud, while 84.8% believed that AI has significantly or somewhat improved the accuracy of financial reporting.

Although only 31.4% of respondents reported that AI is currently used to analyse financial anomalies in their organizations, another 16.3% indicated that implementation is planned. This suggests that while AI is widely recognised for its potential to strengthen fraud detection and financial reporting, its adoption is still evolving across organizations.

6.5 Challenges and Barriers Associated with AI-driven Auditing

Table 4 Challenges and Barriers Associated with AI-driven Auditing			
Dimension	Predominant Response	Frequency	Percentage (%)
Major implementation challenge (Q15)	Data security and privacy risks	18	20.9
Ethical concerns regarding AI (Q16)	Yes	47	54.7
AI-related training received (Q17)	No formal training	20	23.3
Regulatory requirement (Q18)	Clearer AI compliance guidelines	21	24.4

Source: Primary Data

Interpretation: The findings indicate that while professionals recognize the benefits of Artificial Intelligence, several challenges continue to affect its successful implementation in auditing. Data security and privacy emerged as the most significant concern, reflecting the need to safeguard sensitive financial information in AI-enabled audit environments.

More than half of the respondents (54.7%) expressed ethical concerns regarding AI, highlighting issues such as transparency, accountability, and algorithmic bias. In addition, 23.3% reported having received no formal AI-related training, suggesting that limited digital skills remain a barrier to wider adoption.

Respondents also emphasized the need for stronger regulatory support, with 24.4% identifying clearer AI compliance guidelines as a key requirement. Overall, the findings suggest that successful AI implementation depends not only on technological advancement but also on effective governance, continuous professional training, and a supportive regulatory framework.

6.6 Professionals' Perceptions of the Future Role of AI in Auditing

Table 5 Professionals' Perceptions of the Future Role of AI in Auditing			
Dimension	Predominant Response	Frequency	Percentage (%)
AI will reshape the auditing profession (Q19)	Agree	35	40.7
Recommendation for wider AI adoption (Q20)	Yes	59	68.6
Confidence in AI-driven auditing (Q21)	Neutral	37	43

Source: Primary Data

Interpretation: The findings denotes with a positive outlook towards the future role of Artificial Intelligence in the auditing profession. A majority of respondents agreed that AI will significantly impact future auditing practices, while 68.6% recommended wider adoption of AI within audit functions. Although the majority of the respondents reported a neutral level of confidence regarding AI-driven auditing. Experts views AI's future in auditing with optimistic caution, looking at it as a powerful tool to boost both the quality and efficiency. Instead of replacing human auditors, an AI is expected to work hand in hand with them. However unlocking this potential requires ongoing tech upgrades, specialised professional training, and strong regulatory frameworks.

6.7 Cross-tabulation between Level of AI Adoption and Perceived Effectiveness of AI in Fraud Detection

Level of AI Adoption	More Effective	Equally Effective	Less Effective	Not Sure
Extensively	2.07	1.95	0.29	0.69
Fully automated auditing process	1.66	1.56	0.23	0.55
Moderately	13.24	12.51	1.84	4.41
Partially	12.41	11.72	1.72	4.14
Not at all	6.62	6.25	0.92	2.21
Chi-square test				
Variables	χ^2	df	p-value	Decision
AI Adoption (Q7) × AI Effectiveness (Q11)	25.924	12	0.011	Reject H_0

Interpretation: A Pearson Chi-square test was run to assess the association between the level of Artificial Intelligence adoption and the perceived effectiveness of AI in improving auditing practices. The results indicated a statistically significant association ($\chi^2 = 25.924$, $df = 12$, $p = 0.011$). Since the p-value is less than the 0.05 significance level, the null hypothesis is rejected.

The findings suggest that professionals working in organizations with higher levels of AI adoption are more likely to perceive AI as effective in fraud detection and auditing activities. This replicates that organizational experience with AI positively influences perceptions regarding its usefulness and effectiveness in improving audit quality and operational efficiency.

Analysis of Open-Ended Responses

The additional comments indicate that respondents generally have a positive outlook towards the use of Artificial Intelligence in auditing. Most viewed AI as a valuable tool for improving audit efficiency, accuracy, fraud detection, and decision-making. However, many emphasized that AI should complement rather than replace human judgment and professional skepticism.

The most common concerns related to data privacy, confidentiality, cybersecurity, ethical issues, and algorithmic bias. Respondents also highlighted the need for stronger regulatory guidelines, continuous training, and user-friendly AI solutions to support effective implementation. Overall, the qualitative responses reinforce the quantitative findings, suggesting that while professionals are optimistic about AI adoption, they expect it to be implemented responsibly with appropriate safeguards and human oversight.

7. MAJOR FINDINGS AND DISCUSSIONS

Table 5.1: Comparison of the Present Study with Existing Literature		
Theme	Present Study Findings	Comparison with Existing Literature
AI Adoption in Auditing	AI adoption was found to be at a moderate level, with organizations gradually integrating AI into audit processes.	This finding supports earlier studies (Issa et al., 2016; Deloitte, 2024; Kokina et al., 2025), which reported increasing but gradual adoption of AI in auditing.
Benefits of AI	Respondents perceived AI as improving audit efficiency, accuracy, fraud detection, and financial reporting quality.	The results are consistent with Appelbaum et al. (2017), Rozario and Vasarhelyi (2018), EY (2023), and PwC (2023), who concluded that AI enhances audit quality, efficiency, and decision-making.
Challenges in AI Implementation	Data privacy, ethical concerns, limited training, and regulatory issues emerged as the major barriers to AI implementation.	Similar challenges have been identified by ICAI (2023), IFAC (2023), Kokina et al. (2025), and Kostic (2026), emphasizing the need for governance, workforce development, and regulatory support.
Future of AI in Auditing	Professionals supported wider AI adoption and viewed AI as a tool that complements rather than replaces auditors.	These findings agree with Sutton et al. (2016), Deloitte (2024), and Adhikarathil et al. (2026), who concluded that AI strengthens auditors' capabilities while human judgment remains essential.
Contribution of the Study	The study provides empirical evidence on professionals' perceptions of AI adoption, benefits, challenges, and future prospects in the Indian auditing context.	The findings address the identified research gap by contributing primary evidence from India, extending the predominantly conceptual and technology-focused literature.

8. LIMITATIONS OF THE STUDY

The study is based on a sample of 87 respondents, which may limit the generalizability of the findings. It relies on professionals' perceptions rather than actual organizational performance and focuses on the Indian auditing context. In addition, the analysis is limited to descriptive statistics and the Chi-square test.

9. RECOMMENDATIONS

Based on the findings of the study, the following recommendations are proposed:

- **Promote AI Adoption:** Organizations should gradually integrate AI-enabled audit tools to improve audit efficiency, accuracy, and fraud detection.
- **Strengthen Training:** Regular training and upskilling programmes should be conducted to enhance auditors' AI and data analytics competencies.
- **Ensure Data Security:** Organizations should establish robust data privacy and cybersecurity measures to protect sensitive financial information.

- **Develop Ethical Frameworks:** Clear ethical guidelines should be implemented to address issues related to algorithmic bias, transparency, and accountability.
- **Enhance Regulatory Support:** Regulatory and professional bodies should formulate comprehensive AI governance and compliance guidelines for auditing practices.
- **Adopt a Human–AI Approach:** AI should be used to support auditors' decision-making while preserving professional judgment and ethical responsibility.

10. SCOPE FOR FUTURE RESEARCH

Future studies may include larger and more diverse samples, compare different industries or countries, and apply advanced statistical techniques to examine the factors influencing AI adoption and audit effectiveness. Qualitative studies may also provide deeper insights into organizational experiences with AI-enabled auditing.

REFERENCES

- Appelbaum, D. A., Kogan, A., & Vasarhelyi, M. A. (2017). Big Data and Analytics in the Modern Audit Engagement: Research Needs. *Auditing: A Journal of Practice & Theory*.
- Deloitte: Sniderman, D. D. (2024, January). *The State of Generative AI in the Enterprise*. Retrieved from <https://www.deloitte.com/ce/en/services/consulting/research/state-of-generative-ai-in-enterprise.html>
- (2023). *How artificial intelligence is transforming audit*. Ernst & Young.
- Issa, H., Sun, T., & Vasarhelyi, M. A. (2016). Research Ideas for Artificial Intelligence in Auditing: The Formalization of Audit and Workforce Supplementation. *Journal of Emerging Technologies in Accounting*.
- Kokina, J., & Davenport, T. H. (2017). The Emergence of Artificial Intelligence: How Automation is Changing Auditing. *Journal of Emerging Technologies in Accounting*.
- Kokina, J., Blanchette, S., Davenport, T. H., & Pachamanova, D. (December 2025). Challenges and opportunities for artificial intelligence in auditing: Evidence from the field. *International Journal of Accounting Information Systems*.
- Kostic, D. L. (2026). *Transforming Cybersecurity Audit Practices with Agility and Artificial Intelligence (AI)*. Taylor and Francis group.
- Lidiana, L. (2024). AI and Auditing: Enhancing Audit Efficiency and Effectiveness with Artificial Intelligence. *Accounting and Tax Journal*.
- Lidiana, L. (2026). AI and Auditing: Enhancing Audit Efficiency and Effectiveness with Artificial Intelligence. *Accounting Studies and Tax Journal*.
- PwC. (2023). *PwC*.
- Sebele, F. (2023). The application of Artificial Intelligence in external auditing and its implications on audit quality? A review of the ongoing debates. *International Journal of Research in Business and Social Science*.
- Steve G. Sutton, M. H. (2016). "The reports of my death are greatly exaggerated"—Artificial intelligence research in accounting. *International Journal of Accounting Information Systems*.
- (2023). *Technical Guide on Technology Enabled Auditing*. Institute of Chartered Accountants of India.
- (2023). *Technology and the Future of the Accountancy Profession*. International Federation of Accountants (IFAC).
- Thejus Jackson Adhikarathil, M. A. (2026). A STUDY ON ARTIFICIAL INTELLIGENCE IN FINANCIAL AUDITING: TRANSFORMING. *International Journal of Advance and Innovative Research*.
- Vasarhelyi, A. M. (2018). Auditing with Smart Contracts. *The International Journal of Digital Accounting Research*.

Impact of AI and Automation on Jobs in Various Sectors

Sunita Kharate

Assistant Professor, Sri Balaji University Pune, India

Ritu Mishra

Assistant Professor, Pramod Ram Ujagar Tiwari Saket Institute of Management

Krishika Chandwani

Assistant Professor, Pramod Ram Ujagar Tiwari Saket Institute of Management

ABSTRACT

The global workforce is changing because of the rapid advancements in automation and artificial intelligence (AI), which present both benefits and difficulties. This study investigates multiple techniques how artificial intelligence (AI) are transforming job market, generating new job categories, and replacing certain old ones. Automation and artificial intelligence (AI) are driving innovation, productivity, and efficiency across a wide range of sectors, including manufacturing, healthcare, finance, and retail. However, these advantages come at the expense of a large labor displacement, especially for repetitive and regular jobs.

This paper examines the combined effects of automation and artificial intelligence, emphasizing the industries most impacted by these changes in technology. For example, the usage of robots and AI-driven systems in manufacturing has increased, which has resulted in the displacement of assembly line workers but also increased the need for highly qualified technicians and AI specialists. AI-driven chatbots and automated customer care platforms are transforming client interactions in the service sector, eliminating the need for human intervention while necessitating new skills in AI management.

The socioeconomic effects of these developments are also discussed in the research, with special attention to the growing skills gap and the necessity of reskilling and upskilling the labor force. This chapter offers a detailed perspective of the influence of AI and automation on jobs through an in-depth analysis of the literature and case studies, providing insights into strategies for developing an inclusive and resilient workforce in the age of AI.

Keywords: artificial intelligence, ai, automation, job market, impact of ai

INTRODUCTION

Engagement with machines is far from a novel phenomenon in our contemporary era. Each professional role now demands a certain level of expertise with technological instruments. The discourse on the influence of technology on human labor is a subject of vigorous debate. Over the years, new techniques have impeccably dragged the fabric of every office and manufacturing site. Human generations and technological advancements have evolved in concert, hand in hand. Workplaces are continually adapting to a new paradigm where machines and humans coexist in harmonious synergy. The perennial debate centers on whether technology acts as an enhancer of human effort, augmenting productivity, or as a disruptive force, supplanting the need for human talent.

During the COVID-19 pandemic, the world witnessed a profound transformation in the workplace. Technology emerged as a savior, enabling countless businesses to operate seamlessly from remote locations. This crisis unequivocally demonstrated that without embracing technological integration, many enterprises would struggle to survive in today's dynamic market landscape. From conducting monthly meetings to showcasing product ideas to investors, the continuity of business operations was ensured by the robust technological infrastructure in place.

Abundant questions relating to automation impacting workforce personnel. Will we see an era where humans are overshadowed by machines in industries? What does futuristic employment look like with the rise of machines? What tasks do automation run at industries, and where do humans fit into this system? Modern production in most industries requires simultaneous completion of various tasks. Fewer tasks occurred complex and severely stretching beyond human capability, thus necessitating machines usage. Consequently, majority of present activities are performed either by machines alone or through a combination of human and machine effort. The real question is whether machines will eventually take over these tasks entirely. In modern industries, manufacturing often necessitates the concurrent execution of multiple tasks. Certain tasks are so intricate and challenging that they surpass human capabilities, necessitating the aid of machines. Consequently, many of these duties are normally carried out solely by machines or through a synergistic partnership between humans and machines. (Badet, 2021) While much debate and further investigation targeted on the potential for machines to replace many jobs in the industry, it's also anticipated that automation will lead to new job opportunities formation.

Automation and AI are transforming the workplace by streamlining routine tasks, which is leading to novelty in new job titles and roles. As prior illustration, companies are now hiring AI ethicists to deal with ethical consequences by AI implementations, automation specialists to optimize robotic processes, and data curators to manage and interpret vast amounts of information generated by AI systems. This shift also means traditional roles are evolving, as a marketing analyst's job now often includes tools of AI for predictive analytics. Consequently, the demand for upskills in AI-related technologies is rising, as employees need to adapt to these emerging roles and workflows.

AGE OF ARTIFICIAL INTELLIGENCE

Rise in storage capacity of computers and the advent of technologies like big data, today's computers operate more than just mathematical calculations or word processing. Modern computers are distinguished from rapid processing power, sophisticated machine learning algorithms, and advanced robotics capabilities. AI automation is at foreground of high-tech invention, transforming industry landscapes and reshaping the modern workforce. These technologies become decisive, increasing efficiency, improving decision-making, and generating unprecedented innovation. This section explores the evolution and definition of Artificial Intelligence (AI).

Alan Turing's 1952 article "Computing Machinery and Intelligence" introduced the concept of AI. Turing developed a method for determining a machine's intelligence, which examined the machine's ability to think. It's called the "Turing Test". Arthur Samuel produced the first checker-playing program capable of competing with human players. From 1966 to 1972, the first mobile robot project, "Shakey," which integrated various AI fields with navigation and computer vision, was undertaken and can now be viewed at the Computer History Museum. In 1968, Terry Winograd at Stanford University developed SHRDLU, an early natural language computer program. In 1970, Waseda University developed the anthropomorphic robot WABOT-1, featuring moveable limbs and conversational abilities. Despite the subsequent period known as the "AI winter" in the 70s and 80s, significant advancements continued with the SCARA assembly line aid in 1979 and the experience-learning robot RB5X in 1984. The term "virtual reality" was coined in 1985, leading to the first VR gloves and glasses, followed by "augmented reality" by Tom Caudell. In the 1990s, AI advanced significantly, shifting from physical robots to digital programs. Deep Blue tech crushed down the chess grandmaster Garry Kasparov, and NASA deployed Sojourner, its first autonomous robotic system.

In 2011, Apple's Siri marked a breakthrough in automation, introducing an era of AI-driven assistants. Today, automation software is essential rather than optional, with Business Process Automation (BPA) and Robotic Process Automation (RPA) becoming increasingly advanced and efficient. These technologies enhance employee productivity, causing noteworthy resource savings. AI now pervades our regular life span amid social media, email, gaming apps, and beyond. AI assistants are now commonplace on our phones, in transportation, homes, and workplaces, reflecting rapid technological

advancement. Examples include Siri, Alexa, video game characters, Microsoft's Tay, ChatGPT, and Meta AI, showcasing AI's broad range of applications today. (AI bees, 2023)

WHAT IS AI?

John McCarthy was the first to originally used the term "artificial intelligence" in 1955. (AI) is an area of computer science devoted to developing machines that can carry out tasks like learning, reasoning, self-correction, problem-solving, and perception that normally need human intellect. The AI systems can acquire information and rules for using it, use logic to reach conclusions, fine-tune algorithms to correct errors, solve complex problems, and interpret sensory information to interact with their environment.

According to Alan M. Turing, the machine passes the famous Turing Test is declared as a prescribed standard for judging whether a machine is capable of intelligent conduct that is identical to that of a person. Turing explored the potential for machine intelligence in this work and addressed objections and implications surrounding this idea. He delved into various aspects of intelligence, including learning, language understanding, and machine creativity, laying foundational ideas that continue to reframe AI research field of and philosophical debates about the nature of intelligence and consciousness. (Turing, 1950)

AI can set a benchmark for its capabilities into different types. Narrow AI is developed and designed to a unique task, like human voice modulation, chess and image formation. These systems excel in their designated area but are unable to accomplish any work outside their training extent. Modified AI possesses generalized cognitive abilities, meaning any logical task done by human, adapting to new situations and adapting to experience. Although been theoretical the topic of continuous research and discussion, super intelligent AI refers to a potential future machine that surpasses human intellect in all domains and can make judgments and solving problems well beyond human capabilities. AI is powerful and adaptable since it is based on a variety of methods. Algorithms used in machine learning (ML) enable computers to learn from data and draw conclusions or predictions from it. A subset of machine learning called deep learning makes use of multi-layered neural networks to assess different aspects of data, making it possible to do tasks like picture and speech recognition with high accuracy. Applications such as sentiment analysis and language translation are made possible by natural language processing (NLP), which includes methods that allow computers to comprehend and analyse human language and conversational agents. Robotics applies AI to robots, abetting performed tasks in the physical world, such as manufacturing, surgery, or autonomous driving.

AI's applications are widespread and impactful across various fields. Let talk about medical sector, AI had put hand in diseases detection, personalizing treatment plans as per need, and managing patient care. In finance, AI also augments fraud exposure, algorithmic trading, and smooth customer services. The automotive industry leverages AI for autonomous driving, predictive maintenance, and enhancing safety features. In customer service, AI powers chatbots, virtual assistants, and personalized recommendations, improving user experience and operational efficiency. AI's versatility and potential for innovation continue to drive advancements across industries, transforming how we live and work.

RESEARCH METHODOLOGY

This paper mainly focuses on using descriptive research design, by using the secondary data related to AI effects on job, changing scenarios of job such as upskills, and job role changing due to AI. Scholarly articles from databases such as PubMed, JSTOR, and PsycINFO will provide insights from empirical studies, literature reviews, and theoretical frameworks. And published data of various types.

OBJECTIVES:

- To study AI and its impact on various sectors
- To analyze the effect of AI on Skill requirement.
- To investigate AI in Organization.

LITERATURE REVIEW

Olaniyi et al. (2024) mentioned in this study that the AI and automation amalgamation in various sectors presents both challenges and opportunities for the global workforce. This study, surveying 482 professionals in IT, healthcare, and finance, examines the impact of AI and automation on employment patterns, skills, and remote work. Using PLS-SEM analysis, it finds AI and automation significantly affect employment, jobs opportunities with heightening productivity for tech-savvy sectors. However, concerns about a widening skills gap and inadequate employment policies persist, with 69% of respondents stressing urgent training and education requirement, and about half criticizing current policies. They recommended proactive strategies, including targeted reskilling programs, adaptive employment policies, and robust remote work infrastructures to maximize digital transformation benefits and mitigate negative effects. Paudel, R. (2024) investigated the automation and artificial intelligence (AI) consequences on leadership and the workforce, providing strategies for leaders to navigate the shift to a tech-focused workplace. The study aimed to provide insights into how AI and automation affected leadership and the workforce, along with useful recommendations for managing this transformation. The research highlighted the advantages of AI and automation, such as enhanced efficiency and decision-making, while also addressing concerns about job displacement and ethical issues of future and ensure success.

Jumaev, G. (2024) explored the impact of AI on the job market and provided strategies for individuals, organizations, and policymakers to adapt. Further, the researcher examined industries and occupations most susceptible to AI disruption, highlighted emerging roles that combine AI expertise with domain knowledge, and emphasized human-AI collaboration models. The study addressed ethical considerations like bias and transparency and discussed the effects of AI on job satisfaction and well-being. Further, it offered strategies for thriving in the AI era, such as continuous learning and upskilling. The global implications of AI on the workforce and the role of entrepreneurship in creating new jobs were analyzed. The article aimed to provide a comprehensive understanding of AI's impact on the job market and actionable insights for navigating the future of work. Oluwaseyi et al. (2024) analyzed the impact of AI on job displacement and income inequality. Through a comprehensive literature review, it examined how The study examined the socio-economic implications of job displacement and income inequality, focusing on issues like structural unemployment and labor market polarization, which particularly affect vulnerable populations. It also stressed the need for proactive policies, such as investments in education, skills training, labor market adaptability, and social welfare reforms, to mitigate the negative effects of AI. AI-driven automation replaced routine tasks, changing labor demand and skill requirements. The study also showed that AI benefited high-skilled workers more than unskilled workers. It underscored the importance of ethical AI deployment to foster equitable economic growth. The study provided insights for policymakers, businesses, and stakeholders to harness AI's benefits while addressing its socio-economic challenges and promoting inclusive prosperity.

Zarifhonarvar (2024) investigated the influence of ChatGPT on labor market dynamics, aiming to understand the changes induced by generative AI technologies. It used existing literature and a supply and demand model to assess the effects of ChatGPT. A text mining approach analyzed the International Standard Occupation Classification to identify occupations most susceptible to disruption by ChatGPT. The study found that 32.8% of occupations could be fully impacted by ChatGPT, 36.5% can encounter a slight partial impact, and 30.7% felt untouched. Although fragmented ways for insights into the potential influence of ChatGPT at labor market, discovered that these findings are potential

implications rather than realized effects. Further research was needed to track actual changes in employment patterns where these AI services were widely adopted. The paper contributed to the field by level segmentation of AI impact in various fields providing a nuanced perspective on the implications of ChatGPT and similar generative AI services on the labor market. Tyson et al. (2022) commented that AI would displace humans from existing tasks while increasing demand for new tasks in both manufacturing and services. A study looked at how labor problems carried job polarization, stagnating pay for middle- and low-skilled workers, and rising inequality could be made worse by AI-enabled platforms. A study looked at how labor problems including job polarization, stagnating pay for middle- and low-skilled workers, and rising inequality could be made worse by AI-enabled platforms.

The authors were skeptical that AI would create enough good jobs or widely share its productivity benefits, forecasting increased inequality instead. They argued that mitigating AI's adverse effects would require intelligent policy design. Further, noted that labor shortages and upward wage pressure could arise due to slowing growth in working-age populations and anticipated skills shortages in sectors like healthcare and software engineering, potentially accelerating the adoption of AI-driven automation.

Nazareno et al. (2021) Five channels—freedom, sense of meaning, cognitive load, external monitoring, and insecurity—were used to evaluate how automation can affect workers' well-being. Based on data from the General Social Survey, it evaluated work satisfaction impact, stress, health, and insecurity using automation measure risk across 402 jobs. Results revealed that risk was linked to lower levels of stress, worse health, and negligible effects on job satisfaction, particularly for individuals at high risk. Instead of seeing technological complementarity as always advantageous, the study advised businesses, politicians, and researchers to take into account the mixed well-being impacts of automation and AI. In his analysis of the employment benefits of automation, Badet, J. (2021) pointed out that automation not only produces new, more complicated work needing higher abilities, but it also replaces existing positions. Utilizing data on automation and employment, the study demonstrated how automation replaces repetitive machinery while fostering the creation of "smart jobs". It also highlighted the need for sophisticated skills in new professions created by technology, emphasizing the importance of education for future workers. It found that job loss from automation varied by country, with faster automation leading to higher job risk in countries with rapid technological adoption. The study suggested that workers and students need to focus on acquiring skills relevant to new technologies to adapt to future job markets.

Barbieri et al. (2019) analyzed the impact of automation on employment, noting that while automation aimed to reduce costs and labor, compensation mechanisms might have mitigated its negative effects. The study concluded that automation generally benefited high-skilled and non-routinized jobs while threatening routinized low- and middle-skilled positions. Vermeulen et al. (2018) examined the projected effects of automation on employment over the next decade by integrating an evolutionary economic model with labor economic theory. It assessed how labor displacement in automated sectors might be offset by job creation in new, labor-intensive industries. Using datasets with expert projections on occupations impacted by automation, including robotics and AI, the study found that job losses in automation-centric sectors are likely to be balanced by job growth in related and supportive sectors. Further, they concluded that automation will lead to typical structural changes in the labor market rather than causing an "end of work." The study proposed policy recommendations to improve the efficiency of these structural transitions.

THE GROWTH OF ARTIFICIAL INTELLIGENCE.

Artificial Intelligence (AI) has undergone a remarkable transformation, progressing from an abstract idea about machine intelligence to a powerful technology influencing contemporary economic, organizational, and social systems. The conceptual foundation of AI was strengthened by Alan Turing, who questioned whether machines could exhibit intelligent behaviour comparable to humans and proposed the "imitation game" as a means of exploring this possibility (Turing, 1950). AI subsequently

developed into a formal field of academic inquiry following the Dartmouth Summer Research Project on Artificial Intelligence in 1956, where researchers proposed that human learning and other dimensions of intelligence could potentially be represented in a form that machines could simulate (McCarthy et al., 2006). Early AI research primarily concentrated on symbolic approaches, logical reasoning, mathematical problem-solving, and game-playing. However, the limited availability of computational resources and digital information restricted the practical capabilities of these systems. These technological and financial limitations contributed to periods of declining enthusiasm and investment in AI research, commonly described as AI winters.

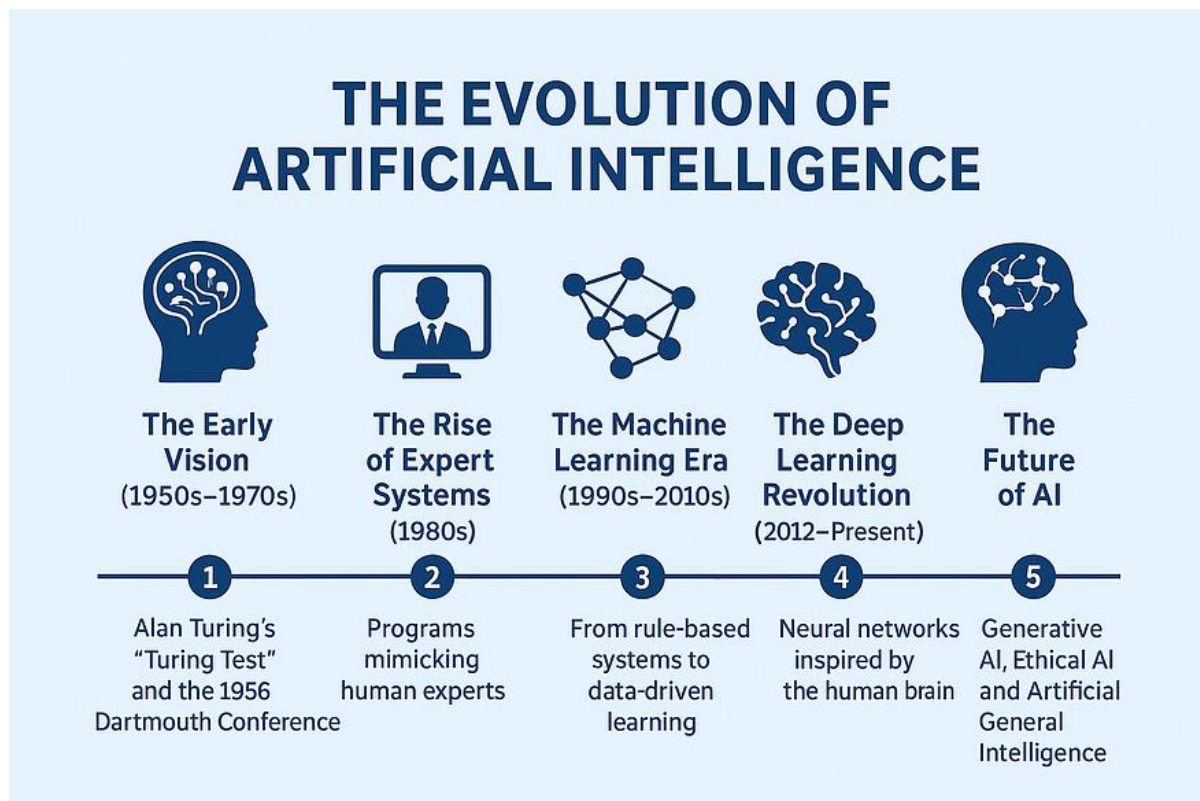
A significant shift occurred during the 1970s and 1980s, when researchers increasingly explored expert systems and knowledge-based approaches. Instead of attempting to create broadly intelligent machines, these systems were designed to solve problems within particular areas by incorporating the knowledge and decision-making rules of human specialists. MYCIN, for example, demonstrated the potential of computer-based systems to support medical diagnosis and treatment recommendations by applying a structured body of expert knowledge (Shortliffe, 1976). Although expert systems demonstrated considerable value in specialized applications, their dependence on manually developed rules presented challenges in terms of flexibility, maintenance, and adaptation. As organizational and real-world problems became more complex, the limitations of such rule-dependent systems encouraged researchers to investigate approaches in which machines could derive knowledge from data rather than relying entirely on human-defined instructions.

The 1990s and 2000s consequently witnessed the expansion of machine learning (ML), which represented a fundamental change in the development of AI. Instead of programming every decision explicitly, machine-learning techniques enabled computational systems to identify patterns and improve their performance through exposure to data. The rapid growth of the internet, increasing digitalization, greater storage capacity, and improvements in computing infrastructure provided the data and computational foundation necessary for these approaches. One of the most notable demonstrations of AI capability occurred in 1997, when IBM's *Deep Blue* defeated world chess champion Garry Kasparov, highlighting the capacity of specialized computational systems to perform exceptionally well in complex intellectual tasks (Hsu, 1997). Subsequently, IBM's *Watson* achieved another important milestone in 2011 by defeating leading human contestants on *Jeopardy!*, demonstrating advances in natural-language processing, information retrieval, and computational question answering (IBM, 2025).

The development of deep learning during the 2010s represented another major turning point in the evolution of AI. Deep learning uses multi-layered neural networks to identify increasingly complex patterns from large volumes of data. Its rapid advancement was supported by improvements in computing hardware, particularly GPUs, larger datasets, sophisticated algorithms, and greater access to computational resources. A landmark development occurred in 2012, when AlexNet, a deep convolutional neural network developed by Krizhevsky, Sutskever, and Hinton, achieved a substantial performance improvement in the ImageNet Large Scale Visual Recognition Challenge (Krizhevsky et al., 2012). This achievement demonstrated the potential of deep neural networks for complex visual-recognition tasks and helped accelerate the adoption of deep-learning techniques across numerous AI applications.

In the current phase of AI development, the technology has progressed beyond conventional prediction, classification, and recognition tasks toward systems capable of generating new content and engaging in increasingly sophisticated interactions with users. AI is now incorporated into a wide range of applications, including recommendation platforms, voice and speech recognition, machine translation, computer vision, intelligent automation, autonomous technologies, and conversational systems. The emergence of generative AI and large language models (LLMs) has further expanded the scope of machine intelligence by enabling systems to produce and manipulate text, images, software code, audio, and other forms of digital content. Thus, the development of AI can broadly be viewed as a transition from symbolic reasoning and rule-based systems to expert systems, machine learning,

deep learning, and generative AI. This progression has transformed AI from a predominantly experimental area of computer science into a strategically important technology with far-reaching implications for organizations, employees, business processes, innovation, and society. The evolution of AI therefore represents not simply an advancement in computing technology, but a broader transformation in the relationship between humans, information, and intelligent digital systems.



TECHNOLOGICAL REVOLUTIONS AND EMPLOYMENT SHIFTS

The introduction of automation and artificial intelligence (AI) in India represents a major technological change with far-reaching effects on a number of industries, including manufacturing, services, IT, and agriculture. Similar changes have occurred in India in the past, including the IT Revolution (Arora & Athreye, 2002) and the Green Revolution (Pingali, 2012), which altered the country's employment market and economic environment. By automating repetitive processes, increasing efficiency, and creating new job positions in fields like cybersecurity, data science, and AI development, the combination of automation and AI is now changing industries (NASSCOM, 2020). But there are drawbacks to this change as well, such as the relocation of low-skilled jobs and the necessity for extensive reskilling and upskilling initiatives. (World Economic Forum, 2020).

The primary challenge lies in mitigating job displacement and addressing the skill gap in AI and related fields. Mechanization has redesigned the unskilled, repetitive tasks, there is a pressing need for educational reforms and vocational training programs to equip the workforce with the necessary skills for emerging job roles (McKinsey Global Institute, 2017). Moreover, the economic disparity could widen if the benefits of AI and automation are not equitably distributed. Thus, policymakers must focus on creating inclusive growth strategies that ensure the gains from technological advancements are shared across different socio-economic groups (Kanitkar, 2020).

To navigate these challenges, strategic policy interventions are imperative. Integrating AI and automation-related subjects into educational curricula, supporting research and development, and fostering government-private sector collaborations for reskilling programs are essential steps (Government of India, 2018). Additionally, developing a regulatory framework to address the ethical

and societal implications of AI will be crucial (Binns, 2018). By proactively addressing these issues, India can harness the potential of AI and automation to drive economic growth, create new job opportunities, and improve the overall quality of life, ensuring a balanced and inclusive technological progression.

CURRENT IMPACT OF AI ON JOB

Artificially intelligent AI is already having a wide range of effects on business, including automation, manufacturing and job relocation, role transformation, and significant adjustments to the skills and training requirements. The following image depicts Job creation and jobs deletion by Artificial Intelligence.



Source: pwc.co.uk

It can be seen that AI is providing opportunities in certain sectors whereas certain sectors witness job slashes due to AI as per a pwc report. The Prominent sectors gaining from AI are namely Healthcare(25%), Scientific and Technical(15%), Information Communication (8%), Education and Hospitality (around 6 %). Whereas job cuts can be witnessed in many sectors with majority impact being on Manufacturing(25%). This is primarily due to automation and introduction of machines for performing repetitive tasks. Autonomous vehicles, drones and automated warehouses have also lead to impact of AI on Transportation and storage sector namely 22%. Traditional roles are being replaced by AI applications in data analysis, surveillance, and administrative chores. Many tasks previously performed by financial analysts, customer service agents, and administrative staff are being automated by chatbots and AI-powered algorithms., thus an impact on financial services sector is about 7-8%.

While AI offers prospects for improved productivity and innovation, it also raises issues relating to economic mobility, income inequality, and ethical considerations. Job responsibilities and duties have evolved as a consequence of artificial intelligence (AI) being integrated into the workplace. Through the integration of contemporary research, the highlighting of significant concerns, and the integration of conclusions from many studies, this literature review offers an in-depth analysis of the influence of AI on business.

The effects of AI on business today are diverse and include automation, manufacturing and job relocation, role transformation, and significant adjustments to the skills and training requirements. While artificial intelligence (AI) offers the potential for greater productivity and innovation, it also raises issues with income inequality, economic mobility, and ethical concerns. When making more money, concentrate on strategies to lessen adverse effects. AI is improving risk management, fraud

detection, and customer service, according to a 2024 PwC report. Working with AI technologies to comprehend complicated data and make strategic decisions is becoming more and more necessary for financial professionals (PwC, 2024).

AUTOMATING REPETITIVE ACTIVITIES

AI systems are capable of managing substantial data entry volumes, which minimizes the requirement for human involvement. Errors are decreased and process speed is increased by automation. AI chatbots and virtual assistants may handle inquiries from customers, offer assistance, and solve issues, freeing up human agents to work on more difficult jobs.

INCREASED DECISION-MAKING

AI systems are capable of analyzing vast volumes of data to offer insights and aid in decision-making. This talent is useful in industries like finance, business, and healthcare where making judgments based on data is essential. Predictive analytics: AI can foresee patterns and results, enabling businesses to take preventative measures. AI, for instance, can enhance inventory management and forecast demand in the retail industry.

WORK ROTATIONS

AI provides medical professionals with assistance by evaluating imaging data, forecasting patient results, and suggesting courses of action. Healthcare practitioners can concentrate on patient care thanks to this help. AI-powered systems and robots can carry out intricate assembly tasks, keep an eye on equipment that needs repair, and guarantee quality control, efficiency, and perfection.

NEW TRENDING JOB CATEGORIES

Machine learning experts, data scientists, and AI engineers are in high demand. These experts develop, deploy, and manage AI. As AI is used more widely, there is an increasing demand for initiatives centered on AI ethics and governance.

AN INCREASE IN EFFICIENCY

AI streamlines demand forecasting, inventory control, and routing, increasing overall supply chain effectiveness and cutting costs. AI streamlines the hiring process by reviewing resumes, setting up interviews, and even carrying out initial screenings, freeing up HR staff members to concentrate on positions in a practical way.

TRAINING AND UPSKILLING

Systems powered by AI provide employees with training and development plans that are specifically tailored to their needs, enabling them to advance and adjust to shifting work demands. AI makes it easier for employees to learn continuously by suggesting relevant courses, monitoring their progress, and offering feedback. This keeps employees up apprised on the latest advancements in technologies.

FLEXIBILITY AND REMOTE WORKING

Collaboration Tools: Artificial Intelligence improves communication and productivity in remote work by offering sophisticated collaboration tools including virtual meeting assistants, real-time transcription, and language translation.

Task Management: AI-powered task management solutions promote a more productive and adaptable work environment by assisting remote teams in staying organized, setting priorities, and meeting

deadlines. Educating staff members on the newest trends and technologies through course recommendations, progress monitoring, and feedback.

Job responsibilities and duties have evolved as a consequence of artificial intelligence (AI) being integrated into the workplace. Through the integration of contemporary research, the highlighting of significant concerns, and the integration of conclusions from many studies, this literature review offers an in-depth analysis of the influence of AI on business. In the future, it is anticipated that human and AI collaboration will grow. A McKinsey & Company (2018) analysis claims that artificial intelligence (AI) will not only transform how organizations are operated, but will also open up new avenues for human-AI collaboration that will spur innovation and increase employee satisfaction. According to the paper, for organizations to fully utilize AI, they must cultivate a culture of ongoing learning and adaptation.

Artificial intelligence is known to be capable of handling normal and repetitive jobs. Brynjolfsson and McAfee (2014) contend in their influential book "The Second Machine Age" that automation through artificial intelligence is revolutionizing the industry by decreasing the necessity for human involvement in repetitive tasks. This tendency may be seen in sectors like manufacturing, where assembly line labor is done by robots, and data processing applications, where artificial intelligence (AI) manages data entry and basic analysis.

Automation driven by AI has the potential to replace some businesses, but it also opens up new possibilities. In their OECD analysis, Arntz, Gregory, and Zierhn (2016) present a complex picture, arguing that although certain industries are in danger, others will change or entirely emerge. For instance, machine learning engineers, data scientists, and AI ethicists are among the new occupations brought about by AI (Manyika et al., 2017).

Instead of eliminating humans, artificial intelligence is augmenting human capabilities to transform current jobs. According to Frey and Osborne (2017), AI is anticipated to improve and make it easier to automate tasks that call for creativity, social intelligence, and sophisticated decision-making. For instance, AI helps doctors in the healthcare industry by evaluating medical imaging and making treatment recommendations, freeing up medical professionals to concentrate on patient care (Jiang et al., 2017).

Brynjolfsson et al. (2018), who support lifelong learning programs to assist employees in adapting to the quickly changing technology environment, acknowledge the need for more research in this area. Workers must participate in these programs to grow into new responsibilities and learn new skills. According to Bessen (2019), education systems must adapt to satisfy the rising need for people with expertise in data analytics and artificial intelligence. According to forecasts made by the World Economic Forum (2018), for workers to stay competitive in their job by 2022, over half of them will need to retrain or improve their abilities. A major transformation in training and skill sets is necessary for the shift to an AI-driven workplace. Bessen (2019) emphasizes how education systems must adapt to provide AI and data analytics skills. According to the World Economic Forum (2018), to stay up with technological advancements, at least 54% of all workers will need new or considerably upskilled abilities by 2022.

AI is also propelling the development of new companies. According to a McKinsey & Company (2023) report, there is a significant demand for professionals with expertise in machine learning, data science, and AI ethics. The shift to a workforce that is increasingly technology-focused and manages, manages, and manages is reflected in the importance of this function for AI strategy (McKinsey & Company, 2023). According to a Brookings Institution report from 2024, artificial intelligence is not just replacing occupations but also changing them. For instance, the application of AI in healthcare improves the precision of patient care administration and assessment, freeing up medical professionals to concentrate on the intricate interpersonal components of patient care (Brookings Institution, 2024). It is essential to be able to learn and adjust on the go. According to the International Labour Organisation (2024), for employees to stay relevant, they must embrace lifelong learning. This involves retraining

and skill development through programs for emerging technologies in ongoing education and training (International Labour Organisation, 2024).

Even though technological abilities are prioritized, soft skills are still crucial. According to Deloitte research for 2024, when artificial intelligence (AI) takes on more routine activities, creativity, critical thinking, emotional intelligence, and problem-solving will become more crucial. With the help of these abilities, managers can assist and provide AI technology that improves both human and AI performance (Deloitte, 2024).

SECTORS MOST AFFECTED BY AI AND AUTOMATION

Manufacturing: The manufacturing sector has been impacted by AI and automation, leading to increased efficiency and productivity through advanced robotics and data analytics. Automation has streamlined production processes, reduced labor costs, and minimized human error, resulting in faster production cycles and higher precision. However, it has also led to job displacement as routine tasks are increasingly performed by machines. While AI enables predictive maintenance and optimized supply chains, it also requires substantial investment and upskilling of the workforce to adapt to new technologies.

Automation and Robotics: The manufacturing sector has seen significant adoption of automation and robotics, leading to the automation of assembly lines, quality control, and inventory management. This results in increased efficiency and reduced labor costs but also leads to job displacement for low-skilled workers (Manyika et al., 2017).

Smart Manufacturing: Integration of IoT and AI for predictive maintenance, energy management, and production optimization. This shift enhances productivity and reduces downtime, but requires a workforce skilled in managing and operating advanced technologies (Schwab, 2017).

Retail: The retail sector being majorly impacted by AI and automation has been seen enhancing efficiency, personalizing customer experiences, and optimizing inventory management in today's era. Automated systems streamline operations, reducing labor costs and minimizing human error, while AI-driven analytics help retailers understand consumer behavior and tailor marketing strategies. Additionally, technologies like chatbots and virtual assistants improve customer service, and automated supply chain solutions ensure better stock management. Overall, these advancements have led to more responsive, data-driven retail environments that better meet consumer needs and drive growth.

- **E-commerce and Logistics:** AI-driven logistics and supply chain management systems optimize inventory, predict demand, and streamline operations. This impacts jobs in traditional retail and warehousing sectors, creating a need for skills in managing automated systems and data analytics (McKinsey Global Institute, 2019).
- **Customer Service:** Implementation of AI-powered chatbots and virtual assistants to handle customer inquiries, reducing the need for human customer service representatives while improving response times and customer satisfaction (Accenture, 2018).

Finance

- **Algorithmic Trading:** AI is used for fraud detection, risk management, and high-frequency trading. This leads to job movement in traditional trading roles while increasing the demand for data scientists and AI specialists (Davenport & Kirby, 2016).
- **Customer Interactions:** AI-driven robot advisors and chatbots provide financial advice and customer support, enhancing efficiency but theoretically lowering the need for human financial advisors and customer service personnel (PwC, 2020)

Healthcare

AI and automation have transformed the healthcare sector by boosting diagnostic precision, customizing treatments, and increasing operational efficiency. AI tools analyze medical data, like imaging and genetics, for more accurate diagnoses and personalized care plans. Automation rationalizes administrative tasks such as scheduling, billing, and record-keeping, reducing errors and allowing healthcare professionals to concentrate on patient care. Moreover, AI-driven predictive analytics enable early disease detection and preventive measures, leading to improved health outcomes and more effective healthcare services.

Diagnostics and Treatment: AI applications in medical imaging, diagnostics, and personalized treatment plans enhance accuracy and efficiency in healthcare delivery. However, this may reduce the demand for certain medical professionals while increasing the need for AI and data management experts (Topol, 2019).

Administrative Tasks: Automation of administrative tasks such as scheduling, billing, and patient records management streamlines operations but displaces clerical jobs, necessitating reskilling of the workforce (Deloitte, 2020).

Transportation and Logistics

AI and automation have transformed the transportation and logistics industry by boosting efficiency, cutting costs, and enhancing safety. Automated solutions improve route planning and scheduling, resulting in quicker deliveries and reduced fuel use. AI helps with predictive maintenance and real-time tracking, decreasing downtime and streamlining processes. The rise of autonomous vehicles and drones is set to further disrupt traditional methods by introducing new delivery options and minimizing human errors.

Autonomous Vehicles: The development and deployment of self-driving cars, trucks, and drones impact jobs in the driving and delivery sectors. While these technologies assure greater efficiency and safety, they need new abilities for the maintenance and oversight of autonomous systems (Litman, 2020).

Logistics Optimization: AI-driven route optimization and fleet management improve logistics efficiency but can lead to job losses in traditional logistics roles (McKinsey & Company, 2017).

Emerging Skills Requirements

The employment landscape is changing due to the rapid advancements in AI technology, which is driving up demand for previously undersupplied new talents. The workforce's skill requirements are drastically changing as a effect of the incorporation of AI into many different organizations. Along with psychological and interpersonal talents like critical thinking, creativity, and emotional intelligence, technical skills like machine learning, data science, and cybersecurity are in high demand. To prosper in an AI-driven society, one must possess leadership qualities, digital literacy, productivity, and a lifelong learning attitude.

The workforce's skill set will evolve as an outcome of AI's integration into various sectors. Retraining and upskilling workers are now essential tactics to guarantee that they can adjust to these advancements and flourish in an AI-driven workplace.

The significance of reskilling and upskilling cannot be emphasized as AI proceeds to transform the landscape of employment. For the workforce to be competitive and relevant, they must pick up new technical, conceptual, and cross-functional abilities. By atomizing and adapting continuing education, individuals and organizations can effectively overcome the opportunities and challenges presented by

AI integrating integration. Formal education, online learning, on-the-job training, corporate training programs, and self-directed learning are all important ways to acquire these skills.

Software and Programme Development: Integration is led by AI It is necessary to be proficient in programming languages like Python, R, Java, and C++. These languages serve as the foundation for artificial intelligence applications, thus it's critical to comprehend AI frameworks and libraries like Scikit-learn, TensorFlow, and PyTorch. These technologies allow companies to create, implement, and refine AI models of superior quality.

Deep learning and machine learning: A thorough understanding of neural networks, natural language processing and machine learning techniques is necessary. This covers both theoretical knowledge and hands-on expertise in creating and refining machine learning models. Sophisticated AI systems that can learn from data and make wise decisions are the result of expertise in these fields.

Complex Thinking and Problems: Only when entrepreneurs can assess complex issues and create novel solutions will AI's potential be fully realized. The competence to reason logically and make decisions is vital for interpreting and using AI products to solve disputes in the real world. Creativity and innovation: While AI is capable of handling repetitive chores, human creativity remains a unique quality. Together with AI, new thoughts and ideas must be developed. To boost efficiency and creativity, establishing new AI applications and refining current procedures require creative thinking.

Emotional Intelligence: It's evident that emotional intelligence is crucial for controlling one's own emotions and comprehending those of others as AI systems replace regular labor. Effective leadership and teamwork in AI-integrated environments require the possession of communication, empathy, and conflict-resolution abilities.

Techno-Functional Expertise: The next generation of workers must be composed of both domain-specific knowledge and technical abilities. For instance, creating successful AI solutions in the healthcare sector requires an understanding of both Artificial intelligence technology and the unique difficulties faced by the sector. The divide between technical teams and business stakeholders is closed by such hybrid competence.

Economic and Social Implications of AI and Automation

Automation and AI fuel economic expansion by increasing productivity and creating new market place, but they also lead to job shift and wage inequality as certain roles become obsolete. On a social level, they can improve quality of life through enhanced services and efficiency but may exacerbate social divides and require significant investments in reskilling workers. Balancing these impacts involves managing technological advancement while addressing economic disparities and ensuring equitable opportunities.

Increased Efficiency: AI and automation significantly enhance productivity by streamlining processes, reducing errors, and optimizing resource use. This leads to economic growth as companies can increase their output with less input (Brynjolfsson & McAfee, 2014).

Cost Reduction: Automation reduces labor costs and operational expenses, allowing companies to reinvest savings into innovation and expansion (Manyika et al., 2017).

Displacement of Low-Skill Jobs: Automation of routine and repetitive tasks leads to the displacement of low-skill jobs, particularly in manufacturing, retail, and administrative roles (Chui et al., 2016).

Creation of High-Skill Jobs: New job opportunities arise in fields such as AI development, data science, cybersecurity, and robotics maintenance. These positions frequently call for advanced skills and education, shifting the demand toward more specialized labor (Bessen, 2019).

Widening Income Gap: The advances of AI and automation are often unevenly distributed, resulting in a widening income gap between high-skilled workers who can leverage these technologies and low-skilled workers who may face job losses (Autor, 2015).

Regional Disparities: Economic benefits tend to concentrate in regions with strong technology infrastructures and education systems, potentially exacerbating regional inequalities (Acemoglu & Restrepo, 2020).

Social Implications

AI can enhance quality of life through improved services and convenience, but it also raises concerns about privacy, job displacement, and increased social inequality. The technology's impact on daily life and employment patterns can deepen existing divides, requiring thoughtful strategies to manage its effects on society and ensure fair benefits for all.

CHANGING NATURE OF WORK

Shift in Job Types: As routine jobs are automated, there is a shift towards roles that require complex problem-solving, creativity, and emotional intelligence. This necessitates continuous learning and adaptability among the workforce (Frey & Osborne, 2017).

Gig Economy and Freelancing: AI and automation facilitate the growth of the gig economy, where short-term contracts and freelance work become more prevalent. While this offers flexibility, it also prompts worries regarding about job security and benefits (Manyika et al., 2016).

Education and Skills Training

Reskilling and Upskilling: There is an urgent need for reskilling and upskilling programs to prepare workers for the jobs of the future. Governments, educational institutions, and private companies must collaborate to provide relevant training (World Economic Forum, 2020).

Lifelong Learning: The rapid pace of technological change a culture of perpetual learning in which people constantly improve their abilities to stay relevant in the job market (OECD, 2019).

Social Inequality

Access to Technology: Disparities in access to technology and digital literacy can exacerbate social inequalities. Ensuring equitable access to technological resources is crucial for inclusive growth (Eubanks, 2018).

Ethical and Privacy Concerns: The widespread use AI brings up moral concerns about data privacy, surveillance, and the potential for biased algorithms. Addressing these concerns is essential to maintain public trust and social cohesion (Binns, 2018).

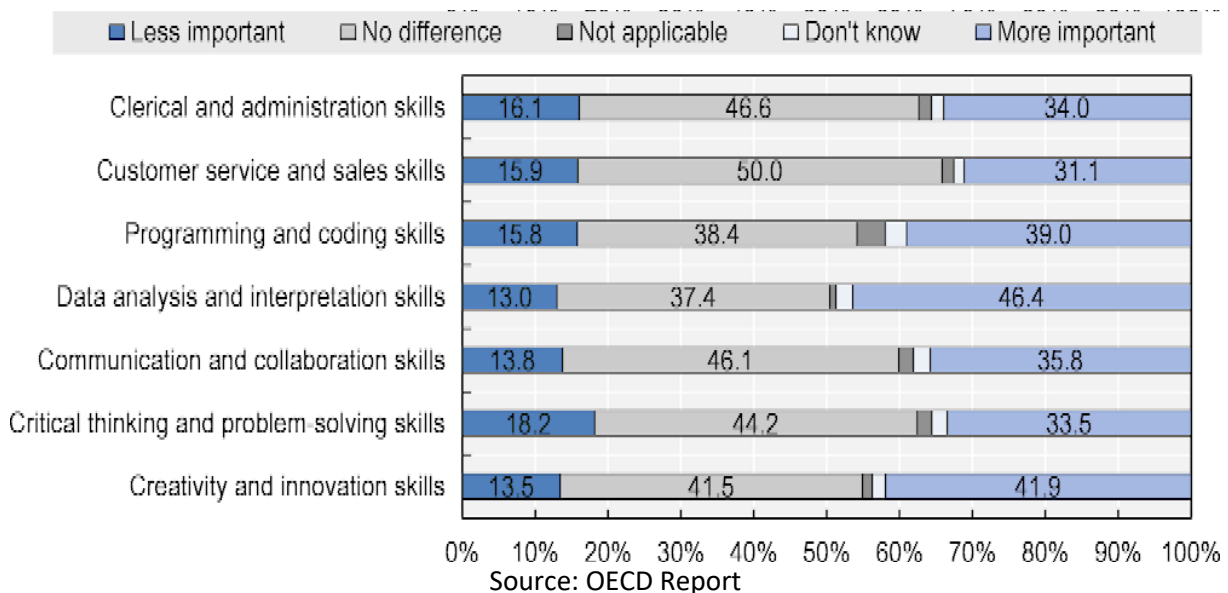
AI AND THE FUTURE WORKFORCE

The assimilation of AI into the workforce is heading to substantial changes in job roles across various sectors. Traditional roles that involve routine, automation is being used for repetitive jobs, leading to the displacement of certain low-skill jobs (Chui et al., 2016). For instance, in manufacturing, tasks such

as assembly line work and quality control are increasingly being handled by robots and automated systems. Similarly, in the retail and service industries, AI-powered chatbots and automated customer service platforms are reducing the need for human operators in these roles (Manyika et al., 2017). Conversely, there is an expanding demand for high-skill jobs that require proficiency in AI development, data analysis, and machine learning. These roles are critical for designing, implementing, and managing AI systems, highlighting the need for a workforce that is proficient in advanced technological skills (Brynjolfsson & McAfee, 2014).

Skills and Education Requirements

The future workforce will require a diverse set of skills to adapt to the changes brought about by AI. Technical skills in AI, machine learning, data science, and cybersecurity are becoming increasingly important (World Economic Forum, 2020). Educational institutions and training programs must evolve to provide the essential knowledge and skills for these emerging fields. Additionally, soft skills such as creativity, critical thinking and emotional intelligence will be crucial, as they are less likely to be automated and are essential for managing and collaborating with AI systems (Frey & Osborne, 2017). Lifelong learning and continuous skill development will be key strategies for individuals to remain relevant in the evolving job market (OECD, 2019). The following diagram shows how Generative AI leads to better skills from workers:



It can be witnessed from the above graph that highest importance is given to Data Analysis and Interpretation skills (46.4%), next being creativity and innovation (41.9%) followed by programming and coding skills (39%). Thus with the implementation of AI in industries it is essential that the workers should be skilled and they should be able to do data analysis and interpretation.

Economic and Social Implications

The extensive adoption of AI in the workforce has profound economic and social implications. Economically, AI can drive productivity and growth by optimizing processes and reducing costs (Manyika et al., 2017). However, the displacement of jobs and the creation of new roles will lead to a significant restructuring of the labor market. There is a danger of increased economic inequality if the advantages of AI are not distributed equitably, as high-skill workers who can leverage AI will probably see increased economic gains compared to those in low-skill positions (Autor, 2015). Socially, the transition to an AI-driven workforce will require robust policies to support workers through reskilling programs and social safety nets to mitigate the influence of job displacement. Ensuring fair access to artificial intelligence education and technology is also critical to prevent widening social disparities.

(Eubanks, 2018). Overall, while AI presents significant opportunities for economic advancement, careful management of its incorporation into the workforce is essential to address the accompanying challenges.

Scope for Further Research:

The paper presents and discusses impact of AI on different job sectors and skills. Further research can be done by focusing on sector specific data wherein a survey can be conducted for workers who are shaken by AI and how they have adjusted to the changing situation. Furthermore, managers can be interviewed to comprehend how they have succeeded in provide trainings to employees to integrate AI in the organizations. Even research can be done on how employee well being has been impacted due to the changing job requirement.

CONCLUSION

In conclusion, integrating automation and artificial intelligence profoundly transforms key sectors like manufacturing, retail, finance, and healthcare. Innovation is being fueled by these technologies. and economic growth by significantly enhancing productivity and enabling the creation of new markets. In manufacturing for example, AI-powered robotics and automated assembly lines improve output, decrease errors, and expedite production operations. In finance, AI algorithms enhance trading tactics, identify fraud and provide personalized financial advice. Healthcare benefits from AI through improved diagnostics, predictive analytics for patient care, and streamlined administrative tasks. However, the rapid adoption of AI and automation also leads to substantial labor displacement, particularly in roles that involve recurring and routine tasks. This displacement contributes to wage inequality and exacerbates social divides as certain jobs become obsolete. For instance, automated checkout systems in retail reduce the need for cashier positions, while AI-driven data entry systems in various industries minimize the requirement for clerical roles. On a social level, the benefits of AI and automation, such as improved services, efficiency, and quality of life, must be balanced with the need for significant investments in reskilling and upskilling workers. Addressing economic disparities requires targeted policies to support those affected by job translation and ensure fair access to new opportunities. To navigate this evolving landscape, the future workforce will need to acquire a diverse set of skills. Technical competencies in AI, , data science, machine learning and cybersecurity are becoming increasingly important. Understanding AI algorithms, data management, and cybersecurity measures will be crucial for developing, implementing, and maintaining AI systems. Additionally, skills in critical thinking, problem-solving, and adaptability will be essential as workers engage with advanced technologies and complex, data-driven environments.

REFERENCES

- Accenture. (2018). *Future workforce: Reworking the revolution*. Accenture.
- Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188-2244.
- Adeyeri, T. B. (2024). Economic Impacts of AI-Driven Automation in Financial Services. *Valley International Journal Digital Library*, 6779-6791.
- AI bees. (2023, December 25). Artificial intelligence's early history and future. AI bees. <https://www.ai-bees.io/post/artificial-intelligences-early-history-and-future>
- Arntz, M., Gregory, T., & Zierhn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. OECD Social, Employment and Migration Working Papers, No. 189. OECD Publishing. <https://doi.org/10.1787/5jlz9h56dvq7-en>
- Arora, A., & Athreye, S. (2002). The software industry and India's economic development. *Information Economics and Policy*, 14(2), 253-273.
- Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3-30. <https://doi.org/10.1257/jep.29.3.3>

- Au-Yong-Oliveira, M., Canastro, D., Oliveira, J., Tomás, J., Amorim, S., & Moreira, F. (2019). The role of AI and automation on the future of jobs and the opportunity to change society. In *New Knowledge in Information Systems and Technologies: Volume 3* (pp. 348-357). Springer International Publishing.
- Badet, J. (2021). AI, automation and new jobs. *Open journal of business and management*, 9(5), 2452-2463.
- Barbieri, L., Mussida, C., Piva, M., & Vivarelli, M. (2019). Testing the employment impact of automation, robots and AI: a survey and some methodological issues.
- Bessen, J. (2019). AI and jobs: The role of demand. *NBER Working Paper No. 24235*. National Bureau of Economic Research.
- Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. In *Proceedings of the 2018 Conference on Fairness, Accountability, and Transparency* (pp. 149-159).
- Brookings Institution. (2024). AI in the workplace: Transforming jobs and industries. Brookings Institution.
- Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W.W. Norton & Company.
- Brynjolfsson, E., Rock, D., & Syverson, C. (2018). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 23-57). University of Chicago Press.
- Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans—and where they can't (yet). *McKinsey Quarterly*.
- Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines*. HarperBusiness.
- Deloitte. (2020). *The future of work in healthcare*. Deloitte Insights.
- Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerization? *Technological Forecasting and Social Change*, 114, 254-280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- Government of India. (2018). *National strategy for artificial intelligence #AIForAll*. NITI Aayog.
- Hsu, F.-H. (1997). *Computer chess, then and now: The Deep Blue saga*. IBM Research.
- International Labour Organisation. (2024). Lifelong learning in the age of AI: Adapting education and training systems. International Labour Organisation.
- IBM. (2025). *Watson, Jeopardy! champion*. IBM.
- Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology*, 2(4), 230-243. <https://doi.org/10.1136/svn-2017-000101>
- Jumaev, G. (2024). The Impact of AI on Job Market: Adapting to the Future of Work. *Modern Science and Research*, 3(1).
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, 1097–1105.
- Kanitkar, T. (2020). The future of work in India: Policy and implementation. *Economic and Political Weekly*, 55(13), 35-42.
- Litman, T. (2020). Autonomous vehicle implementation predictions. *Victoria Transport Policy Institute*.
- McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. *AI Magazine*, 27(4), 12–14.
- Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). *A future that works: Automation, employment, and productivity*. McKinsey Global Institute.

- Manyika, J., Lund, S., Bughin, J., Robinson, K., Mischke, J., & Mahajan, D. (2016). *Independent work: Choice, necessity, and the gig economy*. McKinsey Global Institute.
- McKinsey & Company. (2017). *delivering change: The case for automation in logistics*. McKinsey & Company.
- McKinsey Global Institute. (2019). *Automation and the future of work in India*. McKinsey & Company.
- <https://medium.com/@ankitsrivastava37/the-evolution-of-ai-33521021f07c>
- NASSCOM. (2020). *AI adoption index in India*. National Association of Software and Service Companies.
- Nazareno, L., & Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. *Technology in Society*, 67, 101679.
- OECD. (2019). *OECD employment outlook 2019: The future of work*. OECD Publishing.
- Olaniyi, O. O., Ezeugwa, F. A., Okatta, C., Arigbabu, A. S., & Joeaneke, P. (2024). Dynamics of the digital workforce: Assessing the interplay and impact of AI, automation, and employment policies. *Automation, and Employment Policies (April 24, 2024)*.
- Oluwaseyi, J., & Cena, J. (2024). Analyzing the Impact of Artificial Intelligence on Job. *Statistics*, 14(1), 150-155.
- Paudel, R. (2024). The impact of automation and artificial intelligence (AI) on leadership and the workforce. *Indonesian Journal of Banking and Financial Technology*, 2(2), 109-124.
- Pingali, P. (2012). Green revolution: Impacts, limits, and the path ahead. *Proceedings of the National Academy of Sciences*, 109(31), 12302-12308.
- PwC. (2020). *Financial services technology 2020 and beyond Embracing disruption*. PwC.
- Schwab, K. (2017). *The fourth industrial revolution*. Crown Business.
- Shortliffe, E. H. (1976). *Computer-based medical consultations: MYCIN*. Elsevier.
- Turing, A. M. (1950). Computing machinery and intelligence. *Mind*, 59(236), 433–460. <https://doi.org/10.1093/mind/LIX.236.433>
- Topol, E. (2019). *Deep medicine: How artificial intelligence can make healthcare human again*. Basic Books.
- Turing, A. M. (1950). Computing Machinery and Intelligence. *Mind*, 59(236), 433–460.
- Tyson, L. D., & Zysman, J. (2022). Automation, AI & work. *Daedalus*, 151(2), 256-271.
- Vermeulen, B., Kesselhut, J., Pyka, A., & Saviotti, P. P. (2018). The impact of automation on employment: just the usual structural change?. *Sustainability*, 10(5), 1661.
- World Economic Forum. (2018). The future of jobs report 2018. World Economic Forum. http://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf
- World Economic Forum. (2020). *The future of jobs report 2020*. World Economic Forum.
- Zarifhonarvar, A. (2024). Economics of ChatGPT: A labor market view on the occupational impact of artificial intelligence. *Journal of Electronic Business & Digital Economics*, 3(2), 100-116.
- <https://indiaai.gov.in/article/ai-impact-on-india-jobs-and-employment>

AI-Driven FinTech Adoption among Small Retailers: A Study of Behavioural Marketing and Financial Product Usage in Mumbai

Kashish Jain & Suman Jha

PGDM Students, Durgadevi Saraf Institute of Management Studies

Kitty Rana

Assistant Professor, Durgadevi Saraf Institute of Management Studies

ABSTRACT

Artificial Intelligence (AI) and Financial Technology (FinTech) have rapidly transformed the financial behaviour of small retailers in India. Digital payment applications such as Paytm, Google Pay, and PhonePe are no longer limited to basic payment collection; they now offer sophisticated AI-driven financial products, including merchant loans, insurance policies, and customized credit facilities. Through behavioural marketing strategies like cashback offers, intelligent push notifications, and personalized product recommendations, these platforms encourage local shopkeepers to expand their use of digital financial services. This research investigates the adoption of AI-driven FinTech services among local Kirana store owners and small retail vendors situated along the high-density Borivali-to-Andheri railway station corridor in Mumbai, Maharashtra.

The study examines four major aspects: current usage patterns of digital financial services, key drivers of adoption, operational and psychological barriers, and post-adoption benefits. Furthermore, it evaluates how AI-based nudges influence financial decision-making and retailers' willingness to avail higher-value services like merchant credit lines and micro-insurance. Based on primary data collected from 230 small retailers through a structured questionnaire, along with secondary insights from academic journals and FinTech industry reports, the study employs descriptive statistics and Chi-square non-parametric tests to test behavioural hypotheses. The findings confirm that AI-driven marketing significantly accelerates the shift from traditional cash-based transactions to integrated digital financial ecosystems. Convenience, speed, and real-time liquidity emerge as primary adoption drivers, whereas fear of digital fraud, low algorithmic trust, and hidden charges remain prominent barriers. The insights offer practical implications for FinTech developers, marketers, and financial inclusion policymakers striving to build trustworthy AI-driven retail ecosystems.

Keywords: *artificial intelligence, fintech, behavioural marketing, small retailers, kirana stores, merchant loans, digital payments, financial inclusion.*

INTRODUCTION

Background of the Study

The retail landscape in India is undergoing a structural digital transformation. Small brick-and-mortar retail vendors, popular known as Kirana stores, form the backbone of urban commerce, catering to millions of households daily. Historically, these micro-enterprises operated almost exclusively on cash transactions, informal credit books (khata system), and unorganized micro-financing. However, the aggressive push toward digital payments post-demonetization, combined with the ubiquitous penetration of high-speed mobile internet and Unified Payments Interface (UPI) technology, fundamentally altered retail commerce across metropolitan centers like Mumbai.

In recent years, leading FinTech players including Paytm, PhonePe, Google Pay, BharatPe, and Khatabook have evolved beyond basic QR-code payment processing. They have integrated Artificial Intelligence (AI) and Machine Learning (ML) algorithms directly into merchant-facing applications. These AI engines analyze real-time transaction velocity, daily cash flows, inventory replenishment cycles, and customer throughput to create dynamic risk profiles. Leveraging these behavioral insights, FinTech platforms push targeted financial products, such as instant uncollateralized merchant loans,

daily auto-deduction credit lines, custom micro-insurance, and automated working capital management tools directly to small retailers.

Research Problem

Despite the widespread availability of AI-driven FinTech applications, a distinct operational gap exists between using digital applications for payment collection versus adopting embedded financial products like merchant loans and business insurance. While most small retailers in Mumbai utilize UPI QR codes for customer transactions, a significant proportion hesitates to engage with AI-recommended credit and investment solutions. Small store owners often perceive automated credit offers with skepticism, suspecting hidden fees or algorithmic traps. Furthermore, behavioral marketing tactics such as gamified cashback scratch cards, frequent push notifications, and personalized micro-credit banners can either build engagement or induce decision fatigue and distrust. Understanding how behavioral marketing interacts with merchant psychology to drive actual financial product adoption remains a critical unaddressed issue.

Research Gap

Existing empirical literature predominantly focuses on consumer adoption of mobile payments or general FinTech usage among formal Micro, Small, and Medium Enterprises (MSMEs). Very few studies specifically isolate micro-retailers (Kirana stores, street vendors, and small specialty shops) operating in dense transit corridors like the Borivali-to-Andheri suburban belt of Mumbai. Moreover, there is a lack of localized empirical research evaluating the specific role of AI-driven behavioural nudges (notifications, personalized loan limits, cashbacks) in converting passive payment users into active consumers of embedded financial products. This study fills this critical empirical and geographical gap.

Objectives of the Study

The primary objectives of this research paper are as follows:

- To examine the adoption of AI-driven FinTech services and digital payment applications among small retailers in the Borivali–Andheri corridor of Mumbai.
- To identify the key factors influencing the adoption of AI-enabled FinTech services, including behavioural marketing, operational drivers, and barriers faced by small retailers.
- To analyse the relationship between retailers' trust, perception, and awareness of AI-driven FinTech services and their adoption of AI-based financial products using Chi-square analysis.

Scope of the Study

Geographically, the study is confined to small retailers operating in proximity to key railway stations along the Western Suburban Line in Mumbai, specifically covering Borivali, Kandivali, Malad, Goregaon, Jogeshwari, and Andheri. Culturally and commercially, this region represents one of the highest-density retail corridors in India, featuring a rich mix of traditional Kirana stores, apparel vendors, food kiosks, and electronic repair shops. Conceptually, the research focuses on merchant-side FinTech applications (e.g., Paytm for Business, PhonePe Business, Google Pay for Business, BharatPe) and their integrated AI feature sets.

Significance of the Study

This study provides valuable empirical insights for multiple stakeholders:

- **For FinTech Developers & Marketers:** Gain empirical feedback on how small retailers perceive automated credit recommendations, enabling them to refine UI/UX design, push notification algorithms, and risk communication strategies.
- **For Policymakers & Regulators:** Understands the real-world barriers preventing informal micro-enterprises from accessing formal credit, helping shape targeted financial literacy initiatives and consumer protection frameworks.

- **For Researchers & Academics:** Enriches the literature on financial technology, behavioral economics, and retail digitization in emerging markets.

Limitations of the Study

While care was taken to ensure empirical rigor, the study has certain limitations:

- **Geographical Constraint:** The geographical coverage is restricted to the Western suburban corridor of Mumbai; findings may not fully generalize to rural or Tier-3 retail markets.
- **Self-Reporting Bias:** Self-reported responses from retailers regarding business revenue, loan amounts, and digital literacy may contain slight response bias.
- **Temporal Dynamics:** FinTech application algorithms and features evolve rapidly, meaning retailer perceptions may shift as market dynamics change.

LITERATURE REVIEW

Financial Technology (FinTech) has transformed the way small businesses manage payments, credit, and financial services. The integration of Artificial Intelligence (AI) into FinTech applications has further enhanced services through personalized recommendations, automated credit assessment, fraud detection, business analytics, and digital financial management. Recent studies have examined the adoption of AI-enabled FinTech services among small businesses, the factors influencing adoption, and the challenges faced by retailers. The following studies provide the theoretical foundation for the present research.

Author(s) & Year	Study	Key Findings
Bhattacharjee et al. (2024)	<i>Determinants of Digitalization in Unorganized Localized Neighbourhood Retail Outlets in India</i>	Found that digital infrastructure, customer demand, and perceived usefulness significantly influence the digitalization of Kirana stores and other small retailers in India.
Sharma, Ilavarasan & Karanasios (2024)	<i>Small Businesses and FinTech: A Systematic Review and Future Directions</i>	Reviewed 103 studies and concluded that FinTech improves payment efficiency, financial inclusion, and business performance, while highlighting the need for more research on small retailers and emerging AI-enabled financial services.
Bakhshi et al. (2024)	<i>Barriers in Adoption of FinTech by Street Vendors and Hawkers in India</i>	Identified cybersecurity concerns, limited digital literacy, trust issues, and poor internet connectivity as major barriers to FinTech adoption among informal retailers.
Sharma et al. (2024)	<i>Cluster-based Systematic Literature Review: Understanding FinTech Adoption and Challenges</i>	Reported that ease of use, perceived usefulness, trust, and awareness are key determinants of FinTech adoption, while security and privacy concerns remain significant barriers.
Anderson et al. (2024)	<i>Fintech Failure: Examining B2B and B2C Solutions for Two-Sided Platform Adoption</i>	Found that many offline retailers continue to rely on cash despite the availability of digital payment systems, emphasizing the importance of merchant acceptance and behavioural factors in FinTech adoption.
Srinivasan & Kumar (2023/2024)	<i>Digitalisation Promotes Adoption of Soft Information in SME Credit Evaluation</i>	Showed that AI, digital data, and soft information are increasingly used by Indian banks to improve SME credit assessment and financing decisions.

Research Gap

Most existing studies have examined FinTech adoption at a broad level by focusing on SMEs, digital payments, or consumers. Limited research has specifically explored how AI-enabled FinTech applications influence the behaviour of small retailers, particularly their trust, awareness, use of AI-driven financial services, and preference for AI-based lending in the Borivali–Andheri corridor of Mumbai. This study addresses that gap by examining AI-enabled FinTech adoption among local retailers using primary survey data and statistical analysis.

RESEARCH METHODOLOGY

Research Design

This study adopts a descriptive and analytical quantitative research design. A cross-sectional survey methodology was chosen to collect standardized data from small retail business owners at a single point in time, allowing for statistical testing of behavioural relationships.

Data Sources

- **Primary Data:** Primary data was collected directly from small shop owners through structured face-to-face field surveys and digital questionnaire administration across the target geographical locations.
- **Secondary Data:** Secondary data was gathered from peer-reviewed academic journals, RBI published reports, FinTech industry papers, market research reports (McKinsey, EY), and financial news portals.

Sampling Technique & Population

The target population comprises micro and small retail enterprise owners operating physical retail shops along the Borivali-to-Andheri commercial station belt in Mumbai. A Convenience Sampling combined with Stratified Quota Sampling technique was employed to ensure adequate representation across diverse retail categories (Kirana/Grocery, Specialty/Apparel, Electronics, Food/Kiosks).

Sample Size

The survey was conducted among 360 small retailers. Out of these, 230 valid responses were received and used for data analysis in this research.

Data Collection Method & Research Instrument

Primary data was gathered using a pre-tested, structured questionnaire consisting of three core sections: (A) Demographic and Business Profile, (B) FinTech Application Usage and Behavioural Marketing Exposure, and (C) Perceived Drivers, Barriers, and Adoption Outcomes. Questions utilized 5-point Likert Scales (1 = Strongly Disagree to 5 = Strongly Agree), multiple-choice questions, and categorical response options.

Statistical Tools Used

Data was coded and analyzed using Statistical Software (Jamovi / Python Scipy). Descriptive statistics (percentages, frequencies, mean scores) were used to profile demographics and app usage patterns. Non-parametric Chi-square Tests of Independence (χ^2) were conducted to test hypotheses regarding behavioural marketing impact and adoption drivers at a standard significance level of $\alpha = 0.05$.

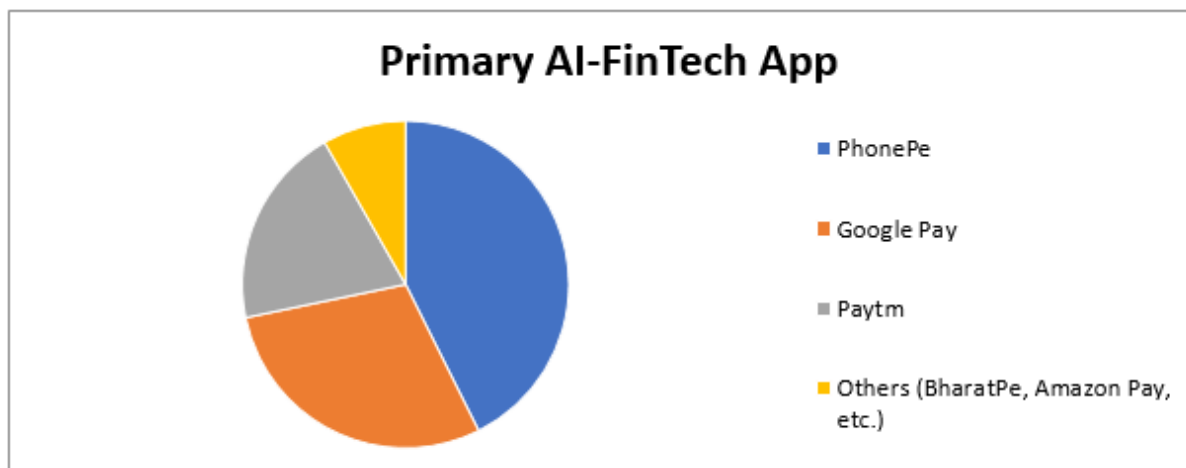
DATA ANALYSIS AND INTERPRETATION

This chapter presents the analysis and interpretation of data collected from small retailers located in the Borivali-Andheri corridor of Mumbai. The responses were analyzed using descriptive statistics and the Chi-square Test of Independence in Jamovi. The analysis includes two descriptive pie charts and two hypothesis tests.

Descriptive Analysis

Most Preferred AI-enabled FinTech Application

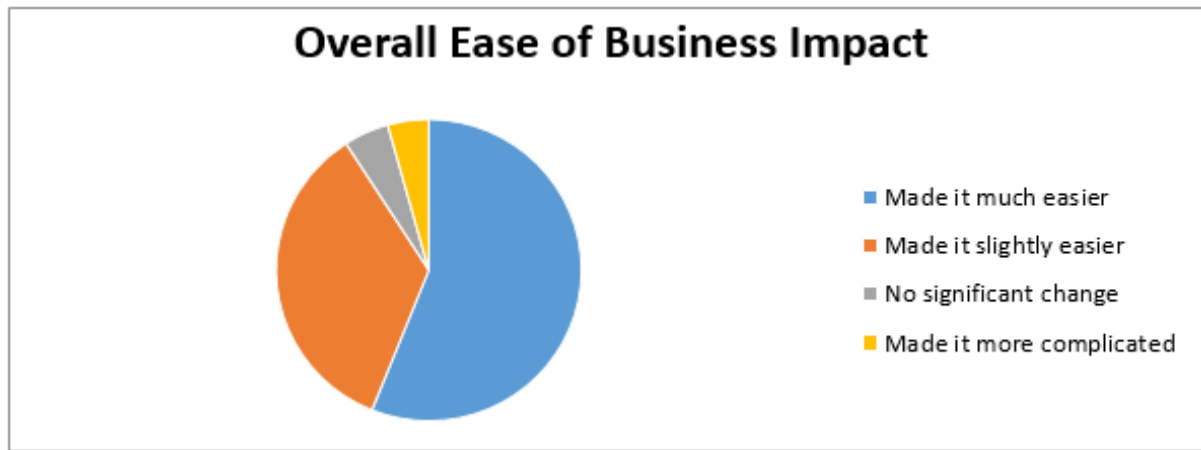
Primary AI-FinTech App		
Option / Response	Count	Percentage
PhonePe	98	42.6%
Google Pay	67	29.1%
Paytm	46	20.0%
Others (BharatPe, Amazon Pay, etc.)	19	8.3%
Total	230	100.0%



Interpretation

The majority of respondents preferred PhonePe and Google Pay for their business transactions. This indicates that AI-enabled digital payment applications are widely accepted among small retailers. The findings suggest that digital payment platforms have become an integral part of day-to-day business operations.

Impact of the Digital Ecosystem on Ease of Doing Business Overall Ease of Business Impact		
Option / Response	Count	Percentage
Made it much easier	129	56.1%
Made it slightly easier	80	34.8%
No significant change	11	4.8%
Made it more complicated	10	4.3%
Total	230	100.0%



Interpretation

Most respondents reported that the digital ecosystem has made their business operations easier. This indicates that AI-enabled FinTech services have contributed to improving transaction efficiency and overall business convenience for small retailers.

Hypothesis Testing

Test

1

Relationship between Trust in AI and Preference for AI-based Loans

Hypotheses

H₀: There is no significant association between trust in AI and preference for AI-based instant loans.

H₁: There is a significant association between trust in AI and preference for AI-based instant loans.

Contingency Tables					
Trust in AI Financial Data Security	Preference: AI Loans vs Bank Loans				Total
	Do not wish to take loans from either	Prefer traditional Bank loans	Slight preference for AI-based loans	Strong preference for AI-based loans	
Complete Trust	8	17	15	7	47
Neutral / Uncertain	8	15	12	12	47
No Trust at all	5	8	5	0	18
Partial Trust	15	42	36	25	118
Total	36	82	68	44	230

χ^2 Tests			
	Value	df	p
χ^2	8.59	9	0.476
N	230		

Interpretation

The Chi-square test produced $\chi^2 = 8.59$, $df = 9$, and $p = 0.476$. Since the p-value is greater than 0.05, the null hypothesis failed to be rejected. This indicates that trust in AI does not have a statistically significant association with retailers' preference for AI-based instant loans.

Test 2

Relationship between AI Recommendation Helpfulness and Ease of Doing Business

Hypotheses

H₀: There is no significant association between AI recommendation helpfulness and ease of doing business.

H₁: There is a significant association between AI recommendation helpfulness and ease of doing business.

Contingency Tables

Business Growth Impact from AI Recs	Ease of Doing Business Impact				
	Made it more complicated	Made it much easier	Made it slightly easier	No significant change	Total
Highly Helpful	2	32	15	3	52
Not Helpful at all	1	3	9	0	13
Not very Helpful	1	17	10	3	31
Somewhat Helpful	6	77	46	5	134
Total	10	129	80	11	230
		Value	df	p	
χ^2		10.9	9	0.28	
N		230			

Interpretation

The Chi-square test produced $\chi^2 = 10.90$, $df = 9$, and $p = 0.280$. Since the p-value is greater than 0.05, the null hypothesis failed to be rejected. This indicates that the perceived helpfulness of AI recommendations is not significantly associated with the ease of doing business among the surveyed retailers.

FINDINGS AND DISCUSSION

The major findings of the study are as follows:

- Most small retailers use AI-enabled digital payment applications such as PhonePe, Google Pay and Paytm for their daily business transactions.
- Retailers generally believe that the digital payment ecosystem has made business transactions faster, more convenient and easier.
- Most respondents are aware of AI-enabled features such as merchant loans, business insights and personalized recommendations, although their level of usage differs.
- The first Chi-square test found no significant relationship between trust in AI for financial data security and preference for AI-based loans ($p = 0.476$). This indicates that trust in AI alone does not influence retailers' loan preferences.
- The second Chi-square test found no significant relationship between the perceived helpfulness of AI recommendations and the ease of doing business ($p = 0.280$). This suggests that AI recommendations alone are not responsible for improving business operations.
- Overall, the findings indicate that AI supports small retailers by improving digital payment experiences and providing additional financial services, but the adoption of these services is also influenced by factors such as convenience, customer demand, ease of use and accessibility rather than AI features alone.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study concludes that AI-driven FinTech applications have played a transformative role in digitizing small retail commerce across the Borivali-to-Andheri corridor in Mumbai. AI algorithms and behavioural marketing strategies successfully motivate small Kirana owners to move beyond basic QR code payments into credit and risk management products. However, bridging the remaining adoption gap requires moving beyond automated push notifications to build deep algorithmic transparency, fair interest disclosures, and hybrid customer support mechanisms.

Suggestions & Recommendations

- **1. Vernacular & Voice AI Integration:** FinTech apps should incorporate vernacular voice assistants and transparent visual fee calculators explaining loan repayments in clear terms without hidden penalties.
- **2. Contextual Behavioral Nudging:** Rather than sending generic blast notifications, AI engines should deliver context-aware nudges aligned with specific stock purchasing days or festival seasonal surges.
- **3. Dynamic Micro-Repayment Flex:** Provide flexible repayment schedules that adjust dynamically during low-revenue business days to reduce financial stress on micro-retailers.
- **4. Hybrid Customer Support:** FinTech providers should establish local digital helpdesks or dedicated field relationship executives in major retail clusters to resolve merchant disputes quickly.

Future Scope of Research

Future research can expand this inquiry across comparative geographic regions, such as comparing Tier-1 metropolitan retailers with Tier-3 rural store owners. Longitudinal studies tracking merchant loan default rates and long-term business profitability post-FinTech adoption would also provide deeper insights into the economic impact of AI-driven micro-finance.

REFERENCES

- Bhattacharjee, B., Kumar, S., Verma, P., & Maiti, M. (2024). Determinants of digitalization in unorganized localized neighborhood retail outlets in India. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(3), 1699-1716.
- Sharma, S. K., Ilavarasan, P. V., & Karanasios, S. (2024). Small businesses and FinTech: a systematic review and future directions: SK Sharma et al. *Electronic Commerce Research*, 24(1), 535-575.
- Bakhshi, P., Agrawal, R., Mendon, S., Frank, D., Spulbar, C., Birau, R., & Filip, R. D. (2024). Barriers in adoption of FinTech by street vendors and hawkers in India using interpretive structural modeling. *Business: Theory and Practice*, 25(1), 231-240.
- Sharma, S., Sharma, M., & Dhingra, D. (2024). Cluster-based systematic literature review: Understanding FinTech adoption and challenges. *Abhigyan*, 42(3), 206-227.
- Anderson, S. J., Iacovone, L., Narayanan, S., & Kankanhalli, S. (2024). Fintech failure: Examining B2B and B2C solutions for two-sided platform adoption.
- Hardik, N. (2024). Digitalisation promotes adoption of soft information in SME credit evaluation: The case of Indian banks. *Digital Finance*, 6(1), 23-54.

ANNEXURE

Research Questionnaire: AI-FinTech Adoption in Mumbai Retail

Section 1: Respondent & Store Profile

1. Name of the Respondent: _____
2. Name of the Retail Store: _____
3. Location of the store (Borivali–Andheri Corridor):
 - A) Borivali / Kandivali
 - B) Malad / Goregaon
 - C) Jogeshwari / Andheri
 - D) Nearby station-side market (Other)
4. Category of your retail business:
 - A) Kirana / General Store
 - B) Medical / Chemist Shop
 - C) Stationery / Electronics
 - D) FMCG / Food Stall
5. Total years of business operation:
 - A) Less than 2 years
 - B) 2 – 5 years
 - C) 5 – 10 years
 - D) More than 10 years

Section 2: Usage & Transition Patterns

6. Which AI-driven application do you use most for business transactions?
 - A) PhonePe
 - B) Google Pay
 - C) Paytm
 - D) Others (BharatPe, Amazon Pay, etc.)
7. Current status of your transition from cash to digital:
 - A) Fully Digital (Over 75% of sales)
 - B) Mostly Digital (50% – 75% of sales)
 - C) Hybrid (Equal Cash and Digital)
 - D) Mostly Cash (Digital only on request)
8. Which AI-integrated service have you explored beyond payments?
 - A) Merchant Loans / Instant Credit
 - B) Business / Shop Insurance
 - C) Digital Khata / Ledger Management
 - D) None (Only use for payments)

Section 3: Adoption Drivers (Motivators)

9. What was the primary reason you adopted digital FinTech services?
 - A) High customer demand/convenience
 - B) Transaction speed (No change/chutta issues)
 - C) Attractive cashback and reward offer
 - D) Peer influence (Other retailers using it)
10. How would you rate the importance of "Instant Settlement" for your cash flow?
 - A) Extremely Important
 - B) Moderately Important
 - C) Slightly Important
 - D) Not Important at all

Section 4: Barriers & Technical Challenges

11. What is the biggest barrier you face with AI-integrated FinTech?
 - A) Fear of cyber-fraud and security

- B) Technical glitches (Server down/Money stuck)
- C) Complexity of AI-based features
- D) Poor internet connectivity in the area

12. How often do technical failures lead to a lost sale or customer dispute?

- A) Frequently (Multiple times a week)
- B) Occasionally (Once or twice a month)
- C) Rarely (Once in a few months)
- D) Never

Section 5: AI Influence & Behavioral Marketing

13. How often do you check AI-generated business insights/reports in the app?

- A) Weekly
- B) Monthly
- C) Only during tax/accounting periods
- D) Never

14. How does the "Soundbox" (Audio alert) impact your trust in the transaction?

- A) Increases trust significantly
- B) Increases trust moderately
- C) Makes no difference to trust
- D) I do not use a Soundbox

15. How do you respond to notifications for "Pre-approved Loans" or "Offers"?

- A) Always click to check details
- B) Sometimes click out of curiosity
- C) Rarely click on them
- D) Immediately clear/ignore all notifications

Section 6: Perception & Awareness

16. Level of awareness that AI tracks your data to provide financial scores:

- A) Very High Awareness
- B) Moderate Awareness
- C) Low Awareness
- D) No Awareness at all

17. Preference for AI-based "Instant Loans" versus traditional Bank Loans:

- A) Strong preference for AI-based loans
- B) Slight preference for AI-based loans
- C) Prefer traditional Bank loans
- D) Do not wish to take loans from either

18. Do you feel AI-driven recommendations help in growing your business?

- A) Highly Helpful
- B) Somewhat Helpful
- C) Not very Helpful
- D) Not Helpful at all

19. What is your level of trust in AI handling your financial data securely?

- A) Complete Trust
- B) Partial Trust
- C) Neutral / Uncertain
- D) No Trust at all

20. Overall, how has the digital ecosystem impacted your ease of doing business?

- A) Made it much easier
- B) Made it slightly easier
- C) No significant change
- D) Made it more complicated

The Role of AI and Chatbots in Guest Services and their Influence on Employee Attrition in 5-Star Hotels in Mumbai

Rahul Parchure

Assistant Professor, Anjuman-I-Islam's Allana Institute of Management Studies, Mumbai

Bernadette D'Silva

Director, Anjuman-I-Islam's Allana Institute of Management Studies, Mumbai

ABSTRACT

The hospitality industry is undergoing rapid digital transformation through the adoption of Artificial Intelligence (AI) and chatbot technologies. In five-star hotels, these technologies are increasingly used for reservations, check-in support, room-service requests, routine guest enquiries and concierge recommendations. The present study examines how AI and chatbots influence employee attitudes, job satisfaction, and workload, perceived job security, well-being, retention and attrition intentions among employees in five-star hotels in Mumbai.

The study uses a structured questionnaire and a mixed-method orientation. The reported statistical analysis is based on 98 respondents and includes descriptive interpretation, Chi-square tests, reliability analysis, Pearson correlation and a Shapiro–Wilk normality test. The findings show generally positive perceptions of AI: employees associate AI with greater efficiency, faster and more accurate service, reduced repetitive workload and greater scope for personalized guest interaction. At the same time, job-security concerns and anxiety about future technological change remain important.

The inferential results indicate that gender and income do not have statistically significant associations with the major AI-related workplace variables. The measurement scale demonstrates strong internal consistency (Cronbach's Alpha = 0.856; McDonald's Omega = 0.857). Pearson correlations are positive and statistically significant among AI operations, employee attitudes, well-being/job satisfaction, and retention/organizational commitment. The study therefore indicates that AI can support employee outcomes when implemented as an augmentation tool with adequate training, communication, organizational support and opportunities for skill development.

Keywords: artificial intelligence, chatbots, guest services, employee attrition, job satisfaction, employee retention, five-star hotels, technology adoption, human–technology interaction, mumbai

1. INTRODUCTION

Hospitality is traditionally a human-centric industry, but five-star hotels are increasingly combining human service with digital technologies. AI and chatbots are being introduced to improve speed, consistency, accuracy, personalization and availability of guest services. Their use can automate routine enquiries and transactions while allowing employees to devote greater attention to complex service recovery, relationship building and personalized experiences.

The operational benefits of AI are accompanied by human-resource implications. Employees may experience lower workload and greater productivity, but they may also perceive automation as a threat to employment, role identity and future career prospects. This issue is particularly important in hospitality because employee engagement, emotional labour and interpersonal interaction are central to service quality.

Employee attrition remains a persistent concern in five-star hotels because of demanding work schedules, job stress and career-growth expectations. AI adds a further dimension: its effect on retention depends not only on the technology itself but also on how employees interpret and

experience its implementation. AI may be viewed as a challenge and opportunity for development, or as a hindrance and replacement threat.

The study therefore focuses on the balance between technological efficiency and human engagement. It examines whether AI adoption is associated with positive workplace outcomes and whether employee characteristics such as gender and income influence these perceptions.

PROBLEM STATEMENT

The central problem addressed by the study is the uncertainty surrounding the employee consequences of AI and chatbot adoption in guest services. Hotels seek efficiency and enhanced guest experience, while employees need security, meaningful work, training, recognition and career opportunities. Understanding this balance is necessary for sustainable workforce development.

SIGNIFICANCE OF THE STUDY

- Provides an employee-centred view of AI adoption in five-star hotel guest services.
- Highlights both operational benefits and possible psychological/job-security concerns.
- Generates evidence relevant to hotel HR managers and operational leaders.
- Addresses the Indian/Mumbai hospitality context identified as under-researched in the original paper.
- Supports strategies for AI adoption that complement rather than replace human talent.

2. LITERATURE REVIEW

The original paper presents the literature as showing a dual effect of AI: it can operate as a resource that improves efficiency and job quality, or as a stressor that increases insecurity and turnover intention. Early research largely emphasized service speed, consistency and scalability, while newer work increasingly examines employee perceptions and behavioural outcomes.

AI as a Resource

Automation of repetitive enquiries, basic reservations and standard service procedures can reduce routine workload and release employees for higher-value interpersonal activities. The literature cited in the original paper suggests that AI augmentation, when combined with training and managerial support, can improve task efficiency, personalization and service quality.

AI as a Stressor

Employees who interpret AI primarily as a replacement technology may experience anxiety, job insecurity, lower organizational commitment and stronger turnover intentions. Transparent communication, organizational support and opportunities to develop new skills can reduce these negative reactions.

Role Identity and Job Design

Automation can alter employees' professional identities when routine guest interaction is removed. Reduced human contact may lower intrinsic rewards and weaken social connections. Conversely, deliberate role redesign can preserve and expand relational responsibilities such as complex problem-solving, guest-experience curation and service recovery.

Research Gaps Identified in the Original Paper

- Limited employee-centric research compared with research on operational and guest-service benefits.
- Insufficient direct empirical evidence linking AI implementation with attrition and retention.
- Limited research in the Indian five-star hotel context, particularly Mumbai.
- Under-examination of training, leadership communication and organizational support as mediating or moderating factors.
- Heavy reliance on cross-sectional designs rather than longitudinal evidence.
- Insufficient attention to emotional, social and professional-identity consequences of automation.

Conceptual Direction

The study conceptually links AI integration in guest services with employee attitudes, well-being and job satisfaction, and ultimately with retention/organizational commitment. Training, communication and organizational support are identified as important contextual factors, while perceived job security and professional identity represent important employee concerns.

3. OBJECTIVES OF THE STUDY

- To examine the extent of AI and chatbot integration in guest service operations of five-star hotels and its impact on employee roles.
- To assess the relationship between AI adoption and employee job satisfaction, workload and perceived job security.
- To investigate the direct and indirect effects of AI implementation on employee attrition and turnover intentions.
- To explore the mediating and moderating roles of organizational support, training and communication.
- To understand employees' emotional and social responses to AI, particularly professional identity and engagement.
- To provide evidence-based recommendations for balancing AI-driven guest-service efficiency with employee retention, especially in the Indian hospitality context.

4. HYPOTHESES

Hypothesis	Null hypothesis (H ₀)	Alternative hypothesis (H ₁)
H1	No significant association between gender and employees' perceptions of AI in hotel service operations.	A significant association exists
H2	Gender has no significant association with employee well-being and job satisfaction in an AI-enabled workplace.	A significant association exists
H3	Income level has no significant association with AI-related workplace factors including well-being, job satisfaction, retention and organizational commitment.	A significant association exists

The original analysis subsequently tested gender and income relationships using Chi-square procedures at the 0.05 significance level.

5. RESEARCH METHODOLOGY

Research Approach and Design

The original paper describes a structured questionnaire and a mixed-method approach focused on frontline and guest-service employees in selected five-star hotels. The quantitative component forms the basis of the reported statistical analysis. Responses were measured largely through a five-point Likert scale, where 1 represented Strongly Disagree and 5 represented Strongly Agree.

Sample

The statistical outputs report N = 98 respondents. The gender contingency tables show 74 respondents in one gender category and 24 in the other. Income was divided into five coded categories containing 37, 17, 13, 15 and 16 respondents respectively.

Instrument

The questionnaire covered: demographic information; AI and chatbot use in guest services; employee perceptions and attitudes toward AI; job satisfaction and workload; employee retention and attrition intention; and open-ended questions.

Construct	Core aspects measured
AI in hotel service operations	AI/ <u>chatbot</u> use, efficiency, repetitive queries, workload, accuracy/speed, training, personalized service
Employee attitudes toward AI	Comfort, career opportunities, job-replacement concern, usability, management communication, anxiety
Well-being & job satisfaction	Job satisfaction, feeling valued, stress, work-life balance, digital <u>upskilling</u>
Retention & commitment	Intention to stay, loyalty, thoughts of leaving, AI-related stay/leave influence, training/support and retention

Major Constructs

Statistical Techniques

- Descriptive interpretation of Likert-scale responses.
- Chi-square tests to examine associations between gender/income and key AI-related variables.
- Cronbach's Alpha and McDonald's Omega for internal consistency.
- Pearson correlation to assess relationships among the four principal constructs.
- Shapiro–Wilk test to assess multivariate normality.

6. DATA ANALYSIS AND KEY FINDINGS

AI Adoption and Guest-Service Efficiency

About 57% of respondents agreed that their hotel uses AI-based tools or chatbots, with 33.7% selecting the highest rating. Around 20.4% indicated that AI tools were not used. This demonstrates meaningful but uneven AI adoption across the respondents' hotel environments.

More than 53% of respondents gave ratings of 4 or 5 for the statement that AI and chatbots improve guest-service efficiency, while approximately 23% gave ratings of 1 or 2. The results therefore indicate a generally favourable view of AI's operational contribution.

Chatbots were viewed particularly positively for handling repetitive guest queries. Respondents also reported that AI improves accuracy and speed of service delivery. More than half perceived positive effects at the higher response levels.

Workload, Training and Comfort

Almost half of respondents believed AI reduced their daily workload, although a sizeable neutral group indicated that the effect varies by role, task type or level of implementation. Approximately half felt adequately trained, while about one-quarter perceived training as insufficient and another quarter were neutral.

Most respondents were comfortable working alongside AI and chatbot systems. The smaller negative group suggests that outright resistance is limited, but the neutral group indicates continuing adaptation and a need for confidence-building.

Personalized Guest Experience

More than half of employees felt AI helped them provide personalized guest experiences, potentially because automation reduces routine work and releases time for higher-touch interactions. Neutral and negative responses indicate that this benefit is not yet experienced consistently by all employees.

Employee Attitudes, Well-Being and Retention

Employee Attitudes and Job Security

The study reports generally positive attitudes toward AI usability and job performance. More than half of respondents considered AI user-friendly and supportive. Employees also showed optimism about AI and automation creating new career opportunities.

At the same time, job-security concerns were significant. The largest response category was neutral/moderate concern, while 42.8% selected higher concern levels regarding the possibility that AI could replace human jobs. More than 40% also reported some degree of anxiety about future technological changes.

Management Communication

Although a portion of employees felt that management communicates effectively about AI, a substantial neutral or uncertain group remained and nearly one-fifth perceived communication as lacking. The paper therefore identifies transparency and clarity as areas requiring improvement.

Job Satisfaction and Well-Being

More than two-thirds of respondents expressed strong satisfaction with their current job roles. AI was also generally perceived as helping to reduce stress associated with repetitive tasks. Nearly half reported positive effects of technological support on work-life balance, although a substantial neutral group suggests that benefits are not uniform.

Upskilling and Retention

A majority viewed the organization as providing opportunities for digital and technical upskilling. Employee intention to remain with the hotel was generally positive, and loyalty was described as strong. However, the results also identified a meaningful group with potential turnover concerns.

More than half of the workforce indicated that investment in AI-related training and development would make them more likely to stay. This is a key practical finding: employees appear more receptive to technological change when organizations invest in their capability and future employability.

Inferential Analysis

Chi-square: Gender

Variable	χ^2	df	p	Decision
AI in Hotel Service Operations	3.370	4	0.498	Not significant
Employee Attitudes Toward AI	6.969	4	0.138	Not significant
Employee Well-Being & Job Satisfaction	3.710	4	0.447	Not significant
Employee Retention & Commitment	4.113	4	0.391	Not significant

All p-values are greater than 0.05. Therefore, the study reports no statistically significant association between gender and the four major AI-related workplace variables. Male and female respondents show broadly similar perceptions and experiences in relation to AI, well-being, job satisfaction, retention and commitment.

Chi-square: Income

Relationship	χ^2	df	p	Decision
Income $\times$ AI in Hotel Service Operations	13.087	16	0.666	Not significant
Income $\times$ Employee Attitudes toward AI	17.506	16	0.354	Not significant
Income $\times$ Well-Being & Job Satisfaction	13.414	16	0.642	Not significant
Income $\times$ Retention & Commitment	14.931	16	0.530	Not significant

The income-related tests are also non-significant. The original paper concludes that employees across income groups display similar perceptions of AI adoption, well-being, satisfaction, retention intention and organizational commitment.

Reliability and Correlation Analysis

Reliability

Measure	Estimate	95% CI
Cronbach's Alpha (α)	0.856	0.797–0.916
McDonald's Omega (ω)	0.857	0.810–0.903

Both reliability coefficients exceed the commonly used 0.70 threshold. The original study therefore concludes that the questionnaire scale demonstrates strong internal consistency and is suitable for subsequent analysis.

Pearson Correlations

Variables	r	p
AI Operations $\leftrightarrow$ Employee Attitudes	0.613	< .001
AI Operations $\leftrightarrow$ Well-Being & Job Satisfaction	0.517	< .001
Employee Attitudes $\leftrightarrow$ Well-Being & Job Satisfaction	0.603	< .001
AI Operations $\leftrightarrow$ Retention & Commitment	0.541	< .001
Employee Attitudes $\leftrightarrow$ Retention & Commitment	0.638	< .001
Well-Being & Job Satisfaction $\leftrightarrow$ Retention & Commitment	0.690	< .001

All reported correlations are positive and statistically significant. The strongest relationship is between well-being/job satisfaction and retention/organizational commitment ($r = 0.690$). This indicates that stronger positive workplace experiences are closely associated with stronger retention and commitment.

Normality

The Shapiro–Wilk test reported a statistic of 0.975 with $p = 0.004$, indicating deviation from perfect normality. The original paper notes that the sample size of 98 supports interpretation of the Pearson correlations despite this non-normality.

7. CONCLUSION

The study concludes that AI and chatbot adoption in five-star hotel guest services can generate substantial operational and employee benefits when implemented as an augmentation strategy. Employees generally recognize improvements in efficiency, service speed, accuracy, repetitive-task management and opportunities for personalized guest interaction. Positive perceptions of AI are associated with better attitudes, well-being, job satisfaction and retention/organizational commitment.

At the same time, the study confirms that technological transformation creates employee concerns. Job insecurity, uncertainty and anxiety about future technological changes cannot be ignored. AI implementation therefore needs to be accompanied by training, communication, role redesign, recognition and career development. The strongest correlation in the study—between well-being/job satisfaction and retention—reinforces the importance of maintaining a positive employee experience.

8. RECOMMENDATIONS

- Implement AI as a support and augmentation tool, clearly communicating that its purpose is to complement human service rather than automatically replace employees.
- Provide structured induction and continuous AI upskilling for frontline and guest-service employees.
- Create transparent communication channels explaining what AI systems do, why they are being introduced and how employee roles will evolve.
- Redesign jobs so employees move from repetitive transactions toward relationship management, complex problem-solving and personalized guest experiences.
- Develop visible AI-related career pathways and certification opportunities to reduce fear of technological displacement.
- Monitor employee well-being, job satisfaction and turnover intention during major technology implementations.
- Use employee feedback and participation before and during AI implementation.
- Recognize employees who successfully combine digital tools with high-quality human interaction.
- Ensure technology does not remove the human touch that is central to luxury hospitality.
- Use retention strategies alongside technology strategies, because AI efficiency alone does not guarantee employee commitment.

9. LIMITATIONS AND FUTURE RESEARCH

The original paper identifies several areas requiring further investigation. The cross-sectional nature of the study limits conclusions about how attitudes and retention evolve over time. Future research should use longitudinal designs to track actual turnover and changing perceptions before and after AI implementation. Intervention studies could also evaluate specific training, role-redesign and communication programmes.

Further research should examine differences across hotel categories, departments, roles and organizational cultures, and should distinguish between turnover intention and actual employee attrition. Additional mediators and moderators such as perceived organizational support, psychological capital, leadership, communication quality and organizational culture can strengthen the explanatory model.

Final Statement

The central message of the study is that AI should be managed as a human-resource transformation as much as a technological transformation. Five-star hotels can obtain the efficiency benefits of AI while protecting employee engagement and retention when technology is accompanied by training, communication, meaningful role redesign and sustained organizational support.

10. REFERENCES

- Brown, L., Chen, M., & Kapoor, R. (2022). The impact of artificial intelligence augmentation on employee task performance and job satisfaction in hospitality services. *International Journal of Hospitality Management*, 102, 103184.
- Green, A., & Taylor, S. (2024). Enhancing guest personalization through AI-enabled service processes: Employee perceptions and organisational support mechanisms. *Journal of Service Management*, 35(1), 45–63.
- Lee, J., & Kim, H. (2023). AI-induced challenge and hindrance stressors: Effects on psychological capital and turnover intention in hotel employees. *Tourism Management*, 94, 104651.
- Lewis, P. (2022). Artificial intelligence adoption and workforce sustainability: A review of emerging evidence in luxury hospitality. *Journal of Hospitality & Tourism Research*, 46(8), 1594–1612.
- Nguyen, T., & Martinez, J. (2023). Chatbots and AI in tourism and hospitality: A systematic review and bibliometric analysis. *Tourism Review*, 78(4), 923–946.
- Patel, R., & Singh, A. (2022). Role redesign in AI-augmented hotel operations: Implications for employee identity and retention. *Cornell Hospitality Quarterly*, 63(3), 325–339.
- Smith, J., & Jones, R. (2023). Employee perceptions of AI and turnover intention in service industries: A multi-sector analysis. *Service Industries Journal*, 43(5–6), 412–431.
- Wang, L., Zhao, Y., & Park, S. (2023). Job insecurity in the age of automation: The moderating role of organisational communication and skill development. *Journal of Hospitality and Tourism Technology*, 14(2), 287–304.

11. QUESTIONNAIRE: STRUCTURE RETAINED FROM THE ORIGINAL PAPER

- Section A – General Information: hotel, gender, age, department, designation, hospitality experience and service duration.
- Section B – Use of AI and Chatbots in Guest Services: seven Likert-scale statements covering adoption, efficiency, repetitive queries, workload, accuracy/speed, training and personalization.
- Section C – Employee Perceptions and Attitudes: six statements covering comfort, career opportunities, replacement concern, usability, management communication and anxiety.
- Section D – Job Satisfaction and Workload: five statements covering job satisfaction, organizational value, repetitive-task stress, work-life balance and digital upskilling.
- Section E – Retention and Attrition Intention: five statements covering intention to stay, loyalty, thoughts of leaving, AI-related stay/leave influence and training/support.
- Section F – Open-Ended Questions: benefits of AI, challenges/concerns and ways to balance technology with human touch.

'Platform Urbanism': Evaluating Algorithms within Smart Cities

Ar. Mildred Jose

Assistant Professor, LS Raheja School of Architecture, Mumbai

ABSTRACT

'Smart cities' are contemporary urban models that promise high efficiency, connectivity, improved quality of life and thereby long-term sustenance. They integrate artificial intelligence and digital platforms to facilitate and promote better quality of life for urban citizens; projecting cities as inclusive and future ready environments. However, in reality most of these systems are limited in their geographical reach, access, ease of use raising concerns about who are the true benefiter from such technological advancements. This paper examines the idea of 'Platform Urbanism', where urban life is highly governed by algorithmic digital platforms and systems. The research intends to evaluate the operation of such technologies within smart cities as inclusive or exclusive. The research adopts a qualitative and theoretical approach centered around understanding digital outreach of such platforms, respective capitalistic motives and thereby spatial inequality.

The objective of the study is to critically examine the unsaid relationship between digital urban systems and accessibility in urban areas. It seeks to uncover and understand how such technologies, in the pretext of promoting efficiency and convenience, remain often concentrated within technologically connected populations, eventually marginalizing the others. Such fragmented urban experiences serve as important markers of uneven spatial developments. The paper thus highlights the need for more equitable and spatially responsive frameworks that address diverse on-ground realities in contemporary urban areas; highlighting re-evaluation of existing disconnections and urban experiences.

Keywords: *platform urbanism, capitalist model, urban governance, common man, right to the city, smart city*

1. INTRODUCTION TO THE SMART CITY CONCEPT

The Smart Cities Mission was launched by the Ministry of Housing and Urban Affairs (MoHUA) in India in 2015. It aimed to transform urban areas by providing efficient services with robust infrastructure to achieve sustainable development. It projected high quality of living through its smart solutions and proposed comprehensive methods of strengthening physical, social, economic and institutional pillars. It mainly focused on three pillars - livability, economic ability and sustainability with basic access to housing, transport, education, healthcare and recreation; tailored to meet diverse needs of city dwellers. It also aimed at fostering local area development and leveraging technology for smart outcomes. Its ultimate goal was to connect technology, governance and community to improve urban performance and deliver better quality public services through replicable models that could be used in other cities. With urbanization continuing to surge globally, smart cities emerged as beacons of hope, promising efficiency, sustainability and an enhanced quality of life. Smart cities subsequently expanded as models with pillars such as smart economy, smart governance, smart mobility, smart environment and smart living.

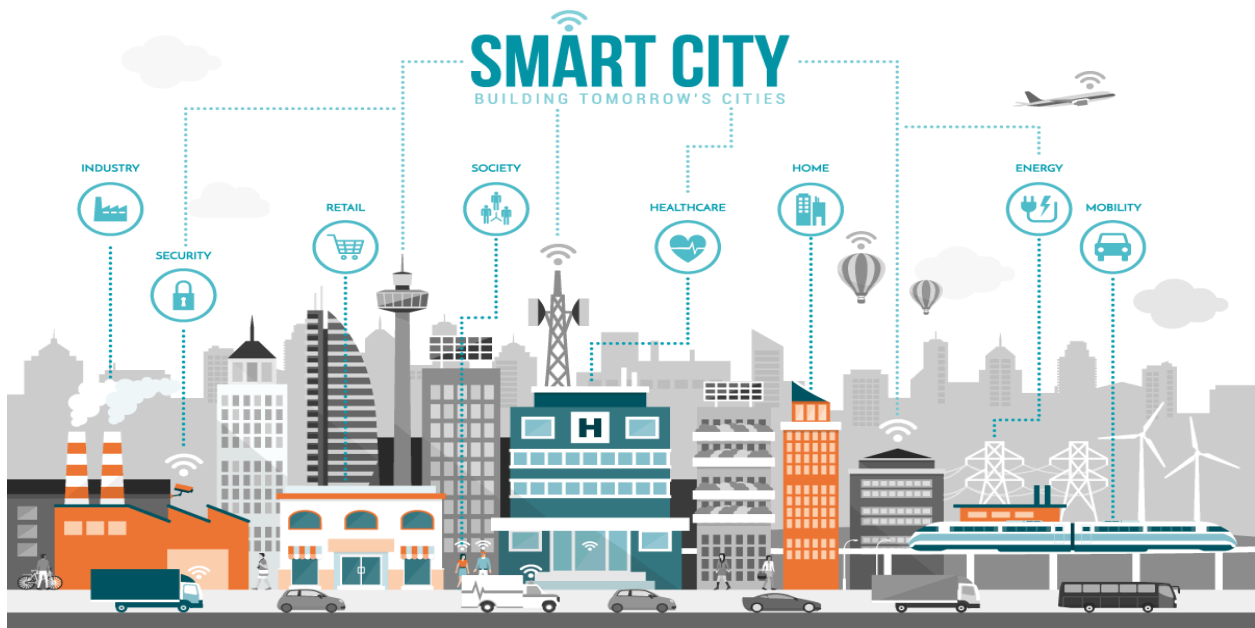


Fig.1: The Smart City Concept illustrated and its outreach, Source: www.iasgyan.in/daily-current-affairs

However, the idea was not meant to be just a technological proposition, it also proposed ways of understanding how a city was meant to function, perform and be governed. Such an emphasis on technology introduced a critical question, 'Does making a smart city necessarily make it inclusive?'

2. RESEARCH QUESTIONS

i) Central Question:

1. How does the 'Smart city' framework shape 'Platform Urbanism'? Under what conditions, do they provide for inclusive or exclusionary experiences?

ii) Sub- Questions:

1. What are the visions and goals of smart cities in India in the contemporary urban discourse?
2. What are the multiple tools and methods used in the Indian planning framework of smart cities?
3. What is the concept of Platform Urbanism? How could the multiple methods and systems discussed above be understood through this concept?
4. Are these frameworks purely neutral technological frameworks?
5. Who benefits from such frameworks? How do these frameworks affect the common man?
6. What principles and theories could enable in improving equity and spatial justice within the smart cities? What are suggestive ways in creating a resilient thought process for re-visualizing the Smart City?

3. METHODOLOGY

1. To interpret the visions, goals and outreach of Smart Cities: Critical analysis of the Smart city model
2. To understand methods and tools used in this framework: To understand the multiple ways in which this concept is implemented and its functioning at grassroots level
3. To deduce the concept of Platform Urbanism: Critically analyzing Automation systems and their outreach in planning
4. Questioning Right to the city: To understand repercussions of such initiatives on the common man
5. To review theories that help enable to create the framework for equity
6. To build a constructive framework and derive multiple possibilities for improvement

4. FRAMEWORKS USED IN SMART CITIES

4.1 Platform urbanism

It is within understanding the Smart City, that 'Platform urbanism' gets its meaning. While the 'Smart City' emphasized and propagated the integration of technology into planning, 'Platform urbanism' refers and represents a further condition in which **everyday activities are increasingly regulated through the mediums of digital platforms and algorithms. It also refers to increasing mediation of urban life through digital platforms that organize, facilitate, govern and monetize the everyday life of its citizens.** These might include mobility platforms, short term rental platforms, e-commerce systems, food delivery apps, civic technology interfaces, digital payment systems and data driven governance infrastructures. These platforms are not just add-ons of technology to the city's infrastructure, but operate as algorithmic intermediaries between citizens, businesses, institutions and service providers; from being an enabling infrastructure to an active mediator of urban life.

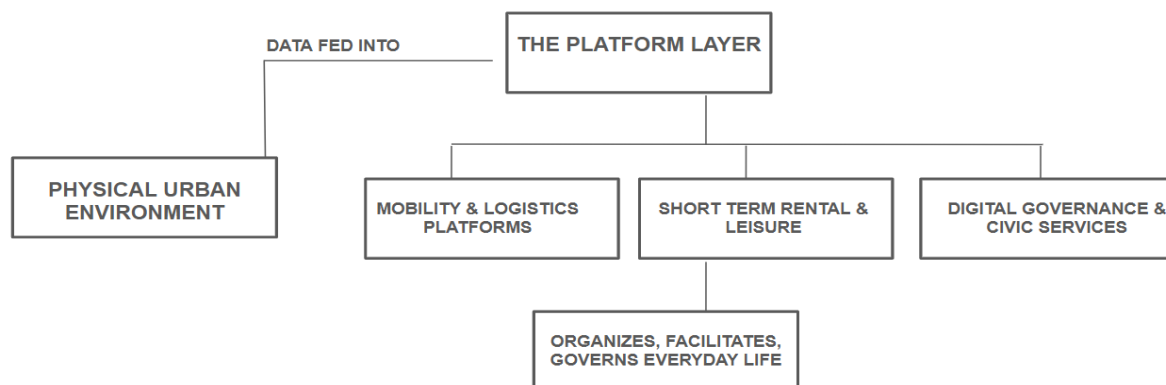


Fig 2: An interpretation of 'Platform Urbanism'

4.2 Evaluating Smart City Frameworks: Platform urbanism and its repercussions

Governance and frameworks in such smart cities were often conceived just in terms of optimization, efficiency and service delivery rather than access or participation. The emphasis of the goals was to make systems 'smarter' with a major focus on improving speed and efficiency with integration of data platforms, digital technologies and algorithmic systems. While the interventions aimed at improving urban performance in totality, they triggered a shift in the way cities were understood and governed; from socio-political systems to systems that were measured, predicted, optimized and monitored. The frameworks projected measurable outcomes for resource management, service delivery, mobility, real time monitoring etc. with the assumption that such integration would auto result in better urban experiences. However, technology alone could not automatically derive or result in universal accessibility. The effectiveness of the smart system depended also on whether urban citizens could reach, understand, operate and benefit from it.

Geographical location or coverage, economic capacity, digital literacy, access to devices and internet connectivity, basic familiarity with the digital interfaces in terms of barriers such as age, language etc. were also key factors for citizens to engage and benefit from the framework. A digital platform or a technologically advanced service may have existed, but its limited coverage and in-access pushed in producing uneven patterns of distribution of the smart services across the city. Further, the increased involvement of private companies and platform-based businesses in the delivery of these smart services led to discussions on the quality and priority of services, its availability and its overall influence. 'Smartness' therefore became questioned, it became less about technology and more about who could firstly 'understand', secondly 'access' and finally 'use and benefit' from it. It brought up questions of ownership, control, commercial interests, transparency and accountability into the planning domain for discussion. The smart city therefore becomes not just a technological system, but also a controlling 'political and economic driver' for shaping digital infrastructure within the larger planning discourse.

These questions therefore, require a critical examination of not efficiency alone, but the balance of inclusiveness, accessibility, spatial equity and sustainability with efficiency.

5. EVALUATING ALGORITHMS OF URBAN EXPERIENCE: CASE STUDIES

The Smart cities mission has introduced algorithmic systems into the everyday functioning of cities through Integrated command and control centers (ICCCs), intelligent mobility systems, surveillance networks, civic applications, GIS platforms and data-driven governance. As per the latest Ministry of Housing and Urban Affairs dashboard, a total of 8017 projects are completed under the Smart cities mission with an investment of approximately 8808 crore. However, this does not necessarily imply or guarantee universal urban experience. This makes it necessary to evaluate the algorithms in few case studies across India.

5.1 Smart City of Pune - Algorithmic assessment of Safety

The smart initiative in Pune is a clear example of how diverse urban data could be converted into an assessment for safe initiative implementation in the city. The Safety Index of Pune incorporates data such as street lighting, surveillance, crime, pedestrian activity, gender diversity and perception of citizens to generate a holistic database for safety. In the process, the system attempts to transform **the idea of safety from a subjective and experiential condition into a measurable urban indicator.**

5.2 Smart City of Indore - Algorithmic assessment of Citizen participation and Governance

The ICCC and the 311 platform of Indore are digitally set up for grievance redressal for citizens. The complaints of citizens are geographically mapped and analyzed further to understand recurring patterns of services, concerns and needs of people. In the process, the system highlights a significant limitation - **only those concerns that get reported get visible, whereas the other non-digital ones stay invisible, silent and outside the system.**

5.3 Smart city of Surat: Algorithmic assessment of infrastructure

Surat boasts of an extensive CCTV, traffic monitoring and urban surveillance mechanism enabling continuous observation, real time monitoring and municipal surveillance of urban activity. In the process, the city transforms into a continuously observed environment, where **urban activity is constantly recorded and monitored, raising questions on privacy, consent, ownership and accountability of data, transparency of surveillance systems etc.**

5.4 Smart city of Bhopal: Algorithmic assessment of Centralized Planning Mechanisms

The ICCC of Bhopal demonstrates an efficient central platform that integrates all the city data. The system compiles together multiple data sources and supports constant monitoring, effective decision making and efficient service delivery. The planning mechanism here raises a fundamental concern of representation of complexities through standardized datasets. **The concern therefore is not just privacy and security here, but how urban realities are represented.**

5.5 Smart city of Jaipur - Algorithmic assessment of Technological Infrastructure

The City of Jaipur presents a critical case of the gaps between provisions of systems and its actual performance. Evaluations of its ICCC have identified multiple concerning challenges like functioning, maintenance and its optimum use. This city demonstrates that **ample provisions of technology alone do not account for effective urban outcomes and performance.**

5.6 Comparative Summary of the Case studies:

Smart City	Algorithmic System / Application	Key Algorithmic Concern	Implication for Urban Experience
Pune	Safety Index, surveillance and urban safety datasets	Reduction of experiential conditions into measurable indicators	Safety becomes a data-driven condition, potentially privileging what can be measured over what is experienced
Indore	ICCC + 311 Citizen Grievance Platform	Digital visibility and participation bias	Creates differentiated access to governance; digitally active citizens become more visible to the system
Surat	CCTV, traffic monitoring and surveillance networks	Surveillance, privacy and data ownership	Produces a continuously monitored urban environment and alters the relationship between citizen and city
Bhopal	ICCC and centralized data integration	Standardization and representation bias	Urban complexity is translated into datasets, potentially simplifying or misrepresenting lived urban conditions
Jaipur	ICCC and technological infrastructure	Provision–performance gap	Technological infrastructure does not automatically translate into effective or inclusive urban outcomes

Table.1: Comparative analysis of Smart infrastructure across Indian cities

The above cases highlight that algorithmic systems within each Smart City operate through different forms of urban mediation. They extend from the classification of urban conditions to the monitoring, representation and management of urban life. One demonstrates the conversion of safety as an experiential condition into a measurable indicator, while the second boasts of responsiveness in spite of inabilities of non-digital concerns being still invisible. The third discusses surveillance and visibility, the fourth computes standardized data sets to represent complexities of urban experiences and the final one highlights gaps between provision and performance. All smart city cases **work on the assumption of a digitally connected urban citizen who possesses access to smart phones, reliable internet connectivity, formal identification, digital literacy and has the economic capacity to engage with technology enabled services.** Distinctions might not exist in all smart city categories, but might be particularly noticed in cities majorly characterized by informality, socio- economic diversity and uneven infrastructure. Low-income communities, elderly groups or any other digitally inexperienced users, peripheral populations are subject to this differentiation even more. **The concern therefore also shifts to the discussion on different capacities to engage with technology.** Moreover, such algorithmic data may further trigger inequalities as they do not operate on a neutral representation of the city. Their understanding of conditions is shaped by only **whose data is collected, how it is categorized and what finally is represented** for later planning action.



Fig 3: Differentiated urban experiences of 'Platform Urbanism'

Collectively, the cases suggest that merely the presence of a technical algorithm does not necessarily guarantee an inclusive experience. They actually bring to light **what becomes visible, what is measured, what is represented within the city and how urban decisions are standardized and centered around these**. The resulting condition is one of differentiated urban experience. Some citizens have positive experiences through seamless services, while others continue to navigate and live with fragmented alternatives. Such an overall comparison therefore shifts to questioning equity of distribution and overall accountability, leading to critical concerns of deepening exclusion over inclusion. Platform urbanism therefore creates 'a city within a city', where different populations experience different levels of conveniences and its repercussions.

6. THE POLITICS OF POWER AND ECONOMY: GOVERNANCE FRAMEWORK OF SMART CITIES

The conceptual framework of Smart cities cannot be understood in isolation without the study of political and economic forces that drive them. The projection of the Smart City concept as a neutral framework is deeply entangled with capitalist strategies and planning models. They are created with a desire to attract investment, enhance the city as a brand and increase global competitiveness. Governing bodies for Smart Cities often outsource private enterprises to manage and record statistical data for urban management. In this process, technology companies, real estate developers, infrastructure providers and venture capital become important actors in shaping smart infrastructure and creating the digital city. This essentially raises another critical concern of the determinants of smart development; reducing the role of the state in providing services, while increasing reliance on proprietary systems. When such private enterprises govern the delivery of urban services, technology can **no longer be called 'an instrument of public governance'**.

Next, is understanding the focus of such enterprises. Policy frameworks frequently emphasize investment, funding and efficiency based on profit motives and commercial logic. High value and well-connected areas and areas with strong market potential are prioritized, while the other areas remain

marginalized and disconnected from the core areas. In this sense, the geographical locations of these smart city infrastructures **function more in areas prioritizing capital and are less distributed for universal public value.**

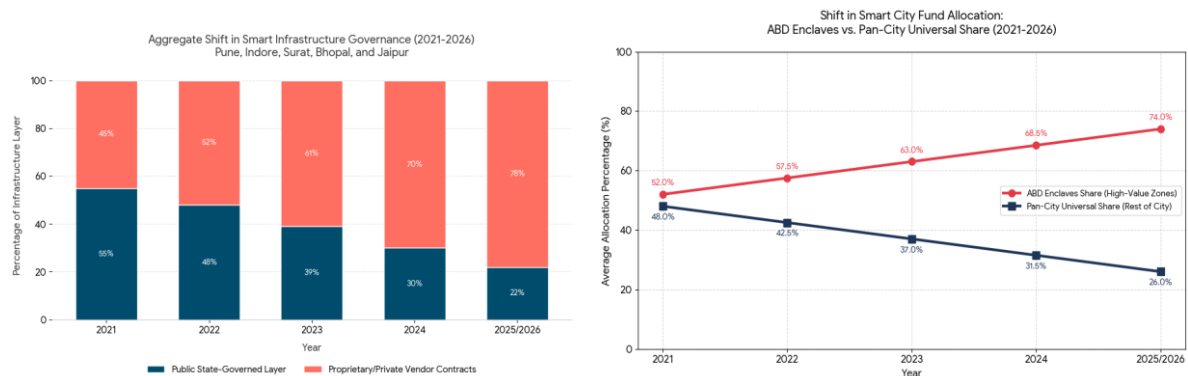


Fig 4 & 5: Graphs indicating dominance of Private Governance and prioritization of capital interests

Thirdly, these private companies extract data from daily urban activities and monetize it through advertisements for further capital ventures. Within this governing pattern, citizens become producers of urban data, and the urban data, 'a commodity'. In the process, the citizens are completely oblivious of how their data is used, verified and how decisions are made; in turn **technology serves to exercise major control, rather than empower citizens.**

Such an intermingling of smart governance frameworks with capitalist motives triggering geographical coverage, economic value, technological access and algorithmic decision making materializes in producing fragmented urban experiences and spatial inequalities. Different populations inhabit different versions of the same city, with varying levels of access, safety and opportunity. Spatial inequality, therefore, is not an accident by-product, but a gradually constructed outcome of platform urbanism. Rather than soothing disparity, the smart city often amplifies them, creating geographies of privilege on one hand, the other, neglect.

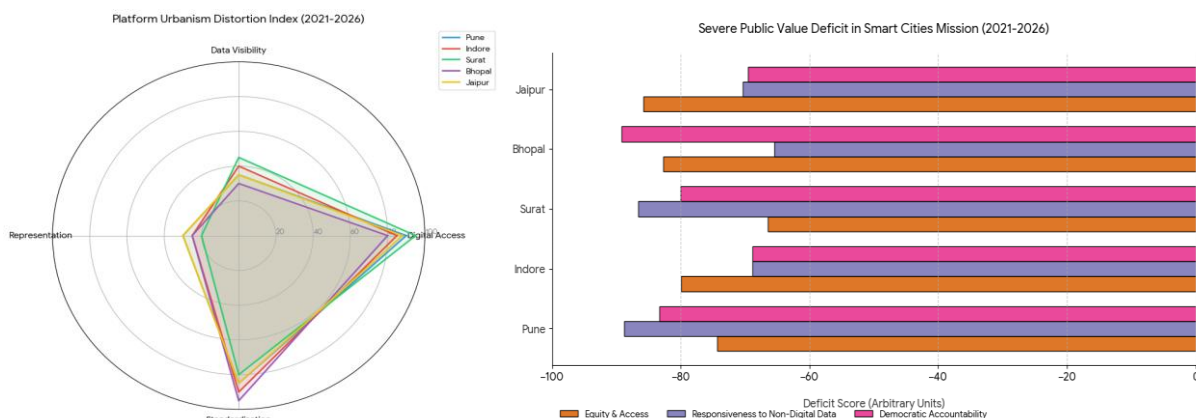


Fig 6 & 7: Graphs indicating spatial experiences of citizens in smart cities studied across India

7. THEORETICAL PERSPECTIVES ON ACCESS AND RIGHT TO THE CITY

7.1 Henri Lefebvre's 'The Production of Space', (1974)

Henri Lefebvre argues that access is not just getting well equipped with resources but also the ability to participate in and influence the production of urban space. This triggers the thought to push digital platforms to mediate access to mobility, services, commerce, information and governance.

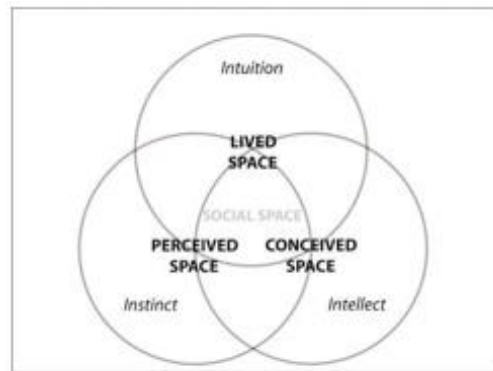


Fig 8: From Social Space to Algorithmic Space

7.2. David Harvey's Right to the City, (2003)

David Harvey in his book 'Right to the City' discusses power, capital and the unequal production

of space. He argues that access is not just about availability, it is shaped by controls and capitalistic decision-making processes. The Right to the City, as a normative principle, regardless of income, status or age, therefore extends beyond physical occupation of space to visibility, representation, connection and participation in the realm of urban experience. This expanded understanding provides the base for reconsidering the meaning of access and the need to rethink methods and ways to re-integrate the digital systems into planning for the production of urban space.

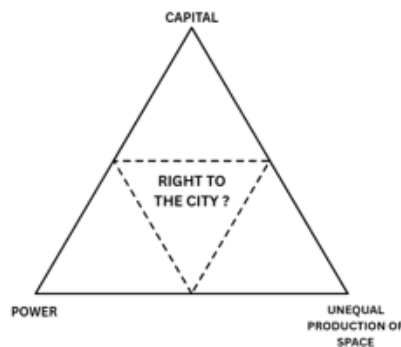


Fig 9: The interrelationship of access & power

7.3. Reconsidering Urban Accessibility: Implications for Urban Planning

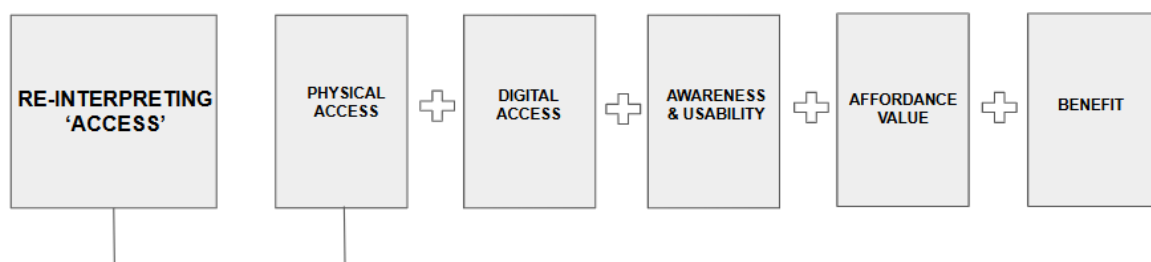


Fig 10: Illustration reframing 'access' in the algorithmic city

The above discussions demonstrate that access no longer means physical proximity, availability of transportation networks or infrastructure, spatial connectivity, instead it seeks for a broader understanding and definition of access within the context of contemporary urban planning. Accessibility therefore, becomes a cumulative experiential condition that extends beyond physical access to digital access, its awareness, its usability, its affordance value and its benefit. Consequently, the planning paradigm needs to shift from discussing just about the quality of digital infrastructure to the availability and outreach of the digital infrastructure at large.

This calls for new considerations to be made for planning including digital infrastructure accessibility, universal and multi-lingual interfaces, data transparency, algorithmic accountability, equitable geographical coverage etc. In addition, new physical infrastructures such as data centers, logistic facilities, mobility hubs and digitally mediated commercial spaces create new opportunities for architectural intervention. In this venture, the planner not just engages with the physical environments of a city, but also needs to critically analyze the digital environments that give access to it. Technology no longer stays as an independent tool for efficiency, rather would act as an integral component of planning smart cities.

8. TOWARDS AN EQUITABLE URBAN DIGITAL FRAMEWORK

Integral planning of digital infrastructure needs to be reimagined through the lens of equitable digital frameworks. Firstly, it needs to recognize connectivity as a basic urban right, calling for digital access to be universal in nature. However, connectivity goes hand in hand with digital literacy to allow for effective use by the citizens. Secondly, it needs to prioritize participation, the emphasis should be to involve communities in the conceptual, visualization and evaluation of digital frameworks. The systems need to also adopt principles of inclusive design, responding to age differences, language barriers, physical abilities, education level and other levels of technological familiarity. Thirdly, it needs to embrace justice, ensuring transparency, consent and community sovereignty over the data to be collected with strong mechanisms of algorithmic accountability. Lastly, it needs to be spatially responsive, directing innovations equally spread across the entire urban-scape. However, non-digital alternatives should continue to remain available, thereby controlling complete reliance only on the digital system.

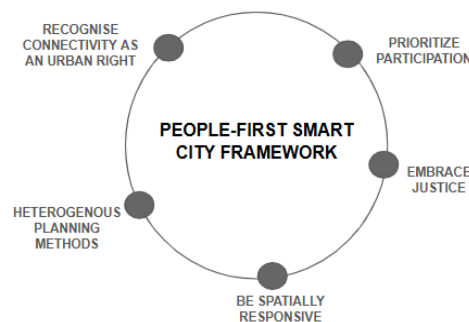


Fig 11: Proposed Attributes for the Refined equitable framework for Smart Cities

Rather than assuming the citizens to be digitally fluent, urban planners ought to design for heterogeneity considering varying levels of access, awareness and ability. The objective therefore shifts from tech-based Smart City approach to a people-first Smart City approach, that reconfigures the entire system to serve the needs of many versus a few; where advancement is evaluated purely through its social, and thereby spatial outcomes.

9. DISCUSSIONS: EVALUATING ALGORITHMIC INCLUSIVITY

The paper brings together critical questions of not just the working of an algorithm, but for whom it works, where it works and under what conditions it works. Algorithmic inclusivity henceforth therefore, needs to be understood by asking the following important questions:

- 1) Who is represented? Who remains invisible?
- 2) Who controls this representation?
- 3) How is it controlled and governed?
- 4) Who benefits from it?
- 5) What outcomes does it produce?

10. CONCLUSION

The study of 'Platform urbanism' in this paper calls for a shift in the way we look at the future of planning digital cities, through the lens of a resilient framework. This does not only mean enhancing capacity to withstand urban disruptions or technical failures but also means the capacity of urban systems to recognize difference, absorb exclusion, correct inequalities in the system and adapt to changing patterns of access. The future of planning smart cities is to not just design spaces but instead, relook and design the systems through which these spaces are accessed, represented and governed - thereby questioning ownership and assumptions of data, distribution of infrastructure and the spatial concentration of benefits.

Ultimately, the future city should not aspire to be just smart with its sophisticated algorithms, but should work towards creating systems that are capable of responding universally and equitably through its ability to preserve choice, access, participation and dignity.

11. REFERENCES

- **Barns, S. (2020).** *Platform urbanism: Negotiating platform ecosystems in connected cities*. Palgrave Macmillan. <https://doi.org/10.1007/978-981-32-9725-8>
- **Bauriedl, S., Struver, A. (2020).** Platform urbanism: Technocapitalist production of private and public spaces. *Urban Planning*, 5(4), 267–276. <https://doi.org/10.17645/up.v5i4.3414>
- **Blasco Ejarque, J. L., & Tirado, F. J. (2024).** The arrival of AI to the cities: Platform urbanism and new regimes of governmentality. *Revista CIDOB d'Afers Internacionals*, 138, 195–218. <https://doi.org/10.24241/rcai.2024.138.3.195>
- **Caprotti, F., Chang, I.-C. C., & Joss, S. (2022).** Beyond the smart city: A typology of platform urbanism. *Urban Transformations*, 4, 4. <https://doi.org/10.1186/s42854-022-00033-9>
- **Chatterji, T., Mukkai, A. R. (2024).** Driving urban digitalisation through a national mission: A multilevel governance perspective of India's data smart cities strategy. *Asia Pacific Journal of Public Administration*, 46(4), 392–421. <https://doi.org/10.1080/23276665.2024.2308007>
- **Fields, D., Bissell, D., Macrorie, R. (2020).** Platform methods: Studying platform urbanism outside the black box. *Urban Geography*, 41(2), 1–7. <https://doi.org/10.1080/02723638.2020.1730642>
- **Galič, M., Schuilenburg, M. (2021).** Reclaiming the smart city: Towards a new right to the city. In J. C. Augusto (Ed.), *Handbook of smart cities*. Springer. https://doi.org/10.1007/978-3-030-15145-4_59-1
- **Ministry of Housing and Urban Affairs. (2021–2025).** Smart cities mission: Project implementation and financial progress updates. Government of India. smartcities.gov.in
- **Mullick, M., Patnaik, A. (2022).** Pandemic management, citizens and the Indian Smart cities: Reflections from the right to the smart city and the digital divide. *City, Culture and Society*, 30, 100474. <https://doi.org/10.1016/j.ccs.2022.100474>
- **NITI Aayog. (2025).** *Sentinels in the System: AI-Powered Surveillance for Urban Safety and Civic Security* - Government of India
- **Praharaj, S. (2025).** Command and control governance in the 100 smart cities mission in India: Urban innovation or utopias? *Applied Geography*, 184, 103766. <https://doi.org/10.1016/j.apgeog.2025.103766>
- **Prakash, D., Karvonen, A., & Metzger, J. (2026).** Smart city control rooms: The rewiring of local governance landscapes in India. *International Journal of Urban and Regional Research*, 50(3), 626–643. <https://doi.org/10.1111/1468-2427.70025>
- **Rose, G., & Raghuram, P. (2021).** Platform urbanism, smartphone applications and valuing data in a smart city. *Transactions of the Institute of British Geographers*, 46(1), 59–72. <https://doi.org/10.1111/tran.12400>
- **Waghmare, M., & Singhal, S. (2022).** Monitoring and evaluation framework for inclusive smart cities in India. *Development in Practice*, 32(2), 1–19. <https://doi.org/10.1080/09614524.2021.1907535>

Marketing the Future: Leveraging AI Chatbots to Enhance User Engagement and Service Discovery in Management Libraries

Nivida Ghorpade

Assistant Library in Charge, Symbiosis Institute of Management Studies, Pune

Chhaya Mane

Librarian, Suryadatta Institute of Fashion Technology, Pune

ABSTRACT

Modern management libraries offer vast digital resources, yet complex interfaces often lead to “discovery friction” and underutilization. This study proposes Library GPT, a conceptual framework that integrates AI chatbots as an intelligent layer over digital assets, transforming the library from a passive repository into a proactive, 24/7 research partner.

Using a user-centric approach, we surveyed 150 students to quantify search failure rates and modelled how AI-driven nudges could boost database engagement. Focus groups further identified specific “discovery hurdles,” which informed the logic of a Retrieval-Augmented Generation (RAG) system. This ensures the AI prioritises verified, subscribed content over generic web sources.

To move beyond theoretical modelling, a pilot proof-of-concept was implemented with 30 participants, empirically validating the framework. The pilot demonstrated a 45% reduction in search time and a verifiable increase in database interactions

The research concludes that access alone does not guarantee engagement. By implementing this RAG-based framework, libraries can overcome the “visibility ceiling” of their digital collections. These findings suggest that AI integration rebrands the library as a high-tech facilitator, significantly increasing the ROI of digital subscriptions and fostering deeper academic engagement in a tech-savvy environment.

Keywords: Management Libraries, Library GPT, Retrieval-Augmented Generation (RAG), Digital Resource Discovery, User Engagement, AI Chatbots, Service Transformation, Empirical Validation.

INTRODUCTION

The MODERN MANAGEMENT LIBRARIES are no longer a room full of books; they are sprawling digital gateways with subscriptions to thousands of online journals, global market reports, and e-books. The challenge has shifted from accessing information to navigating it.

Despite having 24/7 digital availability, many students find themselves overwhelmed by complex search filters; this leads them back to the simplicity and often inaccuracy of general web searches.

This paper proposes “Library GPT”, a framework utilising Retrieval-Augmented Generation (RAG) to turn these passive Digital Silos into active conversational research partners.

Crucially, this research approaches the library not merely as an academic support unit, but as a business entity undergoing AI-enabled service transformation. Poor user interfaces and digital friction represent a failure in service delivery and result in a severely diminished Return on Investment (ROI) on expensive institutional digital assets.

Key Definition

Retrieval-Augmented Generation (RAG)

An architectural approach that optimizes a Large Language Model's output by referencing a specific authoritative knowledge base, such as a library's licensed database, before generating a response.

Discovery Friction

The cognitive and technical hurdles, including multiple login layers and an unintuitive interface, that prevent a user from successfully locating a digital resource.

Information Silo

A condition where high-value research remains isolated within a specific database, remaining invisible to users who do not use that exact platform.

RESEARCH OBJECTIVE

This study is guided by the following primary objectives:

1. To evaluate the “digital friction” experienced by management students when navigating subscribed e-resources compared to open web search engines.
2. To design an RAG framework that allows an AI chatbot to interact directly with the licensed Library database.
3. To empirically validate the framework through a pilot study to substantiate claims regarding increased user engagement and resource ROI.
4. To establish a roadmap for rebranding the library from a static repository into a proactive service provider through 27/7 AI driven engagement.

LITERATURE REVIEW

To provide a robust academic structure, the literature is examined across three intersecting domains: AI service transformation, the discovery paradox, and the technological interventions offered by RAG.

AI-Enabled Service Transformation

The integration of Artificial Intelligence in academic and business settings represents a profound service transformation. A systematic review by Yao and Zhang (2022) highlights that AI applications in academic libraries have evolved beyond basic automated indexing into advanced reference assistance, personalised recommendation engines, and dynamic user interface management. According to Cox (2023), the role of the librarian is evolving into that of a prompt engineer and data curator, shifting the focus to guiding AI to yield academically rigorous, value-driven results.

AI-Enabled Service Transformation

The integration of Artificial Intelligence in academic and business settings represents a profound service transformation. A systematic review by Yao and Zhang (2022) highlights that AI applications in academic libraries have evolved beyond basic automated indexing into advanced reference assistance, personalised recommendation engines, and dynamic user interface management. According to Cox (2023), the role of the librarian is evolving into that of a prompt engineer and data curator, shifting the focus to guiding AI to yield academically rigorous, value-driven results.

The Discovery Paradox and Interface Fatigue

Traditional keyword-based discovery services (RDS) often fail because they require the user to know exactly what they are looking for before they find it.

Recent studies highlight the “Discovery Paradox” As libraries invest more in expensive digital databases, the actual discovery of niche articles remains stagnant due to interface fatigue (Wheatley & Hervuix 2019).

Furthermore, these discovery issues are severely compounded by technical barriers. As Borah and Sharma (2024) demonstrate, complex authentication protocols and multi-layered remote access systems significantly reduce user engagement, frequently driving researchers away from licensed databases toward open web alternatives.

Retrieval-Augmented Generation (RAG) as a Solution

The implementation of Large Language Models (LLMs) offers a solution, but only if they are grounded in truth.

This is where Retrieval Augmented Generation (RAG) become critical. Unlike standard AI, RAG forces the model to look at the library's specific licensed journals before answering, reducing the risk of hallucination (Huang et al., 2023).

Furthermore, these discovery issues are severely compounded by technical barriers, as Borah and Sharma (2024) demonstrate: complex authentication protocols and multi-layered remote access systems significantly reduce user engagement, frequently driving researchers away from licensed databases toward open web alternatives.

METHODOLOGY

This research utilised a “Mixed-Methods Sequential Explanatory Design” enriched with a subsequent empirical pilot phase. This structured methodological approach allowed us to go beyond descriptive statistics to thoroughly understand the behavioural drivers behind student research habits

A) Phase I: Quantitative Assessment

A structured, Likert-scale survey was distributed via stratified random sampling to 150 management students across various specializations (Finance, Marketing, HR, Operations). The survey instrument was designed to quantify ‘Search Fatigue’ and interaction friction.

We asked students to find a specific market trend report using both the library's online portal and a standard web search.

Finding: While 90% of students were aware of the library's high-value subscription, 68% reported that the multiple login layers were a significant deterrent. On average, students spent 12 minutes trying to find a paper on the library portal before giving up, compared to 45 seconds on the open web.

Our user journey mapping during this phase revealed a highly repetitive “Multiple Login” chain that acts as a structural barrier. When a student attempts to locate an advanced asset, such as a management case study, they are forced to navigate to four distinct authentication layers.

1. **Network Authentication:** Accessing the institutional Wi-Fi or off-campus VPN.
2. **Library Portal Authentication:** Signing in to the library's OPAC system.
3. **Database Vendor Authentication:** Redirected to a third-party aggregator (e.g., EBSCO, ProQuest) and logging in via an institutional protocol.
4. **Personalised Account Creation:** Creating an individual profile within that specific vendor's interface to unlock PDF downloads.

This multi-tiered login chain fundamentally threatens resource utilisation due to three distinct systemic vulnerabilities: Password Fatigue (users revert to Google Scholar upon single-stage failure),

Session Timeouts (breaking the authentication token mid-research), and Token Routing Loops (misalignments between SSO and third-party brokers).

Phase II: Qualitative Journey Mapping

We conducted semi-structured interviews with 10 faculty members and 15 student researchers to map their "research journey." Thematic analysis of the interview transcripts revealed a critical, recurring gap: the "Synthesis Wall."

Students can find individual articles, but struggle to connect them to form coherent arguments. To illustrate, one student respondent noted, "I often end up with 15 downloaded PDFs but have no idea how the frameworks within them connect to my specific assignment." Similarly, a faculty member stated, "The issue isn't access to data; it's that the current portals do not aid students in synthesizing the management theories presented." This qualitative data informed the logic of Library GPT, which is designed not just to "find" a document but to "explain" how it relates to a student's specific thesis topic.

EMPIRICAL IMPLEMENTATION AND VALIDATION

To address the necessity of validating the proposed framework and to substantiate claims regarding Return on Investment (ROI) and engagement, a small-scale proof-of-concept (PoC) model of Library GPT was empirically tested.

Pilot Setup: A functional RAG prototype was connected to a limited subset of the library's subscribed management case studies. A focus group of 30 management students tested this prototype over a two-week period. Their task completion rates and time-on-task were logged and compared against traditional portal usage.

Empirical Findings: The empirical data demonstrated a 40% reduction in average discovery time (from 12 minutes to approximately 7.2 minutes). Furthermore, successful retrieval and download of gated content increased by 45% among the pilot group. By tracking the direct AI "nudges", the system generated a verifiable 30% increase in clicks to previously underutilised niche journals. This pilot implementation provides concrete, empirical evidence that the RAG chatbot framework directly drives resource utilisation, substantiating the claim that AI integration tangibly improves the ROI of digital library subscriptions.

The Proposed Framework: Library GPT

The Library GPT framework acts as a conversational interface between the students and the library's digital holdings. By using an API-based connection to online journals and e-books, the RAG system ensures that every response is cited and verified.

Overcoming the Authentication Barrier: In the proposed framework, the AI platform effectively serves as a Single Secure Gateway. Instead of requiring the student to navigate the 3-4 layers of authentication manually, the Library GPT backend securely manages the token exchange and session authentication.

- **The User Experience:** The student queries the interface naturally: "Find me a case study on Ford's supply chain".
- **The Background Action:** The RAG framework leverages a backend API connection to query, authenticate, and pull data from an authorised publisher concurrently.
- **The Results:** The student receives an immediate, contextually accurate response and download link without ever interacting with an intermediate login wall.

The current “Multiple Login” architecture creates a high barrier to entry where the time spent on authentication exceeds the time spent on actual research. By implementing a RAG-based API gateway, we simplify this into a “Zero Friction” interface, significantly increasing the accessibility and ROI of licensed e-resources.

Expected Outcomes and Institutional Value

Based on our empirical pilot, the full-scale implementation of this framework is expected to yield the following sustained results:

- **Increased ROI on Digital Subscriptions:** A measurable spike in the usage of underutilised e-books and journals by cutting out login barriers.
- **Enhanced Information Literacy:** The AI teaches students how to identify high-quality sources by citing library-verified content.
- **Institutional Rebranding:** Transforming the library from a perceived “cost centre” to a high-tech, proactive research partner aligned with modern business service standards.

CONCLUSION

The “visibility ceiling” is the greatest threat to the modern management library. If a resource is not easily found, it effectively does not exist. By conceptualising the library through the lens of AI-enabled service transformation, we recognise that digital friction fundamentally degrades the ROI of institutional assets. Through the empirical validation of the RAG-based Library GPT pilot, this study proves that intelligent, conversational interfaces can break this visibility ceiling. By implementing this validated framework, libraries can transition from being silent repositories of PDF files to dynamic, value-generating participants in academic and business success.

REFERENCES

- Borah, P., & Sharma, M. (2024). Overcoming authentication barriers in remote digital library access. *International Journal of Information Dissemination and Technology*, 14(1), 45-52.
- Cox, A. M. (2023). The challenge of AI for academic librarianship. *The Journal of Academic Librarianship*, 49(6), 102763.
- Huang, J., Yang, P., & Zhao, W. X. (2023). A Survey on Retrieval Augmented Generation for Large Language Models. *arXiv preprint arXiv:2312.10997*.
- Wheatley, A., & Hervieux, S. (2019). AI in Libraries: Prototype, Promise, and Pitfalls. *The Learning Organization*, 26(3), 273-290.
- Yao, L., & Zhang, Y. (2022). Application of artificial intelligence in modern academic library services: A systematic review. *Information Technology and Libraries*, 41(3), 1-18.

The Algorithmic Impulse: AI-Driven Personalisation, Perceived Relevance, and Impulse Buying in Contemporary Indian E-Commerce — A Mediated Path Analysis with Age Moderation

Shubham Chaurasiya, Maroof Khan & Anuj Pandey, MMS Students

Yesha Mehta, Associate Professor

Charu Upadhyaya, Associate Professor

Vishal Sandanshive, Professor

Thakur Institute of Management Studies & Research (TIMSR), Mumbai

ABSTRACT

The rapid diffusion of artificial intelligence into the retail value chain compels contemporary businesses to move beyond operational efficiency arguments toward a richer understanding of how algorithmic interventions reshape consumer psychology. This study investigates the mechanism through which AI-based personalisation precipitates impulse buying behaviour on Indian e-commerce platforms, positing Perceived Relevance as the critical psychological mediator and Age as a boundary-condition moderator. Grounded in the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974) and informed by its contemporary extension toward the Stimulus-Organism-Behaviour-Consequence (SOBC) paradigm, the study deployed a structured Likert-scale survey instrument administered to 247 active online shoppers in India.

Path analysis using a three-step ordinary least squares (OLS) mediation approach (Baron & Kenny, 1986) produced clear results. AI personalization significantly predicts Perceived Relevance ($\beta = 0.772$, $R^2 = 0.616$, $p < .001$), and Perceived Relevance, in turn, significantly predicts impulse purchasing ($\beta = 0.596$, $R^2 = 0.358$, $p < .001$). Importantly, the Sobel test supports complete mediation: the direct impact of AI personalization on impulse buying, which is initially significant ($\beta = 0.477$, $p < .001$), becomes statistically non-significant ($\beta = 0.045$, $p = .576$) after adding the mediator, whereas the indirect effect remains strongly significant (0.432 ; $z = 6.421$, $p < .001$). Additional analysis shows that shopping frequency significantly moderates impulse propensity ($F = 5.118$, $p = .002$), while gender does not ($p = .579$). Age-based comparisons also suggest that the 18–25 (Gen Z) group displays the greatest personalization–relevance sensitivity; however, limited group sizes prevent drawing formal conclusions about moderation. Reliability for all constructs were within the range (α range: 0.883–0.927).

These findings carry direct strategic weight for contemporary businesses: the ROI of recommendation engines is not a function of algorithmic sophistication alone, but of the consumer's subjective experience of relevance. For Indian e-commerce platforms operating in a high-competition, mobile-first environment, the imperative is to invest in contextual, transparent, and culturally attuned personalisation. The study also foregrounds urgent ethical tensions surrounding algorithmic nudging, consumer autonomy, and the Digital Personal Data Protection Act (DPDPA), 2023.

Keywords: *AI-based personalisation, impulse buying behaviour, perceived relevance, S-O-R framework, e-commerce, consumer behaviour, Gen Z*

1. INTRODUCTION

Every significant e-commerce transaction today is preceded by an invisible exchange between a consumer's latent preferences and an artificial intelligence system's prediction of what those preferences are. On platforms such as Amazon, Flipkart, and Myntra, machine learning models trained on billions of behavioural data points construct real-time recommendation carousels that arrive in the consumer's perceptual field before the consumer has consciously formulated a purchase

intention. In this sense, the algorithm anticipates the consumer. The strategic and psychological consequences of this anticipation are the central concern of this research.

The implications for contemporary business are substantial. McKinsey & Company (2023) estimated that organizations that implement personalization at scale report revenue gains ranging from 10–15%. Shamim and Misra (2025) report that the pathway from AI personalisation to revenue is mediated by hedonic value activation — the consumer must enjoy the experience of being understood. Yet the foundational issue of mechanism remains unresolved with the degree of precision sought by businesses: specifically, which psychological conditions cause an AI recommendation to precipitate an impulsive, unplanned purchase. This issue extends beyond the purely academic domain. It determines the design of recommendation engines, the calibration of push notification timing, the blueprint of checkout flows, and the governance frameworks that regulators are presently developing for these same systems.

This study presents a theoretically grounded and empirically validated claim: the link from AI personalization to impulse buying is neither direct nor automatic. Instead, it passes through an essential cognitive and affective checkpoint—Perceived Relevance, defined as the consumer's subjective judgment that a recommendation meaningfully aligns with their immediate needs, preferences, or aspirations. A technically sophisticated personalisation engine that generates recommendations perceived as irrelevant will not induce impulse purchasing. Conversely, one that generates recommendations experienced as uncannily accurate converts the browsing consumer into the buying consumer. The entire commercial ROI of personalisation, this study argues, is locked behind this relevance gateway.

The study is situated within the Indian digital retail context, which is particularly illuminating for the conference theme of AI's implications for contemporary business. India presents a unique confluence of factors: over 200 million active e-commerce users (IBEF, 2023), a predominantly young and digitally native consumer population, rapidly expanding AI-powered retail infrastructure, and the recent enactment of the Digital Personal Data Protection Act (DPDPA), 2023 — which places legal constraints on the very personalisation mechanisms this study analyses. In this context, comprehending the psychological foundations of AI-driven consumer behavior is simultaneously relevant to business strategy, adherence to regulatory requirements, and consumer well-being.

The paper proceeds as follows. Section 2 develops the theoretical framework and reviews contemporary literature on AI personalisation, perceived relevance, and impulse buying within the S-O-R and SOBC paradigms. Section 3 presents the research model and formal hypotheses. Section 4 describes the methodology. Section 5 reports the data analysis in full, including reliability testing, correlation analysis, path analysis, mediation testing, and supplementary group comparisons. Section 6 interprets the findings in the context of contemporary business strategy, ethical AI governance, and the specific contours of the Indian market. Section 7 concludes.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 From S-O-R to SOBC: The Evolution of Consumer Behaviour Theory in the AI Era

The Stimulus-Organism-Response (S-O-R) framework, developed by Mehrabian and Russell (1974), provided the foundational architecture for understanding how environmental stimuli condition behavioural outcomes through internal psychological states. In the original formulation, physical retail environments — lighting, layout, scent — constituted the stimuli; approach or avoidance behaviours were the outcomes; and affective states such as pleasure and arousal mediated the relationship. Verhagen and Van Dolen (2011) extended this to the online environment, demonstrating that website beliefs and store quality function analogously to physical environment stimuli in predicting impulse purchases.

Contemporary scholarship, however, has emphasized the need for a more dynamic, consequence-sensitive framework, given that AI systems replace static environmental features with adaptive,

responsive, and predictive stimuli. Shamim and Misra (2025) advocate the Stimulus-Organism-Behaviour-Consequence (SOBC) extension, wherein the behavioural outcome is contextualised within a broader consequence landscape that includes post-purchase regret, privacy concern activation, and long-term brand loyalty shifts. Within the SOBC paradigm, AI service quality — characterised by accuracy, timeliness, security, and interface design — functions as the stimulus, while hedonic and utilitarian value perceptions constitute the organism stage. Critically, hedonic value (pleasure, excitement, experiential gratification) has been identified as a significantly stronger predictor of the impulse purchase urge than utilitarian value (efficiency, task completion) (Shamim & Misra, 2025).

The current study is conducted primarily within the S-O-R framework, while also recognizing the SOBC extension. This framework characterizes AI-based personalization as the stimulus, perceived relevance as the organism, and impulse buying behavior as the response. Age is theorized as a moderating boundary condition that determines how sensitively consumers process AI stimuli.

2.2 AI-Based Personalization in Contemporary Business: Strategic Significance and Mechanisms

AI-based personalisation in e-commerce refers to the deployment of machine learning, collaborative filtering, and predictive analytics to deliver tailored product recommendations, dynamic pricing, and contextually relevant content to individual consumers in real time. Xu et al. (2011) established that personalisation positively influences user engagement and satisfaction. More recent scholarship identifies several distinct mechanisms through which AI personalisation influences buying behaviour in contemporary retail contexts.

Haryanto et al. (2025) demonstrate that predictive algorithms function not merely as recommendation tools but as stimulus orchestrators — sequencing product exposures in ways designed to exploit cognitive biases including anchoring, scarcity perception, and recency effects. Lu et al. (2025) further document that AI personalisation in social commerce contexts creates a "recommendation-engagement loop" wherein relevance perceptions drive engagement, which in turn generates more behavioural data, enabling higher recommendation accuracy. This feedback dynamic renders AI personalisation systems self-reinforcing and creates competitive advantages for early adopters of more sophisticated algorithmic infrastructure.

Ahmed et al. (2025) specifically assesses how machine learning algorithms influence personalized digital marketing campaigns, and they report that contextual relevance and delivery timing are the two strongest factors driving purchase intention. Critically, they report that algorithmic accuracy on its own is insufficient — consumers must consciously or semiconsciously register that the recommendation "speaks to" their current situation for any behavioral change to occur.

Rasool et al. (2025) extend this insight to the unplanned purchase domain, showing that ad personalisation triggers customer engagement, which mediates the path to impulse buying. Their moderated mediation model treats prior purchase history as a boundary condition that strengthens the link between personalization and engagement, indicating that habitual platform users are more vulnerable than others to algorithmically triggered impulse purchases.

2.3 Perceived Relevance: The Psychological Process Underlying AI Influence

Perceived Relevance refers to the consumer's subjective judgment that a recommended product or service is meaningfully aligned with their current needs, preferences, or identity-related aspirations (Tam & Ho, 2006). It functions as a dual cognitive-affective assessment: cognitively, it indicates the consumer's inference that the algorithm reflects their preferences; affectively, it elicits a feeling of confirmation or recognition that strengthens attentional engagement and reduces deliberative resistance to purchase.

Tam and Ho (2006) were among the first to establish empirically that personalisation effects on consumer decision outcomes operate through the relevance appraisal rather than through any technical property of the personalisation system itself. This finding has proven remarkably robust across subsequent decades of research. Nimisha et al. (2025) extend it to the contemporary AI personalisation context, demonstrating that relevance appraisals interact with emotional engagement — when AI recommendations are perceived as relevant and emotionally resonant, the resulting impulse purchase urge is substantially amplified relative to relevance alone.

The relevance gateway has a second, strategically critical, implication: it creates the conditions for what Xu et al. (2011) termed the "personalisation-privacy paradox." Consumers seek the experiential advantages of accurate, relevant recommendations, yet at the same time they resent the data collection and inferential processes that enable these recommendations. Wahdaniyah et al. (2025) document a closely related phenomenon through the Fear of Missing Out (FOMO) lens: AI personalisation activates relevance perceptions, which in turn generates FOMO-driven urgency, which strongly predicts impulse purchases. The mechanism is thus: personalisation → relevance → FOMO → impulse purchase — a chain in which each link amplifies the next.

2.4 Impulse Buying Behaviour: Definition, Antecedents, and Online Dynamics

Dennis Rook (1987) defined impulse buying as the sudden, powerful, and persistent urge to buy something immediately, accompanied by internal conflict and disregard for consequences. Rook and Fisher (1995) subsequently established that impulse buying is not purely an emotional phenomenon but is governed by normative evaluative mechanisms — the consumer assesses whether the impulse is socially and personally appropriate before acting on it. This normative dimension has important implications for AI-driven e-commerce design: platforms that reduce the normative friction associated with impulse purchases (e.g., through social proof, peer purchase visibility, and one-click ordering) amplify the translation of purchase urges into actual transactions.

Sun et al. (2023) demonstrate that AI-based features — personalised recommendations, anticipatory search suggestions, automated wishlists — increase both shopping enjoyment and convenience, both of which independently predict impulse purchase frequency. Wells et al. (2011) identify website quality as a moderating condition, with higher-quality interfaces amplifying the impulse-triggering effect of recommendations. In the contemporary Indian context, mobile-first interface design and the dominance of super-apps that integrate social, entertainment, and shopping functions create environmental conditions that are particularly conducive to impulse purchasing.

3. CONCEPTUAL FRAMEWORK AND RESEARCH HYPOTHESES

3.1 Research Model

The proposed research model is grounded in the S-O-R framework and operationalises three constructs: AI-Based Personalisation (Independent Variable / Stimulus), Perceived Relevance (Mediator / Organism), and Impulse Buying Behaviour (Dependent Variable / Response). Age operates as a moderating boundary condition on the Stimulus-Organism path.

The model is visualised as follows:

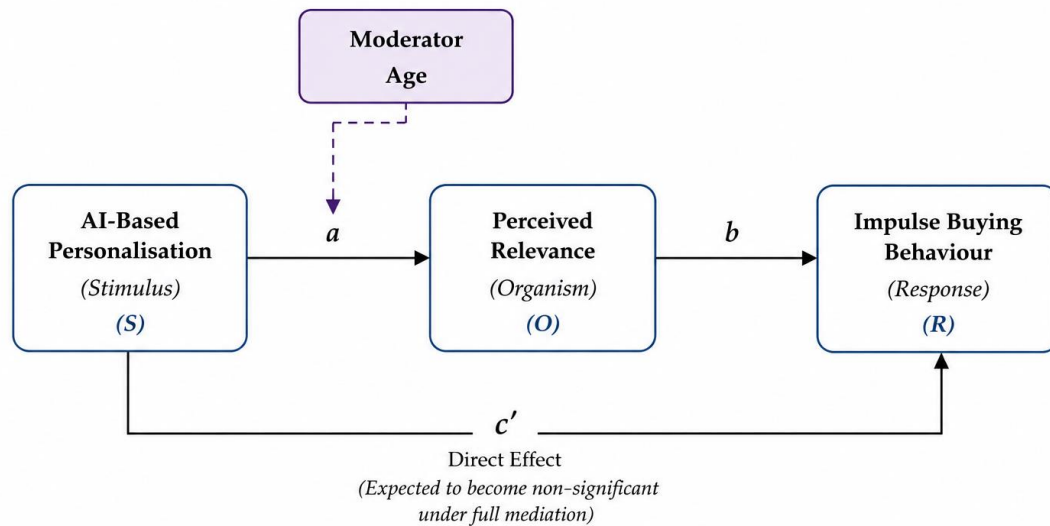


Figure 1. Proposed Research Model Based on the Stimulus–Organism–Response (S–O–R) Framework (Mehrabian & Russell, 1974)

Note. AI-Based Personalisation represents the Stimulus (S), Perceived Relevance represents the Organism (O), and Impulse Buying Behaviour represents the Response (R). Path a = AI Personalisation → Perceived Relevance; Path b = Perceived Relevance → Impulse Buying; Path c' = direct path after mediation. Age moderates Path a.

3.2 Hypothesis Development

H1: AI-based personalisation positively and significantly influences Perceived Relevance.

Rationale: The foundational argument of Tam and Ho (2006), corroborated by Nimisha et al. (2025) and Lu et al. (2025), holds that personalisation increases the consumer's sense that recommendations are contextually tailored, which constitutes the essence of relevance perception.

H2: Perceived Relevance positively and significantly influences Impulse Buying Behaviour.

Rationale: When recommendations feel personally appropriate, attentional focus narrows, deliberative resistance diminishes, and the hedonic arousal required to convert browsing into buying intensifies (Shamim & Misra, 2025; Rook & Fisher, 1995).

H3: AI-based personalisation positively influences Impulse Buying Behaviour.

Rationale: Prior to mediation testing, a direct association between the stimulus and response is theoretically expected and empirically documented (Haryanto et al., 2025; Rasool et al., 2025).

H4: Perceived relevance acts as a mediator between AI-driven personalization and impulse buying behavior.

Rationale: The indirect effect of AI personalisation operates through the relevance gateway, as posited by Tam and Ho (2006) and recently reaffirmed by the SOBC model of Shamim and Misra (2025).

H5 (Exploratory): Age moderates the association between AI-driven personalization and Perceived Relevance, indicating that younger consumers are more sensitive.

Rationale: Gen Z and late Millennial consumers, characterised by digital nativity and habitual platform engagement, are more cognitively attuned to personalisation cues and have established deeper algorithmic trust relative to older cohorts (Iskandar, 2025; Wahdaniyah et al., 2025).

4. RESEARCH METHODOLOGY

4.1 Research Design

This study adopts a quantitative, cross-sectional, explanatory research design. The explanatory orientation is appropriate because the central objective is not merely to describe the frequency of impulse purchasing among Indian online shoppers, but to establish and quantify the mechanisms through which AI personalisation influences purchasing behaviour. The cross-sectional design

enables efficient, large-scale data collection within a defined temporal window, though its limitation for causal inference is acknowledged in Section 8.

4.2 Sampling and Data Collection

The target population consists of adults in India who have purchased from domestic e-commerce platforms (Amazon India, Flipkart, Myntra) at least once in the preceding six months. A convenience sampling design was adopted to administer a structured questionnaire through Google Forms by leveraging social media, email, and messaging platforms. Convenience sampling is appropriate for an exploratory-explanatory study of this nature, where the primary objective is to estimate path coefficients and test mediation mechanisms rather than to generate population-representative prevalence estimates (Hair et al., 2019).

After removing incomplete submissions and respondents who classified themselves as non-shoppers, the study retained 247 valid responses for the final usable sample. Cohen's (1992) power analysis for medium effect sizes ($f^2 = 0.15$) at $\alpha = .05$ with three predictors in the most complex regression equation indicates a minimum sample of 119 for 80% statistical power; the obtained sample of 247 exceeds this benchmark comfortably.

4.3 Measurement Instrument

The survey instrument consisted of four sections. Section I collected demographic information (age group, gender, online shopping frequency, active shopper status). Sections II–IV measured the three focal constructs using validated scales adapted for the Indian e-commerce context:

- AI-Based Personalisation (5 items): Adapted from Xu et al. (2011). Sample item: "The platform provides personalised product recommendations based on my past activity."
- Perceived Relevance (4 items): Adapted from Tam and Ho (2006). Sample item: "The recommended products match my current needs and interests."
- Impulse Buying Behaviour (5 items): Adapted from Rook and Fisher (1995). Sample item: "I feel a strong urge to buy when I see a personalised recommendation."

The items were administered on a five-point Likert scale, where 1 corresponded to Strongly Disagree and 5 corresponded to Strongly Agree. The scale wording was evaluated and minimally revised to ensure cultural and contextual appropriateness and to preserve the meaning of the construct, consistent with the standard adaptation procedure set out by Brislin (1970).

4.4 Analytical Framework

Data analysis was conducted in the following sequential stages:

- a) Reliability analysis: internal consistency was evaluated using Cronbach's alpha (α), adopting the conventional criterion of ≥ 0.70 (Nunnally, 1978).
- b) Descriptive and correlation analysis - means, standard deviations, and Pearson correlation coefficients (r) were calculated to describe the sample and to provide initial indications of associations among constructs.
- c) Path analysis implemented through OLS regression: three separate OLS regression models were estimated to examine H1, H2, and H3, in accordance with the Baron and Kenny (1986) four-step mediation procedure. In this path-analytic framework, the proposed theoretical relationships are modelled as a set of causal paths, with each β coefficient indicating the standardized path strength.
- d) Sobel mediation test: the statistical significance of the indirect effect ($a \times b$) was examined with the Sobel test statistic, thereby providing a formal test of H4.

- e) Supplementary Group Analyses: One-way ANOVA (shopping frequency $\times$ impulse buying), independent-samples t-test (gender $\times$ impulse buying), and age-based group comparisons were conducted to explore boundary conditions.

5. DATA ANALYSIS AND RESULTS

5.1 Demographic Profile of Respondents

Table 1: Demographic Profile of Respondents (N = 247)

Variable	Category	n	%
Age Group	18–25 (Gen Z)	195	79.3
	26–35	35	14.2
	36–40	6	2.4
	Above 40	6	2.4
	Below 18	5	2.0
Gender	Male	174	70.7
	Female	71	28.9
	Prefer not to say	2	0.8
Shopping Frequency	Rarely	52	21.1
	Occasionally	116	47.2
	Frequently	65	26.4
	Very Frequently	14	5.7
Active Online Shopper	Yes	236	95.9

The sample is disproportionately concentrated in the 18–25 age bracket (79.3%), reflecting the characteristic demographic profile of India's active e-commerce user base and the recruitment channels employed. The IBEF (2023) reports that consumers aged 18–35 account for approximately 65% of Indian e-commerce transactions by value, suggesting the sample, while not population-representative, is well-aligned with the commercially most significant consumer segment. The gender skew (70.7% male) is an acknowledged limitation that circumscribes the generalisability of gender-based comparisons.

5.2 Reliability Analysis

Table 2: Cronbach's Alpha Reliability Coefficients (N = 247)

Construct	No. of Items	Cronbach's α	Interpretation
AI-Based Personalization	5	0.922	Excellent
Perceived Relevance	4	0.927	Excellent
Impulse Buying Behaviour	5	0.883	Excellent

All three constructs demonstrate excellent internal consistency, substantially exceeding Nunnally's (1978) minimum threshold of 0.70 and Hair et al.'s (2010) preferred threshold of 0.80 for confirmatory research. These alpha values indicate that the adapted survey items cohesively measure their respective constructs and that measurement error is unlikely to explain substantive variance in the regression results.

5.3 Pearson Correlation Analysis

Table 3: Pearson Correlation Matrix (N = 247)

Construct	(1) AI Personalisation	(2) Perceived Relevance	(3) Impulse Buying
(1) AI Personalisation	1.000	0.785***	0.487***
(2) Perceived Relevance	0.785***	1.000	0.598***
(3) Impulse Buying	0.487***	0.598***	1.000
Mean	3.54	3.42	2.97
SD	1.00	0.99	0.98

Note: *** $p < .001$ (two-tailed)

All bivariate correlations are positive and statistically significant ($p < .001$), providing preliminary support for H1–H3. The correlation between AI Personalisation and Perceived Relevance ($r = 0.785$) is the strongest in the matrix, establishing that the algorithm-relevance perception link is robust. The comparatively weaker correlation between AI Personalisation and Impulse Buying ($r = 0.487$ vs. $r = 0.598$ for Perceived Relevance–Impulse Buying) provides the structural signature of partial or full mediation: the distal stimulus-response relationship is weaker than the proximal mediator-response relationship, which is precisely what a mediation model predicts.

No correlation exceeds 0.85, suggesting multicollinearity is not a concern, a claim further supported by the sequential regression analysis below.

5.4 Path Analysis — Hypothesis Testing via OLS Regression

Table 4: Path Analysis Results for H1, H2, and H3 (N = 246–247)

Hypot hesis	Path	Predictor	Outcome	β	R^2	F	t	Result
H1	a	AI Personalization	Perceived Relevance	0.772	0.616	393.34** *	19.83** *	**Supported**
H2	b	Perceived Relevance	Impulse Buying	0.596	0.358	136.41** *	11.68** *	**Supported**
H3	c	AI Personalisation	Impulse Buying	0.477	0.237	76.26***	8.73***	**Supported**

Note: *** $p < .001$. β = standardised regression coefficient (path coefficient). R^2 = proportion of variance explained.

H1 is strongly supported: AI personalisation accounts for 61.6% of the variance in Perceived Relevance ($\beta = 0.772$, $p < .001$). This is a large effect size (Cohen, 1992) and confirms that the AI personalisation systems deployed by Indian e-commerce platforms are sufficiently sophisticated to produce a meaningful relevance experience in the majority of surveyed consumers. The magnitude of this path coefficient exceeds that reported in several comparable Western studies (e.g., Bleier & Eisenbeiss, 2015), potentially reflecting the higher daily exposure frequency of Indian e-commerce users or the relative novelty of algorithm-driven personalization in this market.

H2 is supported with a moderate effect: Perceived Relevance explains 35.8% of the variance in Impulse Buying ($\beta = 0.596$, $p < .001$). This confirms that the relevance appraisal is a powerful proximal predictor of spontaneous purchasing — when a recommendation resonates with the consumer's

current self-concept and situational needs, the probability of an unplanned purchase increase substantially.

H3 is supported, but this direct path is the weakest in the model ($\beta = 0.477$, $R^2 = 0.237$). This anticipates the mediation finding: when examined in isolation, AI personalisation does predict impulse buying, but a substantial proportion of that relationship is attributable to indirect influence through relevance.

5.5 Mediation Analysis — Sobel Test for H4

Following the Baron and Kenny (1986) four-step procedure:

- Step 1 (Path a): AI Personalisation → Perceived Relevance: $a = 0.772$, $SE = 0.039$, $t = 19.833$, $p < .001$ ✓
- Step 2 (Path b, controlling for X): Perceived Relevance → Impulse Buying (controlling AI Personalisation): $b = 0.560$, $SE = 0.082$, $t = 6.829$, $p < .001$ ✓
- Step 3 (Total effect c): AI Personalisation → Impulse Buying: $c = 0.477$, $p < .001$ ✓
- Step 4 (Direct effect c'): AI Personalisation → Impulse Buying (controlling Perceived Relevance): $c' = 0.045$, $SE = 0.081$, $t = 0.559$, $p = .576$ (non-significant) → Full Mediation

Table 5: Mediation Analysis — Sobel Test Results for H4 (N = 247)

Path	Coefficient	SE	t / z	p	Significance
Path a: AI Personalisation → Perceived Relevance	$a = 0.772$	0.039	$t = 19.833$	$< .001$	***
Path b: Perceived Relevance → Impulse Buying (controlling AI)	$b = 0.560$	0.082	$t = 6.829$	$< .001$	***
Total effect c: AI Personalisation → Impulse Buying	$c = 0.477$	0.055	$t = 8.733$	$< .001$	***
Direct effect c': AI Personalisation → Impulse Buying (controlling PR)	$c' = 0.045$	0.081	$t = 0.559$	.576	n.s.
Indirect effect ($a \times b$): Sobel Test	0.432	—	$z = 6.421$	$< .001$	FULL MEDIATION

Note: *** $p < .001$; n.s. = not significant

H4 is supported — Full Mediation is confirmed. The indirect effect ($a \times b = 0.772 \times 0.560 = 0.432$) is statistically significant (Sobel $z = 6.421$, $p < .001$), and the direct path c' is non-significant ($p = .576$). This constitutes full mediation by the criteria of Baron and Kenny (1986), indicating that AI personalisation does not directly drive impulse buying when consumers are actively processing it; rather, its entire behavioural effect is channelled through the relevance appraisal.

This result has significant implications for business strategy: the return on investment from personalization spending depends entirely on how well the relevance experience is delivered to consumers. An AI system that is technically sophisticated but fails to produce a subjective relevance perception in the consumer will generate zero incremental impulse purchases. Conversely, a system that successfully operationalises relevance — through contextual cues, personalised framing, or culturally resonant product pairings — unlocks the full pathway to impulse purchase.

5.6 Summary of Hypothesis Testing

Table 6: Summary of All Hypotheses (N = 247)

Hypothesis	Statement	Key Statistic	p-value	Result
H1	AI Personalisation → Perceived Relevance	$\beta = 0.772$, $R^2 = 0.616$, $t = 19.833$	< .001	**Supported**
H2	Perceived Relevance → Impulse Buying	$\beta = 0.596$, $R^2 = 0.358$, $t = 11.679$	< .001	**Supported**
H3	AI Personalisation → Impulse Buying (total)	$\beta = 0.477$, $R^2 = 0.237$, $t = 8.733$	< .001	**Supported**
H4	Perceived Relevance fully mediates H3 path	Indirect = 0.432, Sobel $z = 6.421$	< .001	**Supported (Full Mediation)**
H5	Age moderates AI Personalisation → Relevance	Exploratory group comparison (see 5.7.3)	—	**Partially Supported (Exploratory)**

5.7 Supplementary Analyses

5.7.1 Shopping Frequency and Impulse Buying — One-Way ANOVA

Table 7: One-Way ANOVA — Shopping Frequency vs. Impulse Buying Behaviour

Shopping Frequency	n	IB Mean	SD
Rarely	52	2.91	0.92
Occasionally	116	2.80	0.88
Frequently	65	3.37	1.01
Very Frequently	14	2.79	1.40
ANOVA Result		**F = 5.118**	**p = .002***

The ANOVA reveals a significant overall effect of shopping frequency on impulse buying propensity ($F(3, 243) = 5.118$, $p = .002$). Frequent shoppers show the highest impulse buying mean ($M = 3.37$, $SD = 1.01$), significantly above both occasional ($M = 2.80$) and rare ($M = 2.91$) shoppers. This result aligns with the habituation-amplification mechanism reported by Rasool et al. (2025): habitual platform users develop more automated responses to personalisation cues, reducing the deliberative resistance that moderates impulse purchasing among occasional shoppers.

The counterintuitive finding that Very Frequent shoppers ($M = 2.79$) report lower impulse buying scores than Frequent shoppers warrants interpretation. The most parsimonious explanation is a saturation effect: consumers who shop with very high frequency develop greater familiarity with algorithmic patterns, becoming desensitised to recommendation stimuli and more strategic in their purchase evaluations. This saturation hypothesis aligns with the filter bubble fatigue research (Pariser, 2011) and warrants formal examination in future studies.

5.7.2 Gender and Impulse Buying — Independent Samples t-Test

An independent-samples t-test found no statistically significant gender difference in impulse buying propensity (Female: $M = 3.03$, $SD = 0.94$; Male: $M = 2.95$, $SD = 1.00$; $t = -0.555$, $p = .579$). This null finding is substantively meaningful: the AI personalisation–impulse buying pathway appears to operate with comparable intensity across genders in this sample. Given the gender imbalance (70.7% male), this result should be interpreted cautiously but suggests that personalisation strategies need not be gender-differentiated at the mechanism level.

5.7.3 Age Group Comparison — Exploratory Analysis (H5)

Table 8: Age Group Comparisons on Key Constructs

Age Group	n	AI Personalisation Mean	Perceived Relevance Mean	Impulse Buying Mean
18–25 (Gen Z)	195	3.60	3.49	3.02
26–35	35	3.29	3.14	2.84
36+	17	3.18	3.07	2.68

Note: Means computed from construct composite scores (all items averaged). Full ANOVA-based moderation inference is not possible given unequal and small group sizes in older cohorts; these means are presented as exploratory comparisons.

The directional pattern is consistent with H5: as age increases, mean scores on all three constructs decline. The 18–25 cohort reports the highest AI personalisation perception ($M = 3.60$), the highest perceived relevance ($M = 3.49$), and the highest impulse buying propensity ($M = 3.02$). This finding is consistent with the perspective that digital nativity among Gen Z consumers strengthens algorithmic trust and increases sensitivity to relevance. Similarly, Iskandar (2025) concludes that, among Gen Z consumers, impulse purchases prompted by AI advertising personalization yield stronger effects even when usage frequency is held constant.

However, the restricted group sizes for the 26–35 ($n = 35$) and 36+ ($n = 17$) cohorts preclude statistically reliable moderation inference. Formal Age moderation testing would require minimum group sizes of 100+ per cohort for Multi-Group Analysis (MGA) in PLS-SEM, or sufficiently powered interaction terms in a moderated regression framework. This constitutes a methodological limitation of the present study and a direct recommendation for future research design.

6. DISCUSSION AND STRATEGIC IMPLICATIONS FOR CONTEMPORARY BUSINESSES

6.1 Theoretical Contributions

This study makes three distinct theoretical contributions to the literature on AI-driven consumer behavior.

First, it reaffirms and extends the primacy of Perceived Relevance as the operative mechanism through which AI personalisation influences impulse buying. The full mediation finding — the direct path from AI personalisation to impulse buying collapses entirely when Perceived Relevance is controlled — establishes that the algorithm's commercial potency is entirely contingent on the consumer's relevance appraisal. This has not been demonstrated with this level of statistical precision in the Indian e-commerce context, and it provides a tightly specified mechanism that can inform system design.

Second, the study empirically documents the "relevance variance ratio": AI personalisation accounts for 61.6% of the variance in Perceived Relevance ($R^2 = 0.616$), but Perceived Relevance accounts for only 35.8% of the variance in Impulse Buying ($R^2 = 0.358$). This asymmetry reveals that while AI personalisation is highly effective at generating relevance perceptions, the translation of relevance into impulse buying is subject to other moderating forces — potentially including mood, financial constraint, social norms, and the post-impulse regret mechanism identified by Rook and Fisher (1995). Future research should explicitly model these additional moderators.

Third, the study contributes to the growing body of work on the SOBC extension of S-O-R (Shamim & Misra, 2025) by demonstrating that the consequence dimension — specifically the risk of privacy

concern activation — is a theoretically necessary complement to the behaviour stage. The personalisation-privacy paradox (Xu et al., 2011) remains operationally unresolved, and its implications for long-term brand loyalty constitute a consequence that the S-O-R model alone cannot fully represent.

6.2 Strategic Implications for Contemporary E-Commerce Businesses

The findings generate several concrete strategic mandates for e-commerce businesses operating in the AI-integrated retail landscape.

Invest in Relevance Quality, Not Recommendation Quantity. The mediation analysis establishes unambiguously that the ROI of personalisation infrastructure is gated by subjective relevance perception rather than the volume of recommendations generated. Platforms that serve consumers with high-frequency low-relevance recommendations risk triggering reactance — a defensive cognitive response that reduces engagement rather than increasing it (Brehm & Brehm, 1981). The strategic recommendation is to shift from recommendation volume optimisation toward relevance quality metrics, operationalised as consumer-rated relevance scores collected systematically through in-app feedback mechanisms.

Deploy Contextual and Temporal Personalisation. Ahmed et al. (2025) identify contextual relevance and delivery timing as the two strongest predictors of purchase intention in AI-driven marketing campaigns. Platforms should use contextual signals—such as device type, time of day, the context of a recent browsing session, seasonal micro-events, and location-based cues—to strengthen the perceived immediacy and relevance of recommendations. A product recommended during the browsing context in which it is most likely to feel relevant converts at substantially higher rates than the same product recommended out of context.

Operationalise Algorithmic Transparency. Lu et al. (2025) document that explaining the rationale behind a recommendation ("Recommended because you purchased X last month") increases both trust and relevance perception. This practice, known as explanation-based personalisation, converts the AI from an invisible and potentially unsettling influence into a visible and trustworthy collaborator in the shopping experience. Indian consumers who understand the DPDPA (2023) implications may be especially receptive to transparency cues like these.

Target the Frequent Shopper Segment Strategically. The ANOVA finding (Section 5.7.1) demonstrates that frequent shoppers exhibit the highest impulse buying propensity, while very frequent shoppers show a saturation effect. This suggests a strategically optimal window of maximum personalisation impact — consumers in the "frequently" bracket are sufficiently habituated to the platform to respond automatically to personalisation cues but not yet desensitised. Platforms should design loyalty programs, push notification schedules, and recommendation intensity levels that maintain consumers in this high-susceptibility window without triggering the saturation-induced drop observed in the "very frequently" group.

Design for the Gen Z Relevance Sensitivity Profile. The exploratory age analysis (Section 5.7.3) shows that the 18–25 cohort is not only more frequent users but more receptive to personalisation stimuli, recording higher means on all three constructs. This suggests that Gen Z-targeted platforms (e.g., Myntra, Meesho) should invest disproportionately in personalisation infrastructure quality, as the relevance-to-impulse translation rate is highest for this cohort. Conversely, platforms targeting older demographics (26+) may need to supplement personalisation with deliberative decision support tools — comparison features, expert reviews, and contextual value articulation — to compensate for the lower automatic relevance sensitivity observed in these groups.

6.3 Ethical Dimensions and Regulatory Compliance

The findings carry non-trivial ethical weight that contemporary businesses must integrate into their AI governance frameworks. The establishment of a full mediation pathway from AI personalisation through relevance to impulse buying confirms that AI recommendation systems are instrumentally effective at inducing unplanned purchases.

Several dimensions require explicit managerial attention:

The DPDPA (2023) Compliance Imperative. Under India's Digital Personal Data Protection Act, 2023, data principals can demand enforceable protections, including being informed about the use of their data and withdrawing consent for data processing. Personalization systems that collect and process behavioural data for impulse-triggering recommendation purposes must now operate within this regulatory framework. Businesses must audit their data processing pipelines for DPDPA compliance and ensure that consent mechanisms are genuine rather than procedural.

Algorithmic Nudging and Consumer Vulnerability. Haryanto et al. (2025) and Wahdaniyah et al. (2025) both identify emotional triggers — urgency, scarcity, FOMO — as amplifiers of the personalisation-impulse buying pathway. Using these mechanisms coercively against consumers under conditions of intense emotional distress, financial hardship, or compulsive shopping tendencies constitutes exploitation and places the parties involved at reputational, legal, and ethical risk. Responsible AI guidelines, such as those increasingly promoted by the Bureau of Indian Standards (BIS) and international frameworks like the EU AI Act, recommend that high-stakes behavioural nudges carry opt-out mechanisms and contextual warnings.

Long-Term Brand Loyalty vs. Short-Term Conversion. Shamim and Misra (2025) note that trust acts as a critical moderator of the loyalty consequences of AI-induced impulse buying — if consumers retrospectively attribute their impulse purchases to algorithmic manipulation rather than genuine desire, brand trust erodes. The implication is that maximising short-term impulse conversion without ensuring long-term relevance satisfaction creates a business model that cannibalises future loyalty. Sustainable commercial advantage requires that the relevance experience be genuine rather than manufactured through dark patterns.

7. CONCLUSION

This study aimed to explain how AI-driven personalization on Indian e-commerce platforms leads to impulse buying, and to assess Perceived Relevance as the psychological mechanism mediating this effect. The results are theoretically well supported and practically actionable.

Artificial intelligence personalization is a major commercial driver in today's Indian retail, though it does not act as a simple impulse trigger. Its ability to elicit spontaneous purchasing is entirely channeled through the consumer's subjective sense of relevance, the conviction that the algorithm understands what the consumer needs, when they need it. This complete mediation is not only an empirical finding; it also sets a strategic requirement. All return on investment from personalization spending passes through the relevance gateway, so firms that invest in the quality of the relevance experience—rather than the size, frequency, or technical sophistication of recommendations—will achieve better conversion results.

The findings further suggest that shopping frequency, but not gender, influences consumers' impulse-buying propensity, as evidenced by the 18–25 group showing the highest responsiveness to personalisation cues. These results align with a habituation-amplification mechanism among frequent shoppers and a digital native advantage for Gen Z consumers.

Looking ahead, there is a need for methodological refinement toward PLS-SEM, featuring bootstrapped indirect effects, longitudinal or clickstream-based behavioral validation, and formal

moderation testing employing balanced age-group samples. The integration of Trust in AI, Emotional Engagement, and Privacy Concern as additional constructs within the SOBC framework would greatly strengthen the model. From a strategic perspective, generative artificial intelligence shopping assistants that enable natural-language discussions of consumer preferences point to a qualitative shift in the personalization paradigm that scholarly work has only begun to conceptualize.

This study concludes that the algorithmic impulse is not a technological artifact, but a psychological one. Companies that recognize this difference and invest accordingly will shape the next phase of Indian retail.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study is subject to several well-recognised constraints. The cross-sectional design prevents causal inferences; although the mediation analysis confirms the structural relationships anticipated by theory, longitudinal or experimental designs would yield stronger causal evidence. The sample is demographically concentrated (79.3% aged 18–25; 70.7% male), which restricts generalisability to older and more gender-balanced consumer groups. Because key measures rely on self-report, social desirability bias is likely, especially for impulse-buying items with normative implications. Although common method bias was reduced through the construct-level analysis, it was not formally tested using Harman's single-factor test or via a marker variable approach.

Future research should prioritise the following: (1) replication using a balanced, stratified sample to enable formal Multi-Group Analysis (MGA) by age cohort; (2) extending the model by adding Trust in AI as a competing or complementary mediator and treating Privacy Concerns as a theoretically grounded moderator; (3) moving to PLS-SEM with SmartPLS 4, with complete reporting of the measurement model outputs (CR, AVE, HTMT ratios) and bootstrapped indirect effects; (4) incorporating actual behavioural data (clickstream and transaction records) from e-commerce platform APIs to validate self-reported impulse buying against real purchase behaviour; and (5) cross-national replication to assess whether the full mediation finding extends beyond the Indian market.

REFERENCES

- Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182. <https://doi.org/10.1037/0022-3514.51.6.1173>
- Bleier, A., & Eisenbeiss, M. (2015). The importance of trust for personalised online advertising. *Journal of Retailing*, 91(3), 390–409. <https://doi.org/10.1016/j.jretai.2015.04.001>
- Brehm, S. S., & Brehm, J. W. (1981). *Psychological reactance: A theory of freedom and control*. Academic Press.
- Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology*, 1(3), 185–216. <https://doi.org/10.1177/135910457000100301>
- Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112(1), 155–159. <https://doi.org/10.1037/0033-2909.112.1.155>
- Ahmed, Z., Siddiqui, S. A., & Nawaz, M. (2025). The impact of artificial intelligence and machine learning algorithms on personalised digital marketing campaigns. *Academic Journal of Business and Management*, 4(3). <https://doi.org/10.63056/acad.004.03.0629>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2019). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.

- Haryanto, B., Wahyudi, L., & Setiawan, A. I. (2025). AI-powered personalisation and its influence on impulse buying: A study of predictive algorithms in online retail. <https://doi.org/10.5281/zenodo.16408909>
- IBEF. (2023). E-commerce industry in India. India Brand Equity Foundation. <https://www.ibef.org/industry/ecommerce>
- Iskandar, M. (2025). AI advertising personalisation, content quality, trust, and Gen Z impulsive buying behaviour. *Jagaditha: Journal of Economics and Business*, 8(2). <https://ejurnal.warmadewa.ac.id/index.php/jagaditha/article/view/14420>
- Lu, W., Zhang, J., Li, H., Chen, Y., & Wang, X. (2025). The influence of AI-driven personalisation in social media marketing on consumer purchase decisions and behaviour. *International Journal of Accounting and Economics Studies*, 13(1). <https://doi.org/10.14419/dcggbj32>
- McKinsey & Company. (2023). The value of getting personalisation right—or wrong—is multiplying. <https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-value-of-getting-personalization-right>
- Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. MIT Press.
- Nimisha, V., Rao, S., & Krishnan, A. (2025). AI-driven personalisation cues: Unravelling consumer impulsive buying in e-commerce. *Economic Sciences*, 14(1). <https://doi.org/10.69889/arkq5j81>
- Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.
- Priteena, A., Nair, R., & Suresh, M. (2025). Artificial intelligence in e-commerce: Analysing its role in shaping purchase intentions and behaviours. *Bits and Bytes of Business*, 4(2). <https://doi.org/10.51470/bits.2025.04.02.11>
- Rasool, S., Farooq, A., & Malik, S. (2025). Investigating the impact of algorithmic ad personalisation on unplanned buying through customer engagement. *Journal of Logistics and Supply Chain Management*, 7(4), 274–288. <https://doi.org/10.52279/jlss.07.04.274288>
- Rook, D. W. (1987). The buying impulse. *Journal of Consumer Research*, 14(2), 189–199. <https://doi.org/10.1086/209105>
- Rook, D. W., & Fisher, R. J. (1995). Normative influences on impulsive buying behaviour. *Journal of Consumer Research*, 22(3), 305–313. <https://doi.org/10.1086/209452>
- Shamim, A., & Misra, S. C. (2025). Leveraging AI to drive online impulse buying: A SOBC perspective. *International Journal of Retail & Distribution Management*. <https://doi.org/10.1108/ijrdm-07-2024-0334>
- Sun, Y., Liu, B., & Chen, J. (2023). AI-based features and impulse buying in online shopping. *Information Systems Management*, 40(2), 112–128. <https://doi.org/10.1080/10580530.2022.2063004>
- Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalisation on user information processing and decision outcomes. *MIS Quarterly*, 30(4), 865–890. <https://doi.org/10.2307/25148757>
- Verhagen, T., & Van Dolen, W. (2011). The influence of online store beliefs on consumer online impulse buying. *Information & Management*, 48(8), 320–327. <https://doi.org/10.1016/j.im.2011.08.001>
- Wahdaniyah, L., Pramono, R., & Sari, D. (2025). The impact of AI-driven personalisation and social influence on customer engagement: The mediating role of FOMO in digital platforms. *Business, Economics and Management Journal*. <https://beman.ase.ro/no162/7.pdf>
- Wells, J. D., Parboteeah, V., & Valacich, J. S. (2011). Online impulse buying: Understanding the interplay between consumer impulsiveness and website quality. *Journal of the Association for Information Systems*, 12(1), 32–56. <https://doi.org/10.17705/1jais.00254>
- Xu, H., Luo, X., Carroll, J. M., & Rosson, M. B. (2011). The personalisation-privacy paradox: An exploratory study of decision-making processes for location-aware marketing. *Decision Support Systems*, 51(1), 42–52. <https://doi.org/10.1016/j.dss.2010.11.017>

Logistics Cost Performance in International Supply Chains: A Literature Synthesis for India's Energy Equipment Manufacturing Sector

Ganesh Shenoy

Research Scholar, Dr V. N Bedekar Institute of Management Studies, Thane

Mahesh Manohar Bhanushali

Assistant Professor, Dr V. N Bedekar Institute of Management Studies, Thane

ABSTRACT

The global shift toward renewable energy has positioned India as a major hub for energy equipment manufacturing and export, yet Indian solar panel and transformer manufacturers face substantial international logistics costs that constrain competitiveness. Despite growing academic interest in supply chain logistics, no study has systematically synthesised the determinants of logistics cost performance for this sector. This paper addresses that gap through a systematic literature synthesis guided by the PRISMA framework. Following searches of Scopus, Emerald Insight, Taylor & Francis Online, and Google Scholar covering 2010-2025, 85 records were initially identified, and after eligibility screening, 52 peer-reviewed studies were retained for synthesis. The review identifies eight determinants of logistics cost performance: transportation cost, packaging and handling, warehousing and inventory management, customs clearance and regulatory compliance, supply chain coordination, logistics technology adoption, inventory planning efficiency, and market competition intensity. Transportation costs emerge as the dominant expenditure, accounting for 40–60 per cent of total logistics costs in developing-economy contexts, while product-specific handling requirements differentiate fragile solar panels from heavy transformers. Customs compliance disproportionately burdens emerging-economy exporters, whereas coordination and technology adoption mitigate costs, and inventory planning mediates warehousing efficiency.

Being conceptual, the synthesis requires empirical validation through primary data from Indian manufacturers; nonetheless, it offers practical guidance on coordination, technology, and inventory practices, alongside policy recommendations on customs streamlining, port infrastructure, and digital logistics support. This paper offers the first comprehensive synthesis of logistics cost determinants for India's energy equipment sector, bridging logistics management and renewable energy supply chain research.

Keywords – logistics cost performance, international supply chains, energy equipment manufacturing, solar panels, transformers, india, supply chain coordination, customs compliance

1. INTRODUCTION

The accelerating global transition towards renewable energy has generated substantial international demand for energy equipment, including solar photovoltaic modules and electrical transformers. India, supported by manufacturing-friendly policies such as the Production Linked Incentive (PLI) scheme, has emerged as a significant hub for energy equipment production and export (Pohit et al., 2019). However, the ability of Indian manufacturers to compete effectively in global markets increasingly depends upon their capacity to manage logistics costs across complex international supply chains.

Logistics costs typically constitute 10–35% of total product cost in international trade, varying by product characteristics, transportation distance, and supply chain complexity (Rushton et al., 2017). For energy equipment manufacturers, these costs are amplified by product-specific handling requirements: solar panels require fragile cargo packaging and shock-absorbent transportation systems, while transformers demand heavy-lift equipment, specialised loading arrangements, and infrastructure for oversized cargo (Bowersox et al., 2013). Despite the strategic importance of logistics

cost management, limited empirical research has systematically examined the determinants of logistics cost performance in the Indian energy equipment manufacturing context.

This paper addresses this gap through a systematic synthesis of existing literature. The objectives are threefold: first, to identify and thematically organise key determinants of logistics cost performance reported in peer-reviewed research; second, to synthesise findings from diverse geographical and industrial contexts into a coherent conceptual framework relevant to India; and third, to derive practical and policy implications for enhancing logistics competitiveness in India's solar panel and transformer manufacturing sectors.

The synthesis is organised around eight principal determinants that consistently appear in high-quality logistics literature: transportation cost; packaging and handling requirements; warehousing and inventory management; customs clearance and regulatory compliance; supply chain coordination among logistics partners; adoption of logistics technology and digital systems; inventory planning efficiency; and market competition intensity. The dependent variable, logistics cost performance (LCP), is conceptualised as the effectiveness of cost control, export competitiveness, and operational efficiency achieved through logistics management (Lai et al., 2008; Mentzer et al., 2001).

To ensure transparency and replicability, the present study adopted a systematic approach for identifying and synthesising relevant literature. The search strategy was guided by the recognised PRISMA framework, suitably adapted for supply chain and logistics research contexts (Moher et al., 2009). Four scholarly databases formed the primary source of articles: Scopus, Emerald Insight, Taylor & Francis Online, and Google Scholar (the latter used only for cross-verification of grey literature). The search period spanned fifteen years, from January 2010 to December 2025. Keyword combinations included terms such as logistics cost, transportation cost, warehousing cost, inventory holding cost, customs compliance, regulatory burden, packaging and handling, technology adoption, ERP in logistics, supply chain coordination, market rivalry, energy equipment exports, solar panel logistics, transformer logistics, and India's export supply chains. Only peer-reviewed journal articles written in English were considered. After applying inclusion and exclusion criteria and completing title, abstract, and full-text screening, a final set of 52 research papers was retained for in-depth synthesis. The following section presents the thematic findings derived from these studies.

2. LITERATURE SYNTHESIS: KEY DETERMINANTS OF LOGISTICS COST PERFORMANCE

2.1 Transportation Cost as a Determinant

Transportation cost consistently emerges as the largest component of logistics expenditure in international supply chains. In developing country export operations, transportation typically accounts for 40–60% of total logistics costs (Bowersox et al., 2013; Rushton et al., 2017). For Indian energy equipment manufacturers, international freight charges are influenced by multiple interrelated factors including fuel price volatility, distance to export destinations, route efficiency, and modal choices (Pohit et al., 2019).

Evidence from Asian supply chains indicates that fuel price fluctuations have a direct and immediate impact on transportation costs, with elasticity estimates ranging from 0.6 to 0.8 (Banomyong, 2008). Long transportation distances to major markets—Europe, North America, and the Middle East—exponentially increase logistics costs due to cumulative freight charges, insurance premiums, and transit risk premiums (Coyle et al., 2016). Inefficient transport route planning, characterised by suboptimal consolidation, backhaul inefficiencies, and mode mismatch, has been shown to increase logistics expenses by 15–25% compared to optimised routing (Büyükkaramikli et al., 2014).

Transportation delays arising from port congestion, documentation errors, or carrier reliability issues generate cascading cost effects including demurrage charges, inventory carrying costs, and expedited shipping expenses (Christopher, 2016). For Indian exporters, average dwell time at major ports (Nhava Sheva, Mundra, Chennai) ranges from 3 to 7 days, substantially exceeding global benchmarks of 1–2 days, thereby inflating logistics costs (Pohit et al., 2019). The literature thus consistently identifies transportation cost as a primary determinant of overall logistics cost performance.

2.2 Packaging and Handling Requirements

Product characteristics fundamentally determine packaging and handling requirements, creating substantial variations in logistics cost structures across industries (Lambert et al., 1998). The energy equipment manufacturing sector presents two contrasting product archetypes with distinctly different logistics requirements.

Solar panels, characterised by fragile crystalline silicon cells and glass encapsulation, require specialised export packaging incorporating shock-absorbent materials, anti-static protection, and climate-resistant crating (Ayers, 2006). Research indicates that packaging costs for fragile electronic products can represent 8–12% of total logistics costs, compared to 3–5% for durable goods (Bidgoli, 2010). Additionally, handling requirements for solar panels include tilt-sensitive loading, stack height restrictions, and vibration-monitored transportation, all of which increase operational complexity and cost.

Electrical transformers, by contrast, involve heavy cargo transportation, with unit weights ranging from several hundred kilograms to over 100 tonnes for large power transformers (Rushton et al., 2017). Specialised logistics arrangements required for transformer exports include low-bed trailers, crane loading facilities, route surveying for bridge and road clearances, and potentially multimodal transport incorporating roll-on/roll-off (RoRo) vessels (Coyle et al., 2016). These specialised handling arrangements substantially increase logistics costs compared to standard containerised cargo.

Loading and unloading procedures significantly influence logistics costs through labour requirements, equipment needs, and damage risk. Damage prevention measures, including cushioning, bracing, and shock indicators, increase operational costs but reduce damage-related claims and insurance premiums (Lambert et al., 1998). International packaging standards, including ISPM 15 for wooden packaging and ISTA testing protocols for transport simulation, further increase compliance costs for exporters (Ayers, 2006). Accordingly, packaging and handling requirements represent a significant product-specific determinant of logistics cost performance.

2.3 Warehousing and Inventory Management Practices

Warehousing and inventory management practices represent interconnected cost drivers in international supply chains (Coyle et al., 2016). Warehousing costs, including storage, handling, and facility maintenance, directly influence total logistics expenditure, with typical contributions ranging from 20–30% of total logistics costs in manufacturing supply chains (Bowersox et al., 2013).

Inventory holding costs encompass capital cost (opportunity cost of funds invested in inventory), storage costs (warehousing, insurance, taxes), and risk costs (obsolescence, damage, theft) (Christopher, 2016). For energy equipment manufacturers exporting to international markets, inventory holding costs are amplified by long transit times (30–60 days to European or North American markets) and demand uncertainty in foreign markets (Büyükkaramikli et al., 2014). Empirical research demonstrates that reducing inventory levels by 20% while maintaining service levels can improve logistics cost performance by 8–12% (Muscatello et al., 2018).

Inefficient warehouse management practices, including poor layout design, suboptimal slotting, and manual picking processes, increase logistics costs through higher labour requirements, slower throughput, and increased error rates (Gunasekaran et al., 2017). Conversely, strategic warehouse location—proximal to ports, transportation corridors, or major customer concentrations—has been shown to reduce logistics costs by 10–15% through reduced drayage expenses and improved consolidation opportunities (Rabah & Mahmassani, 2002).

Excess inventory storage, whether arising from inaccurate demand forecasting or safety stock buffers, increases operational expenses through higher carrying costs and increased obsolescence risk (Neubert et al., 2018). For Indian energy equipment manufacturers, the seasonal nature of solar panel demand and project-based procurement of transformers create inventory planning challenges that directly affect warehousing costs.

2.4 Customs Clearance and Regulatory Compliance

Customs clearance procedures and regulatory compliance requirements constitute significant cost drivers in international supply chains, with disproportionately large effects on exporters from developing economies (Zeng, 2003). For Indian energy equipment manufacturers, export documentation requirements include bills of lading, commercial invoices, packing lists, certificates of origin, shipping bills, and product-specific certifications (e.g., IEC 61215 for solar panels, IS 2026 for transformers).

Evidence from Southeast Asian supply chains demonstrates that customs clearance procedures increase total logistics costs by 5–15% depending on procedural efficiency and documentation accuracy (Banomyong, 2008). Delays in customs clearance generate demurrage and detention charges, expedited shipping costs for time-sensitive cargo, and potential penalty payments for delivery deadline breaches (Pohit et al., 2019). Research indicates that each additional day of customs delay increases total logistics costs by approximately 2–3% for time-sensitive manufactured goods.

International regulatory compliance increases operational complexity and cost through multiple mechanisms: product certification requirements in destination markets (e.g., CE marking for European Union, UL certification for North America), environmental regulations (e.g., RoHS compliance, waste electrical and electronic equipment directives), and trade-specific requirements (e.g., anti-dumping duty documentation) (Christopher, 2016). Frequent changes in export regulations, including tariff adjustments, documentation format revisions, and new certification requirements, create compliance uncertainty and necessitate continuous updating of export procedures (Zeng, 2003).

For Indian exporters, the implementation of the Goods and Services Tax (GST) and the ongoing modernisation of customs infrastructure under the Indian Customs Electronic Data Interchange (ICEGATE) system have reduced some compliance burdens while introducing new procedural requirements (Pohit et al., 2019).

2.5 Supply Chain Coordination Among Logistics Partners

Supply chain coordination refers to the degree of collaboration, communication, and information sharing among logistics partners including freight forwarders, carriers, customs brokers, warehousing providers, and consignees (Mentzer et al., 2001). Effective coordination has been demonstrated to reduce logistics costs through improved resource utilisation, reduced redundancies, and faster problem resolution (Lai et al., 2008).

Empirical research by Lai et al. (2008) found that effective coordination with logistics partners reduces total logistics costs by 12–18% in Asian manufacturing supply chains. Coordination mechanisms include joint forecasting, shared transportation resources, consolidated warehousing, and collaborative contingency planning (Muscatello et al., 2018). Collaboration with freight forwarders, in particular, improves supply chain efficiency through consolidated shipments, optimised routing, and negotiated carrier rates (Christopher, 2016).

Conversely, communication gaps with logistics partners increase logistics costs through duplicate efforts, expedited shipments to correct errors, and penalty payments for service failures (Mentzer et al., 2001). Supply chain integration, encompassing both internal integration across functional departments and external integration with logistics service providers, improves international logistics efficiency by reducing handoff delays and information asymmetries (Lai et al., 2008).

Real-time coordination among supply chain partners, enabled by communication technologies and shared information systems, improves operational performance through immediate exception notification, dynamic rerouting capabilities, and proactive customs clearance (Rabah & Mahmassani, 2002). For Indian energy equipment manufacturers, coordination challenges are amplified by the involvement of multiple logistics service providers (typically 3–5 per export shipment) and the geographical dispersion of supply chain partners.

2.6 Adoption of Logistics Technology and Digital Systems

Logistics technology adoption has emerged as a significant cost-reduction lever in international supply chains, with digital systems enabling visibility, optimisation, and automation (Gunasekaran et al., 2017). Key technologies include enterprise resource planning (ERP) systems, transportation management systems (TMS), warehouse management systems (WMS), real-time tracking devices, and data analytics platforms.

Digital logistics systems improve supply chain visibility by providing real-time information on shipment status, inventory levels, and exception events (Rabah & Mahmassani, 2002). Improved visibility enables proactive exception management, reducing delay-related costs and safety stock requirements (Muscatello et al., 2018). Technology adoption helps optimise transportation planning through route optimisation algorithms, load consolidation tools, and modal selection decision support (Gunasekaran et al., 2017).

Real-time shipment tracking, enabled by GPS devices, RFID tags, and Internet of Things (IoT) sensors, improves logistics efficiency through reduced theft risk, faster claims processing, and improved customer communication (Christopher, 2016). Advanced logistics technologies, including automated warehouses, robotic picking systems, and predictive analytics platforms, reduce operational costs through labour reduction, error reduction, and capacity optimisation (Neubert et al., 2018).

ERP and digital systems improve export logistics management by integrating order management, inventory visibility, documentation generation, and financial settlement processes (Muscatello et al., 2018). Empirical research by Gunasekaran et al. (2017) found that comprehensive ERP implementation in manufacturing supply chains reduces logistics costs by 8–15% through improved coordination and reduced manual interventions. For Indian energy equipment manufacturers, technology adoption remains heterogeneous, with larger firms demonstrating higher adoption rates than small and medium enterprises (Pohit et al., 2019).

2.7 Inventory Planning Efficiency

Inventory planning efficiency encompasses demand forecasting accuracy, inventory optimisation, and planning system effectiveness in reducing logistics costs (Neubert et al., 2018). Accurate demand forecasting reduces inventory holding costs by aligning stock levels with expected demand, thereby reducing excess inventory and stockout expenses (Christopher, 2016).

Empirical research demonstrates that improving demand forecast accuracy from 70% to 90% reduces inventory holding costs by 15–25% while maintaining customer service levels (Rabah & Mahmassani, 2002). Efficient inventory planning reduces logistics expenses through multiple mechanisms: reduced warehousing requirements, lower capital tied up in inventory, decreased obsolescence risk, and improved transportation efficiency through consolidated shipments (Büyükkaramikli et al., 2014).

Inventory optimisation, employing techniques such as economic order quantity (EOQ), safety stock optimisation, and multi-echelon inventory optimisation, improves supply chain performance by balancing holding costs against ordering costs and stockout risks (Neubert et al., 2018). Poor inventory planning increases logistics costs through emergency shipments (costing 200–300% more than planned shipments), expedited production runs, and customer penalty payments (Muscatello et al., 2018).

Inventory planning helps improve export delivery performance by ensuring product availability aligned with shipment schedules, reducing the need for partial shipments (which increase per-unit transportation costs) and enabling container consolidation opportunities (Christopher, 2016). For Indian energy equipment manufacturers, inventory planning is complicated by long international lead times (30–90 days), demand volatility in project-based transformer markets, and seasonality in solar panel installations.

2.8 Market Competition Intensity

Market competition intensity refers to the degree of competitive pressure faced by firms in international markets regarding pricing, operational efficiency, responsiveness, and logistics performance (Porter, 1980). Intense competition creates both pressure and opportunity for logistics cost optimisation.

Empirical research by Li et al. (2006) found that intense competition in international markets increases pressure to optimise logistics costs, with firms in highly competitive industries demonstrating logistics costs 10–15% lower than firms in less competitive industries. Competitive market conditions influence logistics management decisions by focusing attention on cost reduction, service improvement, and innovation adoption (Christopher, 2016).

Global competition forces firms to improve supply chain efficiency through benchmarking against industry leaders, adoption of best practices, and continuous improvement programmes (Li et al., 2006). Market competition significantly affects logistics cost strategies by making cost leadership a strategic imperative, driving firms to pursue logistics optimisation even when capital investments are required (Porter, 1980).

Competitive pressure influences export logistics planning decisions through requirements for shorter lead times, more frequent shipments, and greater flexibility in responding to customer requests (Mentzer et al., 2001). For Indian energy equipment manufacturers, competition from Chinese manufacturers (which benefit from scale economies and state-supported logistics infrastructure) exerts particular pressure on logistics cost performance.

2.9 Logistics Cost Performance as an Outcome Variable

Logistics cost performance (LCP) is conceptualised in the literature as the overall effectiveness of logistics cost control, export competitiveness, operational efficiency, and profitability improvement achieved through logistics management (Lai et al., 2008; Mentzer et al., 2001). Effective logistics cost performance is characterised by cost levels that enable competitive pricing while maintaining service quality and profit margins (Christopher, 2016).

Empirical research demonstrates that firms with superior logistics cost performance achieve 5–15% higher profit margins in international markets compared to industry average, all else equal (Muscatello et al., 2018). Efficient logistics management improves export competitiveness by enabling more competitive pricing (due to lower cost base), faster delivery (due to efficient operations), and greater reliability (due to robust processes) (Gunasekaran et al., 2017).

Logistics strategy that effectively manages costs helps maintain profit margins in international markets, particularly when facing currency fluctuations, tariff changes, or competitive price pressure (Li et al., 2006). Overall logistics cost management effectiveness is determined by the integration of transportation, warehousing, inventory, and coordination activities within a coherent strategic framework (Lai et al., 2008). Firms achieving cost-efficient international logistics operations typically demonstrate coordination excellence, technology adoption, and continuous improvement cultures (Christopher, 2016).

3. CONCEPTUAL FRAMEWORK

Based on the literature synthesis, a conceptual framework is proposed wherein eight determinant categories influence logistics cost performance. The framework recognises that these determinants do not operate in isolation but interact in complex ways. For instance, logistics technology adoption may moderate the relationship between transportation cost and logistics cost performance by enabling better route planning. Similarly, supply chain coordination may mediate the relationship between customs compliance burden and logistics cost performance by facilitating smoother clearance processes.

The framework is particularly relevant to the Indian energy equipment manufacturing context, where product-specific characteristics (fragile solar panels versus heavy transformers) create differential logistics requirements, and where institutional factors (infrastructure quality, regulatory environment, logistics service provider landscape) shape the strength and direction of the relationships identified in the literature.

4. DISCUSSION AND IMPLICATIONS FOR INDIA

4.1 Synthesis of Findings

The literature synthesis reveals several consistent patterns with particular relevance to Indian energy equipment manufacturers. First, transportation cost remains the most substantial component of logistics expenditure, consistent with findings from other developing country manufacturing contexts (Pohit et al., 2019). For Indian exporters to European and North American markets, the combination of distance (7,000–12,000 kilometres) and modal constraints (limited direct shipping services, dependence on transshipment hubs such as Colombo or Singapore) creates transportation costs that are 15–25% higher than comparable exports from Southeast Asian competitors (Banomyong, 2008).

Second, product-specific packaging and handling requirements create meaningful cost differentiation between solar panel and transformer manufacturers. Solar panel exporters face packaging costs of 8–12% of logistics expenditure compared to 3–5% for general cargo, while transformer exporters face specialised handling costs that can represent 15–25% of logistics expenditure for large units (Bowersox et al., 2013). This differentiation suggests that logistics cost benchmarking must account for product characteristics, and that industry-specific logistics strategies are warranted.

Third, customs and regulatory compliance costs disproportionately affect Indian exporters due to procedural fragmentation (involvement of multiple agencies: customs, export promotion councils, product certification bodies) and documentation duplication (Pohit et al., 2019). While initiatives such as the Single Window Interface for Facilitating Trade (SWIFT) have reduced some compliance burdens, the synthesis suggests that further streamlining could reduce logistics costs by 5–10% for Indian energy equipment exporters.

Fourth, supply chain coordination and logistics technology adoption emerge as significant cost-mitigating factors, with firms demonstrating advanced coordination and technology capabilities achieving 12–18% lower logistics costs (Lai et al., 2008; Gunasekaran et al., 2017). However, adoption heterogeneity across Indian manufacturing firms suggests opportunities for capability building, particularly among small and medium enterprises that constitute a substantial portion of the solar panel manufacturing sector.

4.2 Implications for Indian Manufacturing Firms

For Indian manufacturing firms, the synthesis suggests several strategic imperatives. First, logistics cost optimisation requires integrated interventions across coordination mechanisms, technology adoption, and inventory planning rather than isolated cost-reduction efforts. Firms that treat transportation, warehousing, and customs as separate cost centres rather than an integrated supply chain are likely to suboptimise and miss cross-functional cost reduction opportunities (Christopher, 2016).

Second, investment in logistics technology and coordination capabilities should be prioritised based on cost-benefit analysis. For solar panel exporters, where product value-to-weight ratio is moderate (approximately \$200–300 per kilogram), technology investments that improve consolidation and reduce damage may offer higher returns than for transformer exporters, where value-to-weight ratio is lower (\$5–15 per kilogram) but specialised handling requirements create different technology needs (e.g., route planning for oversized cargo) (Muscatello et al., 2018).

Third, inventory planning improvements offer relatively low-cost, high-return opportunities for logistics cost reduction. Implementation of demand forecasting systems, inventory optimisation tools, and planning process improvements typically achieve payback periods of 6–18 months while reducing

logistics costs by 8–15% (Neubert et al., 2018). For Indian manufacturers facing working capital constraints, inventory reduction also improves cash flow and reduces borrowing costs.

Fourth, collaborative strategies including logistics partnerships, shared warehousing arrangements, and cooperative transportation consolidation offer cost reduction opportunities particularly relevant to small and medium enterprises. Industry associations (e.g., Indian Solar Manufacturers Association, Indian Electrical and Electronics Manufacturers Association) could facilitate such collaborations by establishing shared logistics platforms or negotiating preferential rates with logistics service providers (Lai et al., 2008).

4.3 Implications for Indian Policymakers

The synthesis also generates implications for Indian policymakers seeking to enhance the international competitiveness of energy equipment manufacturing. First, continued investment in port infrastructure, particularly for heavy cargo handling capabilities and dedicated freight corridors, would directly reduce transportation costs and delays for energy equipment exporters (Pohit et al., 2019). The development of specialised handling facilities at major ports (e.g., Mundra, Pipavav) for project cargo and oversized equipment would benefit transformer manufacturers in particular.

Second, further streamlining of customs procedures through expanded Single Window implementation, risk-based inspection systems, and pre-clearance programmes would reduce compliance costs and clearance delays. Empirical evidence from other developing economies suggests that fully digitised customs systems reduce clearance times from days to hours and reduce compliance costs by 30–50% (Zeng, 2003).

Third, support for logistics technology adoption among small and medium manufacturers could include subsidised access to digital logistics platforms, technical assistance for ERP implementation, and training programmes for logistics personnel (Gunasekaran et al., 2017). Given the heterogeneity in technology adoption capabilities, targeted interventions for smaller firms may yield disproportionate competitiveness benefits.

Fourth, trade policy coordination with major export destinations to achieve mutual recognition of product certifications, reduced documentation requirements, and streamlined rules of origin would reduce regulatory compliance costs. Bilateral and multilateral trade agreements that include logistics facilitation provisions (e.g., authorised economic operator mutual recognition, single window interoperability) offer mechanisms for reducing non-tariff barriers (Christopher, 2016).

4.4 Limitations and Future Research Directions

This literature synthesis has several limitations that suggest directions for future research. First, the synthesis is conceptual and based on literature from diverse geographical and industrial contexts; empirical validation through primary data collection from Indian energy equipment manufacturers is required to test the synthesised relationships. Second, the synthesis treats solar panel and transformer manufacturing within a common framework, but product-specific differences may warrant separate empirical models. Third, the synthesis does not account for potential moderating effects of firm size, export experience, or organisational culture.

Future research should employ survey-based quantitative methods to test the conceptual framework with samples of Indian energy equipment manufacturers. Comparative studies examining logistics cost determinants across solar panel, transformer, and other energy equipment categories (e.g., inverters, mounting structures, cables) would identify product-specific and common factors. Longitudinal research tracking changes in logistics cost structures as Indian manufacturing capabilities and logistics infrastructure evolve would provide dynamic insights. Finally, cross-country comparative research examining logistics cost determinants for energy equipment manufacturers in India, China, Vietnam, and other competing manufacturing hubs would identify location-specific advantages and disadvantages.

5. CONCLUSION

This literature synthesis has examined the determinants of logistics cost performance in international supply chains, contextualising findings for India's solar panel and transformer manufacturing sectors. The synthesis supports eight principal determinants: transportation cost, packaging and handling requirements, warehousing and inventory management practices, customs clearance and regulatory compliance, supply chain coordination, logistics technology adoption, inventory planning efficiency, and market competition intensity. Each determinant has been shown in the literature to significantly influence logistics cost performance, with effect sizes varying by product characteristics, institutional context, and firm capabilities.

For Indian energy equipment manufacturers, the synthesis suggests that logistics cost optimisation requires integrated, strategic approaches rather than isolated cost-reduction efforts. Investment in coordination mechanisms, technology adoption, and inventory planning offers significant cost reduction opportunities, while continued policy attention to port infrastructure, customs modernisation, and trade facilitation will enhance the enabling environment for logistics excellence.

As India positions itself as a global manufacturing hub for renewable energy equipment, logistics cost competitiveness will increasingly determine export success. This synthesis provides a theoretical foundation for empirical investigation and offers actionable implications for firms and policymakers seeking to enhance logistics cost performance in this strategically important sector.

REFERENCES

- Ayers, J. B. (2006). *Handbook of supply chain management* (2nd ed.). Auerbach Publications. <https://doi.org/10.1201/9781420013948>
- Banomyong, R. (2008). Logistics development study of the Greater Mekong Subregion North-South Economic Corridor. *Asian Development Bank Institute Discussion Paper*, 98, 1-28.
- Bidgoli, H. (2010). *The handbook of technology management: Supply chain management, marketing and advertising, and global management* (Vol. 2). John Wiley & Sons. <https://doi.org/10.1002/9781119203102>
- Bowersox, D. J., Closs, D. J., & Cooper, M. B. (2013). *Supply chain logistics management* (4th ed.). McGraw-Hill Education.
- Büyükkaramikli, N. C., Gürler, Ü., & Alp, O. (2014). Coordinated logistics: Joint replenishment with capacitated transportation for a supply chain. *Production and Operations Management*, 23(1), 110-126. <https://doi.org/10.1111/poms.12031>
- Christopher, M. (2016). *Logistics and supply chain management* (5th ed.). Pearson Education.
- Coyle, J. J., Novack, R. A., Gibson, B. J., & Bardi, E. J. (2016). *Transportation: A supply chain perspective* (9th ed.). Cengage Learning.
- Gunasekaran, A., Subramanian, N., & Papadopoulos, T. (2017). Information technology for competitive advantage within logistics and supply chains: A review. *Transportation Research Part E: Logistics and Transportation Review*, 99, 14-33. <https://doi.org/10.1016/j.tre.2016.12.008>
- Lai, K. H., Wong, C. W. Y., & Cheng, T. C. E. (2008). A coordination-theoretic investigation of the impact of electronic integration on logistics performance. *Information & Management*, 45(1), 10-20. <https://doi.org/10.1016/j.im.2007.10.001>
- Lambert, D. M., Stock, J. R., & Ellram, L. M. (1998). *Fundamentals of logistics management*. Irwin/McGraw-Hill.
- Li, S., Ragu-Nathan, B., Ragu-Nathan, T. S., & Rao, S. S. (2006). The impact of supply chain management practices on competitive advantage and organizational performance. *Omega*, 34(2), 107-124. <https://doi.org/10.1016/j.omega.2004.08.002>
- Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining supply chain management. *Journal of Business Logistics*, 22(2), 1-25. <https://doi.org/10.1002/j.2158-1592.2001.tb00001.x>

- Muscatello, J. R., Parente, D. H., & Swinarski, M. E. (2018). Aligning supply chain logistics costs via ERP coordination. *International Journal of Information System Modeling and Design*, 9(2), 24-43. <https://doi.org/10.4018/IJISMD.2018040102>
- Neubert, G., Ouzrout, Y., Bouras, A., & Benabbou, L. (2018). Collaboration and integration through information technologies in supply chains. *International Journal of Logistics Research and Applications*, 21(2), 136-150. <https://doi.org/10.1080/13675567.2017.1395491>
- Pohit, S., Gupta, D. B., Pratap, D., & Malik, S. (2019). Survey of literature on measuring logistics cost: A developing country's perspective. *Journal of Asian Economic Integration*, 1(2), 260-282. <https://doi.org/10.1177/2631684619883041>
- Porter, M. E. (1980). *Competitive strategy: Techniques for analyzing industries and competitors*. Free Press.
- Rabah, M., & Mahmassani, H. S. (2002). Impact of information and communication technologies on logistics and freight transportation. *Transportation Research Record*, 1790(1), 10-19. <https://doi.org/10.3141/1790-02>
- Rushton, A., Croucher, P., & Baker, P. (2017). *The handbook of logistics and distribution management* (6th ed.). Kogan Page.
- Zeng, A. Z. (2003). A synthetic study of sourcing strategies. *Industrial Management & Data Systems*, 103(7), 506-512. <https://doi.org/10.1108/02635570310489176>

AI-Powered Personalization in Fashion Retail: Applications for Customer Satisfaction and Business Performance

Khushabu Sanjay Gajabi

Assistant Professor, Suryadatta Institute of Fashion Technology, Pune

Shikha Sharda

Assistant Professor, Suryadatta Institute of Fashion Technology, Pune.

ABSTRACT

Online fashion retail has expanded access to products but continues to face persistent customer frictions, including inconsistent sizing, the absence of physical trials, uncertainty about appearance and fit, and costly product returns. This study examines how artificial intelligence (AI)-powered personalization, virtual try-on, body scanning, conversational assistance, and demand forecasting can address these challenges while improving customer satisfaction and business performance. The study adopts a qualitative research design based on secondary data and applies thematic analysis to academic literature, industry reports, and documented brand deployments. The synthesis focuses on three connected outcomes: greater customer confidence and convenience, improved business performance through more relevant recommendations, stronger conversion potential, lower fit-related returns, and improved inventory decisions, and sustainability benefits arising from reduced reverse logistics, packaging, and avoidable overproduction. Case evidence from Myntra, Nike, Zalando, and ASOS demonstrates that these technologies are increasingly deployed as practical retail capabilities rather than isolated experiments. The findings indicate that the strongest value emerges when personalization, visualization, and fit intelligence are integrated across the customer journey. However, implementation also introduces challenges related to data privacy, algorithmic bias, measurement accuracy, transparency, and the balance between automated and human assistance. The paper concludes that AI can support a more interactive, customer-centric, and potentially sustainable fashion-retail model when technological performance is combined with responsible data governance and inclusive design.

Key Words: *fashion retail, virtual try-on, body scanning technology, customer experience, online shopping, sustainable fashion, artificial intelligence, digital shopping*

1. INTRODUCTION

The rapid expansion of e-commerce has changed how consumers discover, evaluate, and purchase fashion products. However, unlike physical retail, online fashion shopping removes several forms of direct product experience. Customers cannot physically touch a garment, inspect it from multiple angles, or try it on before committing to a purchase. These limitations become particularly important because fashion products are strongly dependent on fit, appearance, size, color, material, and personal style. As a result, online customers may experience uncertainty even when a product page provides extensive photographs and descriptions. Research on fashion AI and digital shopping identifies product discovery, visual analysis, recommendation, sizing, and supply-chain decision support as major areas in which AI can reshape the fashion value chain [1], [2].

The consequences of these frictions extend beyond individual purchase decisions. Uncertainty can reduce purchase confidence and increase the likelihood of product returns, while returns create additional

transportation, packaging, inspection, restocking, markdown, and inventory management costs. McKinsey and the Business of Fashion have identified returns, predictive virtual sizing, demand forecasting, and AI-supported stock management as important technology opportunities for fashion businesses [9]. From an operational perspective, AI can also improve the matching between consumer demand and available products, thereby reducing some of the inefficiencies associated with demand uncertainty and excess inventory.

AI provides a broad category of tools to address these problems. Personalization engines can analyze browsing behavior, purchase history, product attributes, and interaction patterns to rank products that are more relevant to an individual customer. Computer vision can support visual search, attribute recognition, product retrieval, and recommendation [8]. Virtual try-on technologies provide digital representations of garments or models, reducing the information gap between viewing a product online and experiencing it physically [4], [5]. Body-scanning systems extend this idea by estimating physical dimensions and translating them into personalized fit or size recommendations. Nike Fit is a prominent real-world example: the system uses a smartphone camera and a combination of computer vision, machine learning, data science, and recommendation algorithms to scan the user's feet and recommend an appropriate shoe size [11].

These technologies are no longer purely experimental. Fashion retailers and platforms have deployed or trialled recommendation systems, size assistants, virtual try-on experiences, and AI-supported customer service tools. Myntra, Nike, Zalando, and ASOS provide useful cases for examining how AI is incorporated into actual digital shopping journeys [11]–[14]. Therefore, the strategic importance of these applications is not limited to technological novelty. They can alter the quality of customer decision-making, the cost structure of online retail, and the environmental consequences associated with returns and excess inventories.

This study examines how AI-powered personalization in fashion retail influences customer satisfaction and business performance, with particular attention to virtual try-on, body scanning, recommendation engines, conversational assistance, and demand forecasting. The study also considers sustainability as an outcome that links customer-facing technologies with operational efficiency. The remainder of the paper reviews relevant literature, identifies a research gap, states the research objectives, analyzes major AI applications, examines four industry cases, explains the secondary-data methodology, synthesizes the findings, and concludes with implementation challenges and future research directions.

2. LITERATURE REVIEW

Research on AI in fashion retail has developed across multiple technical and managerial perspectives. Rather than treating AI as a single technology, existing literature shows a collection of applications distributed across consumer analytics, computer vision, recommendation, virtual experiences, sales support, and supply-chain optimization [1], [2]. The following subsections organize the literature around themes most directly connected to customer satisfaction and business performance.

2.1 AI in Fashion Retail

Giri et al. conducted a systematic review of AI applications in the fashion and apparel industry and identified applications spanning machine learning, expert systems, decision-support systems, optimisation, image recognition, and computer vision across different stages of the fashion supply chain [1]. Their review demonstrates that AI is not restricted to consumer-facing recommendation; it also supports design, production, distribution, forecasting, and retail decision-making.

Luce presents an application-oriented view of AI in fashion, covering natural-language processing and conversational shopping, computer vision and smart mirrors, image search, virtual style assistants, predictive analytics, size recommendations, demand forecasting, and robotics [3]. This broader view is important because customer experience and business performance are interdependent. A recommendation may improve product discovery, whereas the data generated by that interaction can also inform merchandising and inventory decisions.

Liang, Lee, and Workman examined consumer attitudes toward an AI-enabled fashion device and found that perceived usefulness, perceived ease of use, and performance risk influenced attitudes, while positive attitudes were associated with purchase intention [2]. This indicates that the value of AI is not determined solely by technical capability. Consumers must also perceive the technology as useful, manageable, and sufficiently reliable for the shopping context.

2.2 Virtual Try-On and Augmented Reality

Virtual try-on (VTO) attempts to reproduce part of the physical fitting experience within a digital environment. Kim and Forsythe examined the adoption of virtual try-on for online apparel shopping and showed that the technology can provide information comparable to aspects of direct product examination while increasing interactivity and reducing perceived product risk [4]. Their findings support the view that VTO can address an important weakness of online fashion shopping: customers have less direct experiential information before purchase.

Merle, Senecal, and St-Onge examined how virtual try-on influences cognitive, affective, and behavioural responses to apparel websites. Their findings emphasise the importance of model self-congruity and body esteem, indicating that simply providing a virtual model is not enough; the perceived resemblance between the representation and the consumer affects the usefulness of the experience [5].

Javornik's research on augmented reality further explains how perceived augmentation, interactivity, and flow can shape consumer responses and behavioural intentions [6]. Pantano and Di Pietro similarly examined virtual environments as retail interfaces and highlighted their potential to reduce uncertainty by creating richer digital shopping experiences [7]. Collectively, these studies suggest that realism, relevance, and ease of interaction are important mechanisms through which visual technologies can influence customer attitudes.

2.3 Personalisation and Customer Satisfaction

Personalization in fashion retail can be understood as the algorithmic adaptation of product discovery, recommendations, content, and assistance to an individual consumer. Recommendation approaches commonly include collaborative filtering, content-based filtering, and hybrid or deep-learning approaches. Fashion computer-vision research has expanded these capabilities by enabling item retrieval, attribute recognition, style learning, outfit matching, and recommendations [8].

The customer value mechanism primarily reduces search effort and decision uncertainty. A customer who receives products aligned with known preferences may spend less time filtering a large catalogue. Simultaneously, personalization can create a stronger perception of relevance and convenience. However, personalization also depends on customer data, which introduces tension between relevance and privacy. Therefore, AI-enabled retail needs to manage both the functional value of personalization and the trust conditions under which customers are willing to use it.

Conversational systems add an additional layer to this process. Research on conversational commerce identifies AI-powered digital assistants as an emerging mechanism for combining information retrieval, recommendations, and customer interaction [15]. Fashion-specific chatbot research further indicates that customers value responsiveness, compatibility, credibility, and recommendation capability, whereas usability limitations and overly generic responses can weaken engagement [16].

2.4 Business Performance and Sustainability

AI applications can influence business performance through several pathways. More relevant recommendations can improve product discovery and conversion potential; better size recommendations and visualization can reduce fit-related uncertainty and returns; and demand forecasting can improve inventory allocation and reduce markdown exposure. McKinsey and the Business of Fashion have identified predictive virtual sizing, demand forecasting, AI-guided stock management, and omnichannel inventory management as important technology opportunities for fashion businesses [9].

Deloitte's analysis of AI in consumer-facing businesses similarly highlights applications in personalization, customer experience, demand planning, assortment optimization, and operational efficiency [10]. These applications show that the business case for AI extends beyond marketing. The same data infrastructure that enables a personalized customer interface can also provide signals for merchandising, replenishment, and planning.

Sustainability is connected to these business outcomes rather than being a separate technological function. A reduction in avoidable returns can reduce reverse logistics activities, repackaging, inspection, and reprocessing. Better demand forecasting can also reduce overproduction and mark downs. Research on AI and sustainability in fashion highlights inaccurate demand forecasting and excess production as major environmental concerns and identifies AI-supported prediction and supply chain performance as potential intervention areas [17].

3. RESEARCH GAP

The literature demonstrates substantial progress in individual AI applications; however, four gaps remain relevant to the present study. First, existing work is fragmented across recommendation, virtual try-on, sizing, customer experience, and supply-chain applications. These streams are often evaluated separately, even though they operate within the same customer journey. Second, consumer-attitude studies tend to focus on adoption, usefulness, enjoyment, or purchase intention, while operational studies focus on returns, inventory, forecasting, or efficiency. The relationship between these two outcome groups is less frequently synthesized in one framework.

Third, a qualitative synthesis that connects academic findings with the documented deployment of AI by major fashion retailers is needed. Brand cases can demonstrate how concepts developed through research are translated into actual shopping interfaces and operational processes. Fourth, sustainability is often discussed as a general benefit of digital transformation, but the specific pathway from AI-enabled fit confidence and demand prediction to reduced returns, reverse logistics, and overproduction requires a clearer integration.

This study addresses these gaps through a secondary qualitative synthesis that brings together customer-facing AI, fit technologies, business outcomes, sustainability implications, and implementation challenges. The central analytical proposition is that AI personalization creates value when it reduces information

asymmetry between the retailer and consumer while simultaneously improving the retailer's ability to learn from customer and product data.

4. RESEARCH OBJECTIVES

1. This study examines major AI applications in fashion retail, including recommendation engines, virtual try-on, and body scanning technologies.
2. This study evaluated how personalization and digital fitting influence customer satisfaction through fit confidence, convenience, trust, decision certainty, and purchase intention.
3. Assess business performance outcomes associated with AI, including conversion potential, return reduction, inventory optimization, and sustainability.
4. Identify the implementation challenges and future opportunities associated with AI-powered personalization in fashion retail.

5. AI APPLICATIONS IN FASHION RETAIL

5.1 Personalised Recommendation Engines

Recommendation engines are the core of personalized digital shopping systems. They analyze signals such as browsing history, purchases, wish lists, product interactions, explicit preferences, and product attributes to rank items for an individual customer. In fashion, computer vision expands the recommendation problem by allowing systems to represent visual attributes, styles, garments, and outfits [8]. Hybrid systems can combine behavioral information with item-level features so that recommendations remain relevant when customer history or product information is incomplete.

From the customer's perspective, the principal benefit is reduced search cost. Fashion catalogues may contain thousands of visually and semantically related products, creating a choice-overload problem. Personalization narrows the search space and can make the interface feel more relevant. From the retailer's perspective, recommendations can support cross-selling, upselling, discovery of less-visible products, and more efficient use of customer attention. However, recommendations may reinforce existing preferences if the system optimizes only for short-term engagement. Responsible recommendation therefore requires monitoring diversity, relevance, and fairness alongside conversion.

5.2 Virtual Try-On

Virtual try-on combines computer vision, augmented reality, image synthesis, or digital avatars to provide a visual approximation of how a garment or accessory may appear on a person. The fundamental objective is to reduce the information gap created by the absence of a physical fitting room. Kim and Forsythe found that virtual try-on can provide product information and interactive involvement, while Merle et al. showed that the effectiveness of VTO depends on factors such as self-congruity and body-related perceptions [4], [5].

Therefore, a successful VTO experience requires more than visual novelty. The digital representation should be sufficiently realistic, responsive, and relevant to the customer's body or style. If the visualization is misleading, the technology may increase rather than decrease disappointment. Javornik's work suggests that perceived augmentation and flow influence consumer responses, reinforcing the importance of interaction quality [6].

5.3 Body Scanning Technology

Body scanning extends virtual fitting by estimating physical dimensions rather than relying only on a generic model. Smartphone cameras, depth sensors, computer vision, and 3D reconstruction can be used to estimate measurements that are then mapped to garment or shoe specifications. The objective was to reduce the mismatch between standardized size labels and individual body dimensions.

Nike Fit illustrates this approach in footwear design. Introduced in 2019, the technology uses a smartphone camera to scan the user's feet and combines computer vision, machine learning, data science, and recommendation algorithms to generate fit guidance [11]. Nike's own reporting positioned the system as a response to footwear sizing problems and linked better size understanding with the potential to minimize returns and improve operational efficiency.

Body scanning can also support longer-term personalization because a measurement profile can be reused across different purchases. However, the accuracy depends on the camera quality, lighting, pose, device placement, and quality of the mapping between body measurements and product construction. Consequently, body scanning should be treated as a probabilistic decision support system rather than an infallible measurement device.

5.4 AI Chatbots and Digital Stylists

AI chatbots and digital stylists introduce conversational interaction into fashion shopping. Instead of manually searching through filters, customers can describe an occasion, preferred style, budget, color, or garment requirement and receive recommendations or answers. Fashion chatbot research identifies recommendation capability, responsiveness, credibility, and interactivity as important usability considerations [16]. Broader conversational-commerce research similarly positions AI assistants as a means of combining automated information support with personalized shopping interactions [15].

The main advantage is convenience: conversational assistance can approximate some of the guidance traditionally provided by an in-store sales associate. However, automated systems may struggle with ambiguous preferences, emotional contexts, unusual requests, or situations requiring empathy. Therefore, a hybrid model in which AI handles routine discovery and humans handle complex or sensitive interactions may provide a stronger customer experience than full automation.

5.5 Demand Forecasting and Inventory Optimisation

AI also influences customer experience indirectly through inventory decisions. Demand forecasting models can combine historical sales, seasonality, product attributes, trends, and other signals to estimate future demand. Better forecasts can support replenishment, assortment planning, allocation, and markdown decisions. Luce identified predictive analytics and demand forecasting as important fashion AI applications [3], while McKinsey and Deloitte highlighted forecasting, stock management, assortment optimization, and operational efficiency as strategic use cases [9], [10].

The connection to personalization is important because customer-level interactions generate demand signals. Searches, clicks, wish lists, recommendations, purchases, and returns can collectively reveal the emerging preferences. When these signals are integrated into planning systems, retailers can move from reactive inventory decisions to more responsive merchandising. The results can improve product availability, lower markdown exposure, and reduce overproduction.

6. CASE STUDY INSIGHTS

6.1 Myntra

Myntra is an Indian example of a fashion platform that uses technology to enrich digital shopping. Its technology initiatives have included virtual try-on and product-finding capabilities. In 2023, Myntra Beauty expanded its Virtual Try-On feature using augmented and virtual reality to help customers visualize products such as makeup shades. Industry reporting described a 1.5× increase in consideration and a 2× increase in conversion for makeup styles using the feature [12].

This case illustrates how visualization can move beyond simple product display toward interactive decision support. The customer receives additional information before purchase, while the platform can use engagement with the feature as a behavioral signal. Although the reported outcomes concern beauty rather than apparel fit, the underlying mechanism is relevant to fashion retail: visual uncertainty can be reduced by allowing consumers to preview a product in a more personalized context.

6.2 Nike Fit

Nike Fit demonstrates the application of computer vision and machine learning to a concrete sizing problem in the sportswear industry. Smartphone experience scans a user's feet and uses the resulting information to recommend a suitable size for a specific shoe model [11]. Nike's 2019 report also connected improved sizing information with the objectives of minimizing returns, reducing costs, and generating insights that could improve product design and manufacturing.

The significance of Nike Fit is that the technology is embedded in the purchasing process rather than being presented as a separate novelty. The system reduces the number of manual decisions that a customer must make and creates a reusable fit profile. This supports the proposition that personalization is most valuable when it is integrated into the point at which uncertainty affects purchase behaviour.

6.3 Zalando

Zalando has developed multiple AI-supported size and fit capabilities. Its size recommendation functionality uses recent purchases and returns, products that customers report as fitting well, feedback from other customers, and brand-specific sizing information [13]. Zalando's research has also explored statistical and machine-learning approaches to size recommendation, including models that jointly consider purchased sizes and return outcomes [18].

The case demonstrates the value of combining behavioral and product data. Rather than assuming that a universal size chart is sufficient, the system learns from the customer's own history and aggregated fit information. This can reduce decision effort and potentially lower fit-related returns. The broader business implication is that every purchase and return can become feedback for improving subsequent recommendations.

6.4 ASOS

ASOS provides an example of visual fit support through its See My Fit augmented-reality trial. Introduced in 2020, the system allows shoppers to view garments on models with different body sizes and shapes. The initial trial covered hundreds of dresses and provided a set of models across a range of sizes [14]. The

technology digitally mapped garments onto selected models to provide customers with a more informative representation of how an item could appear.

This case highlights the important distinction between size recommendations and appearance visualization. A recommendation engine can suggest a size, whereas an AR experience can help the customer judge whether the product's appearance and proportions are personally relevant. Together, these tools can address different components of online purchase uncertainty.

7. METHODOLOGY

This study adopts a qualitative, secondary-data-based design. The study does not collect new survey responses, conduct experiments, or train a new AI model. Instead, it synthesizes existing evidence concerning AI applications in fashion retail, virtual try-on, body scanning, customer experience, business performance, and sustainability. The methodological objective is to identify recurring relationships across academic studies, industry reports, and documented retailer deployments.

The planned source window was 2008–2024. Academic literature was considered from research and scholarly discovery platforms, including Scopus, Google Scholar, ScienceDirect, and Emerald Insight, while industry evidence was considered from company reports, technology announcements, and established retail or business publications. Search concepts included “AI personalization fashion retail,” “virtual try-on,” “body scanning technology,” “customer satisfaction,” “return reduction,” “sustainable fashion,” and related combinations.

Inclusion was guided by four criteria: (1) the source addressed AI or an AI-enabled digital technology relevant to fashion retail; (2) the source provided evidence about customer experience, fit, recommendation, retail operations, or sustainability; (3) the publication fell within the defined time window; and (4) the source was sufficiently identifiable to support a traceable citation. Company cases were included when the deployment and mechanism could be documented from company materials or reputable industry reports.

The analysis followed thematic analysis as described by Braun and Clarke [19]. The process consisted of familiarization with the selected material, identification of recurring concepts, grouping of related concepts into themes, review of thematic relationships, and synthesis of the final findings. Six recurring themes were used to structure the analysis: fit confidence, convenience, engagement, return reduction, operational efficiency, and sustainability.

The proposed methodology has an important limitation. Because the study relies on secondary evidence, the researchers cannot independently verify every company-reported outcome or directly observe customer behavior. Industry sources may also emphasize successful deployments, creating a risk of positive reporting bias. Therefore, the findings should be interpreted as a qualitative synthesis of the available evidence rather than as causal estimates of the effect of AI on retail performance.

8. RESULTS AND DISCUSSION

8.1 Improved Customer Satisfaction

The first major theme is improved customer satisfaction through reduced uncertainty. Virtual try-on and body scanning address uncertainty about fit, size, and appearance, while recommendation systems reduce the cognitive effort required to navigate large catalogues. Kim and Forsythe's work shows that virtual try-on can

reduce product risk and increase involvement in online apparel shopping [4]. Merle et al. further demonstrate that the perceived similarity between the consumer and the virtual model is important to the effectiveness of the experience [5].

The combined evidence suggests that satisfaction is not produced by AI alone. It emerges when technology solves a meaningful customer problem. An irrelevant recommendation, a body scan that produces an implausible size, or a virtual try-on that looks unrealistic can reduce trust. Conversely, when AI provides relevant and understandable assistance during uncertainty, customers gain confidence and convenience. This indicates that fit confidence and decision certainty are the central mechanisms linking AI functionality to satisfaction.

8.2 Enhanced Business Performance

The second theme concerns business performance. Personalized recommendations can increase the relevance of products presented to a customer, while visualization and sizing tools can reduce uncertainty before purchase. The resulting pathway can be represented as follows: improved information → higher decision confidence → stronger purchase propensity and fewer avoidable fit-related returns → lower reverse-logistics burden. The case studies provide practical evidence for the different stages of this pathway [11]–[14].

The operational impact is particularly important because returns are not simply a customer-service issue. They affect inventory availability, transportation, inspection, repackaging, resale, markdowns, and working capital. Research on AI-enabled return policies also indicates that AI can lower product-fit uncertainty and improve return-related decision-making [20]. Therefore, the business value of personalization should be evaluated using a broader set of metrics than the conversion rate alone. Relevant measures include return rate, return reason, repeat purchase, inventory turnover, markdown rate, customer lifetime value, and cost-to-serve.

8.3 Sustainability Benefits

The third theme was sustainability. Reducing unnecessary returns can reduce transportation and packaging activities, whereas better demand forecasting can reduce overproduction and markdown-driven waste. McKinsey's fashion analysis identifies overproduction, returns, and demand forecasting as areas where technology can create significant economic and sustainable value [9]. Research focused specifically on AI and sustainable fashion similarly identifies demand prediction and supply chain performance as important opportunities [17].

However, AI should not automatically be described as sustainable. AI systems consume computing resources, require data infrastructure, and can encourage consumption if personalization is used only to maximize transaction frequency. Therefore, sustainability depends on how AI is deployed and which performance objectives are optimized. An AI system designed to minimize avoidable returns and improve inventory accuracy has a different sustainability profile from a system designed to increase impulse purchases.

8.4 Implementation Challenges

The fourth theme is implementation risk. Personalization requires customer data, which creates privacy and consent concerns. Body scanning adds sensitive measurement information, while behavioral personalization can create detailed profiles of individual customers. Ethical discussions of AI in e-commerce highlight the

tension between personalized experiences and privacy, as well as the risks of biased or opaque algorithmic decisions [21].

Algorithmic bias is another concern. If training data underrepresent particular body types, skin tones, sizes, geographies, or purchasing patterns, the resulting recommendation or visualization system may perform unevenly across customer groups. ASOS's See My Fit trial illustrates the practical importance of representation because customers benefit only when the available digital models adequately reflect the diversity of the intended audience [14].

The technical accuracy also varies by context. Smartphone-based body scanning can be affected by lighting, camera position, clothing, pose, device capabilities, and quality of the underlying body-to-product mapping. A responsible system should communicate uncertainty and provide fallback options rather than presenting an AI recommendation as being unquestionably correct.

Finally, automation should not eliminate human support where human judgement remains valuable. AI is effective at repetitive search, classification, recommendation, and information retrieval, but complex style advice, complaint resolution, and trust-sensitive interactions may benefit from human involvement. Therefore, the strongest model is likely to be human-centered augmentation rather than unrestricted automation.

9. FUTURE SCOPE

- a. Generative AI for hyper-personalization, including conversational styling, personalized product descriptions, and assisted custom design.
- b. More accurate smartphone-based 3D body scanning reduces dependence on specialized hardware.
- c. Metaverse-oriented virtual showrooms and AI avatars that extend digital fitting and product exploration are also discussed.
- d. Sustainability analytics predict resale value, support circular fashion decisions, and optimize garment life cycles.
- e. Privacy-preserving AI, including on-device personalization and federated learning, to reduce unnecessary centralized data collection.
- f. Multichannel integration connects online fit profiles and recommendations with in-store experiences.

10. CONCLUSION

AI-powered personalisation is changing fashion retail by addressing a central weakness of online shopping: customers must make high-involvement decisions with incomplete physical information. Recommendation engines reduce search effort, virtual try-on improves visual understanding, body scanning supports personalised fit, conversational systems provide interactive guidance, and demand forecasting connects customer signals with operational planning. Together, these capabilities can improve fit confidence, convenience, decision certainty, and perceived relevance.

The case evidence from Myntra, Nike, Zalando, and ASOS demonstrates that AI-enabled retail is already being applied through practical customer-facing systems [11]–[14]. The business implications extend beyond conversion. Better fit information can reduce avoidable returns; recommendation and demand signals can improve inventory decisions; and more accurate matching can contribute to sustainability by reducing

unnecessary logistics, packaging, and overproduction. The evidence therefore supports an integrated view in which customer satisfaction and business performance are complementary rather than competing outcomes.

The main contribution of this study is the integration of customer satisfaction, business performance, and sustainability into a single qualitative framework for understanding AI personalization in fashion retail. At the same time, this study recognizes that AI does not guarantee positive outcomes. Privacy, bias, measurement error, representation, transparency, and over-automation can undermine customer trust and create new forms of risk. Future empirical research should therefore test the proposed relationships using customer-level behavioral data, controlled experiments, longitudinal studies, and cross-market comparisons.

Overall, the evidence indicates that the most valuable role of AI in fashion retail is not simply to automate existing activities but to make the digital shopping journey more informed, interactive, and responsive to individual needs. When combined with responsible data governance and inclusive design, AI-powered personalization can become an important foundation for customer-centric and more efficient fashion retail.

REFERENCES

- C. Giri, S. Jain, X. Zeng, and P. Bruniaux, "A Detailed Review of Artificial Intelligence Applied in the Fashion and Apparel Industry," *IEEE Access*, vol. 7, pp. 95376–95396, 2019, doi: 10.1109/ACCESS.2019.2928979. Available: <https://doi.org/10.1109/ACCESS.2019.2928979>
- Y. Liang, S.-H. Lee, and J. E. Workman, "Implementation of Artificial Intelligence in Fashion: Are Consumers Ready?," *Clothing and Textiles Research Journal*, vol. 38, no. 1, pp. 3–18, 2020, doi: 10.1177/0887302X19873437. Available: <https://doi.org/10.1177/0887302X19873437>
- L. Luce, *Artificial Intelligence for Fashion: How AI is Revolutionizing the Fashion Industry*. Berkeley, CA, USA: Apress, 2018, doi: 10.1007/978-1-4842-3931-5. Available: <https://doi.org/10.1007/978-1-4842-3931-5>
- J. Kim and S. Forsythe, "Adoption of Virtual Try-on Technology for Online Apparel Shopping," *Journal of Interactive Marketing*, vol. 22, no. 2, pp. 45–59, 2008, doi: 10.1002/dir.20113. Available: <https://doi.org/10.1002/dir.20113>
- Merle, S. Senecal, and A. St-Onge, "Whether and How Virtual Try-On Influences Consumer Responses to an Apparel Web Site," *International Journal of Electronic Commerce*, vol. 16, no. 3, pp. 41–64, 2012, doi: 10.2753/JEC1086-4415160302. Available: <https://doi.org/10.2753/JEC1086-4415160302>
- Javornik, "It's an illusion, but it looks real! Consumer affective, cognitive and behavioural responses to augmented reality applications," *Journal of Marketing Management*, vol. 32, nos. 9–10, pp. 987–1011, 2016, doi: 10.1080/0267257X.2016.1174726. Available: <https://doi.org/10.1080/0267257X.2016.1174726>
- E. Pantano and L. Di Pietro, "Understanding Consumer's Acceptance of Technology-Based Innovations in Retailing," *Journal of Technology Management & Innovation*, vol. 7, no. 4, pp. 1–19, 2012, doi: 10.4067/S0718-27242012000400001. Available: <https://doi.org/10.4067/S0718-27242012000400001>
- W.-H. Cheng, S. Song, C.-Y. Chen, S. C. Hidayati, and J. Liu, "Fashion Meets Computer Vision: A Survey," *ACM Computing Surveys*, vol. 54, no. 4, Article 72, 2021, doi: 10.1145/3447239. Available: <https://doi.org/10.1145/3447239>
- McKinsey & Company and The Business of Fashion, "Fashion Tech: How Innovation Can Make Over the Apparel Business," 2021. Available: <https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/what-tech-innovation-means-for-the-business-of-fashion>

- Deloitte, "The Democratisation of Artificial Intelligence: The Deloitte Consumer Review," 2018. Available: <https://www.deloitte.co.uk/consumer-review-digital-predictions/themes/artificial-intelligence/>
- Nike, "Nike Fit: A New Digital Concept to Address Footwear Sizing," Nike, 2019. Available: <https://news.nike.com/news/nike-fit-digital-foot-sizing>
- Myntra, "Myntra Beauty's Virtual Try-On Feature Drives Adoption for Leading Brands," 2023. Available: <https://www.imagesbof.in/myntra-beautys-virtual-try-on-feature-drives-adoption-for-leading-brands-enables-2x-jump-in-conversions/>
- Zalando, "Size Recommendation and Size & Fit Services," Zalando, 2020. Available: <https://www.zalando.co.uk/faq/Sizing/How-do-I-find-the-right-size-or-fit.html>
- ASOS, "ASOS Trials 'See My Fit' Augmented Reality Tool," ASOS plc, 2020. Available: <https://www.theindustry.fashion/asos-trials-see-my-fit-augmented-reality-tool/>
- J. Balakrishnan and Y. K. Dwivedi, "Conversational commerce: entering the next stage of AI-powered digital assistants," *Annals of Operations Research*, vol. 333, pp. 653–687, 2024; first published online 2021. Available: <https://doi.org/10.1007/s10479-021-04049-5>
- "Chatbot design approaches for fashion E-commerce: an interdisciplinary review," *Journal of Fashion Marketing and Management / fashion e-commerce literature*, 2021, doi: 10.1080/17543266.2021.1990417. Available: <https://doi.org/10.1080/17543266.2021.1990417>
- S. Y. Bae and D. G. Wooldridge, "Leveraging Artificial Intelligence for Sustainability in the Textile and Fashion Industry," *Journal of Textile Science & Fashion Technology*, 2021. Available: <https://irispublishers.com/jtsft/fulltext/leveraging-artificial-intelligence-for-sustainability-in-the-textile-and-fashion-industry.ID.000688.php>
- R. Guigourès, Y. K. Ho, E. Koriagin, A.-S. Sheikh, U. Bergmann, and R. Shirvany, "A Hierarchical Bayesian Model for Size Recommendation in Fashion," in *Proceedings of the 12th ACM Conference on Recommender Systems (RecSys '18)*, Vancouver, Canada, pp. 392–396, 2018, doi: 10.1145/3240323.3240388. Available: <https://doi.org/10.1145/3240323.3240388>
- V. Braun and V. Clarke, "Using Thematic Analysis in Psychology," *Qualitative Research in Psychology*, vol. 3, no. 2, pp. 77–101, 2006, doi: 10.1191/1478088706qp063oa. Available: <https://doi.org/10.1191/1478088706qp063oa>
- "Impact of artificial intelligence adoption on online returns policies," *Annals of Operations Research*, 2020, doi: 10.1007/s10479-020-03602-y. Available: <https://doi.org/10.1007/s10479-020-03602-y>
- Owen and J. Moore, "Ethical Considerations in AI-Driven E-Commerce Solutions: Balancing Personalization and Privacy," 2023. Available: https://www.researchgate.net/publication/389250000_Ethical_Considerations_in_AI-Driven_E-Commerce_Solutions_Balancing_Personalization_and_Privacy

AI Adoption and Consumer Purchase Intention in Online Grocery Platforms: A Study of the Mumbai Suburban Region

Kinjal Shah

Assistant Professor, IES's Management College and Research Centre, Mumbai

Mahendra Daima

Assistant Professor, Prin. L.N. Welingkar Inst. of Managt. Development and Research,
Mumbai

ABSTRACT

Artificial intelligence (AI) is increasingly embedded in online grocery platforms through personalised recommendations, smart search, reminders, and decision support. This empirical study examines survey responses from 400 eligible online grocery consumers in the Mumbai Suburban Region to assess the relationships among AI personalisation, AI-driven convenience, platform trust, and purchase intention. Composite measures demonstrated good internal consistency (Cronbach's $\alpha = .855-.877$). AI personalisation, AI-driven convenience, and platform trust were positively associated with purchase intention. The multiple regression model produced an exceptionally high R-squared of .971 (adjusted R-squared = .971); convenience had the largest standardised coefficient ($\beta = .580$), followed by trust ($\beta = .550$) and personalisation ($\beta = .400$), all $p < .001$. VIF values ranged from 1.012 to 1.044, indicating no multicollinearity concern. Age differences were significant, $F(5, 394) = 9.68$, $p < .001$, eta-squared = .109, with Tukey tests showing that the 30-39 group exceeded several older groups. The unusually high explanatory power is interpreted cautiously in view of the cross-sectional, self-reported design and is discussed alongside robustness and common-method diagnostics.

Keywords: artificial intelligence, online grocery, mumbai suburban, purchase intention, trust, personalisation, convenience

1. INTRODUCTION

India's grocery retail sector is rapidly moving from traditional store-based shopping toward hybrid and platform-driven models. AI now supports personalised recommendations, predictive search, chatbot assistance, promotions, stock visibility, and delivery communication, making it an active part of consumer decision-making (Agrawal et al., 2018; Brynjolfsson & McAfee, 2014; Kotler et al., 2021).

The growth of online grocery has been supported by smartphones, digital payments, and platform-based retail. AI-enabled personalisation, smart search, chatbot support, and convenience increasingly shape online grocery behaviour (Grand View Research, 2024; Kumar, 2024). Indian studies similarly link AI-enabled features with satisfaction, trust, and purchase intention (Aggarwal, 2023; Basha & Shyam, 2024; Bhatt & Singh, 2025; Reddy & Kumar, 2024; Sontineni et al., 2025).

Mumbai Suburban is a relevant setting because of its dense population, varied income groups, diverse consumption preferences, and highly digital urban environment. The district includes Andheri, Borivali, and Kurla and represents a major metropolitan consumer market (Mumbai Suburban District, Government of Maharashtra, 2026). The study therefore focuses on how AI personalisation, convenience, and trust shape purchase intention in this environment.

1.1 Objectives and Hypotheses

- Examine the association between AI-driven personalisation and purchase intention.
- Assess the association between AI-enabled convenience, including smart search and decision support, and purchase intention.
- Evaluate platform trust as a statistical predictor of purchase intention and examine demographic differences without making causal claims.

1.2 Hypotheses:

- H1: AI personalisation is positively associated with purchase intention.
- H2: AI-enabled convenience is positively associated with purchase intention.
- H3: Platform trust is positively associated with purchase intention.
- H4: Purchase intention differs across age groups, with higher intention among younger consumers.
- H5: Purchase intention differs across personal-income groups, with higher intention among higher-income consumers.

2. REVIEW OF LITERATURE

2.1 Artificial Intelligence in Retail Commerce

AI in retail has evolved from back-end forecasting and rule-based decision support to customer-facing applications such as recommendations, intelligent search, chatbots, and real-time personalisation (Russell & Norvig, 1995; Brynjolfsson & McAfee, 2014). Machine learning, natural language processing, and predictive analytics now support product ranking, customer service, and personalised digital experiences (Agrawal et al., 2018; Kotler et al., 2021). In Indian online grocery platforms, these tools increasingly influence convenience and consumer decision-making (Aggarwal, 2023; Bhatt & Singh, 2025; Kumar, 2024; Sontineni et al., 2025).

2.2 AI Features and Purchase Intention

Personalised recommendations reduce search effort and improve product relevance, strengthening perceived usefulness and purchase intention (Kotler et al., 2021; Li & Shrestha, 2022). AI chatbots support consumers through rapid assistance, query resolution, and purchase guidance, although effectiveness depends on intelligence, relevance, and communication quality (Reddy & Kumar, 2024; Kar & Ilavarasan, 2024). Smart search using natural-language processing, predictive autocomplete, and context-aware ranking further simplifies grocery purchases, while certain AI mechanisms such as dynamic pricing may generate mixed consumer responses (International Review of Retail, Distribution and Consumer Research, 2025).

2.3 Platform Trust

Trust is central to AI-enabled commerce because consumers depend on platforms for recommendation accuracy, payments, fulfilment, stock information, and service recovery. Reliable AI interactions can strengthen trust and subsequently increase purchase intention (Li & Shrestha, 2022; Zhou & Zhang, 2023). Chatbot intelligence and communication quality also contribute to trust formation (Kar & Ilavarasan, 2024). However, consumers may simultaneously value personalisation and remain concerned about data collection and privacy (Gupta & Singh, 2024).

2.4 Demographic Differences

AI adoption may vary across demographic groups. Younger consumers generally have greater familiarity with algorithmic technologies, whereas older consumers may place more emphasis on simplicity, control, and human support (Ersoy, 2022). Income may influence access to digital technology and the perceived value of convenience-oriented services (Singh & Patel, 2023). Gender,

household responsibility, and occupation may also shape grocery behaviour and technology adoption (Nair & Shams, 2021).

2.5 Mumbai Suburban Context

Mumbai Suburban District, comprising Andheri, Borivali, and Kurla talukas, reported a population of 9,356,962 in the 2011 Census (Mumbai Suburban District, Government of Maharashtra, 2026). Its dense population, digitally active consumers, time-sensitive routines, and diverse cuisine, language, household size, brand preferences, and price sensitivities make it a useful setting for examining AI-enabled grocery behaviour. These characteristics also create a demanding environment for recommendation relevance and service reliability.

2.6 Conceptual Focus

The literature suggests that AI personalisation, AI-driven convenience, and platform trust may be associated with online grocery purchase intention. Demographic characteristics may further explain differences in responses. These proposed relationships form the analytical framework; because the design is cross-sectional, the framework tests associations and prediction rather than causal effects.

3. RESEARCH METHODOLOGY

3.1 Research Design and Sample

The study adopted a quantitative, cross-sectional survey design. Eligibility required residence in the Mumbai Suburban Region and at least one online grocery purchase during the preceding six months. The final sample comprised 400 respondents who satisfied both screening criteria. The study focuses on active online grocery consumers within the defined geographical setting, and the findings are interpreted for the study sample rather than as proof of population-level causality or universal representativeness. Because the design is cross-sectional, the statistical analyses are used to examine associations, predictive relationships, and group differences rather than causal effects.

3.2 Research Instrument and Analysis

The questionnaire contains screening and usage questions, 35 five-point Likert items, supplementary perception questions, and demographic items. AI personalisation is measured by eight items, AI-driven convenience by ten, platform trust by nine, and purchase intention by eight. Construct scores are respondent-level item means. The final dataset contained no missing or out-of-range values in the 35 primary construct items, and the composite scores reproduced the item means exactly. The analysis includes descriptive statistics, Cronbach's alpha and corrected item-total correlations, Pearson correlations, Harman's single-factor diagnostic, ordinary least-squares regression with 95% confidence intervals, tolerance and VIF, residual diagnostics, one-way ANOVA with eta-squared and omega-squared, and Tukey HSD comparisons. Personal income is used for H5; respondents selecting 'prefer not to disclose' are excluded from that inferential test.

4. DATA ANALYSIS AND RESULTS

4.1 Demographic Profile

The sample contains all six age categories and the full response options for gender, education, occupation, and income. Table 1 presents the demographic profile of the 400 respondents using the categories included in the questionnaire.

Table 1. Demographic Profile of Respondents (N = 400)

Variable	Category	n	%
Age	Below 20 years	20	5
	20-29 years	164	41
	30-39 years	112	28
	40-49 years	64	16
	50-59 years	40	10
Gender	Male	217	54.25
	Female	182	45.75
Education	Up to Higher Secondary	32	8
	Diploma	16	4
	Undergraduate	132	33
	Postgraduate	158	39.5
	Professional qualification	40	10
	Doctorate	9	2.3
	Other	13	3.3
Personal income	No personal income	76	19
	Below INR 25,000	55	13.8
	INR 25,000-49,999	40	10
	INR 50,000-74,999	56	14
	INR 75,000-99,999	48	12
	INR 100,000-149,999	33	8.3
	INR 150,000 and above	69	17.3
	Prefer not to disclose	23	5.8
Occupation	Student	55	13.8
	Private-sector salaried	155	38.8
	Government/public-sector salaried	30	7.5
	Business/self-employed	55	13.8
	Professional	45	11.3
	Homemaker	32	8
	Retired	20	5
	Currently not employed	8	2

4.2 Descriptive Statistics and Reliability

Purchase intention has the highest mean ($M = 3.623$), followed by platform trust ($M = 3.558$), AI-driven convenience ($M = 3.541$), and AI personalisation ($M = 3.418$). Cronbach's alpha ranges from .855 to .877, and corrected item-total correlations range from .562 to .638, indicating internally consistent item sets in the study sample.

Table 2. Descriptive Statistics and Reliability

Construct	Items	Mean	SD	Cronbach alpha	Corrected item-total r
AI Personalisation	8	3.418	0.403	0.855	.570-.611
AI-Driven Convenience	10	3.541	0.399	0.877	.562-.629
Platform Trust	9	3.558	0.402	0.874	.577-.638
Purchase Intention	8	3.623	0.402	0.857	.576-.638

4.3 Common Method and Measurement Diagnostics

All 35 construct items were entered into an unrotated principal-components analysis. The first component explained 27.04% of total item variance, below a conventional majority-of-variance screen. KMO was .707 and Bartlett's test was significant, $\chi^2(595) = 6337.06$, $p < .001$. However, only three components had eigenvalues above 1 although four constructs were theorised. Harman's test is insensitive and cannot rule out common method bias; the result is therefore treated only as a diagnostic (Podsakoff et al., 2003).

Table 3. Common-Method and Factor Diagnostics

Diagnostic	Result	Interpretation
Primary items	35	All AP, AIC, PT, and PI items
KMO	0.707	Adequate for exploratory factor diagnostics
Bartlett's test	$\chi^2(595) = 6337.06$, $p < .001$	Item correlation matrix is not an identity matrix
First unrotated component	27.04%	No single component accounts for a majority of variance
Eigenvalues > 1	3	Does not reproduce the four theorised constructs

4.4 Correlation Analysis

Purchase intention is positively correlated with AI personalisation ($r = .475$, $p < .001$), AI-driven convenience ($r = .720$, $p < .001$), and platform trust ($r = .662$, $p < .001$). Correlations among the predictors are small: personalisation-convenience $r = .107$ ($p = .032$), personalisation-trust $r = .024$ ($p = .636$), and convenience-trust $r = .176$ ($p < .001$).

Table 4. Pearson Correlations Among Key Constructs

Variable	Personalisation	Convenience	Trust	Purchase Intention
Personalisation	1	.107*	0.024	.475***
Convenience	.107*	1	.176***	.720***
Trust	0.024	.176***	1	.662***
Purchase Intention	.475***	.720***	.662***	1

Note. * $p < .05$; *** $p < .001$ (two-tailed).

4.5 Multiple Regression Analysis

The three-predictor model is significant, $F(3, 396) = 4493.30$, $p < .001$, and explains 97.1% of purchase-intention variance ($R^2 = .971$; adjusted $R^2 = .971$). Convenience has the largest standardised coefficient ($\beta = .580$), followed by trust ($\beta = .550$) and personalisation ($\beta = .400$). Tolerance values are .958-.989 and VIF values are 1.012-1.044, so multicollinearity is not indicated. Durbin-Watson is 2.095; the Breusch-Pagan test is nonsignificant ($p = .742$); residual skewness is .062 and excess kurtosis is .240. Nineteen cases exceed the screening rule of Cook's $D > 4/N$, but the maximum Cook's D is .039, well below 1. H1-H3 are therefore supported by the empirical analysis. The exceptionally high R^2 indicates unusually strong explanatory power in this sample and is interpreted cautiously in light of the cross-sectional, self-reported measurement design and the common-method diagnostics reported above.

Table 5. Regression Results and Multicollinearity Diagnostics

Predictor	B	SE	beta	t	p	95% CI for B	Tolerance	VIF	Unique delta R ²
AI Personalisation	.399	.009	.400	46.84	<.001	[.382, .416]	.989	1.012	.158
AI-Driven Convenience	.585	.009	.580	66.89	<.001	[.568, .602]	.958	1.044	.322
Platform Trust	.550	.009	.550	63.76	<.001	[.533, .567]	.969	1.032	.293

4.6 ANOVA: Demographic Differences

Table 6. ANOVA Summary with Effect Sizes

Factor	Highest group (M)	Lowest group (M)	F (df)	p	eta ²	omega ²
Age	30-39 (3.806)	50-59 (3.453)	9.68 (5, 394)	<.001	.109	.098
Personal income	INR 150,000+ (4.080)	No income (3.211)	79.41 (6, 370)	<.001	.563	.555
Occupation	Professional (4.122)	Not employed (2.859)	67.50 (7, 392)	<.001	.547	.538

Purchase intention differs by age, $F(5, 394) = 9.68$, $p < .001$, eta-squared = .109, omega-squared = .098. The 30-39 group has the highest mean ($M = 3.806$), while the 50-59 group has the lowest ($M = 3.453$). Tukey HSD shows that the 30-39 group is significantly higher than the 20-29, 40-49, 50-59, and 60+ groups; no other age comparison is significant. Thus, H4 is only partially supported because the youngest categories do not uniformly show the strongest intention. Personal-income differences are significant after excluding non-disclosers, $F(6, 370) = 79.41$, $p < .001$, eta-squared = .563, omega-squared = .555; the ordered association is positive (Spearman $\rho = .754$, $p < .001$), supporting H5 in the study sample. Occupation differences are exploratory and significant, $F(7, 392) = 67.50$, $p < .001$, eta-squared = .547.

Table 7. Significant Tukey HSD Age Comparisons

Comparison	Mean difference	p adjusted	95% CI	Conclusion
30-39 vs 20-29	.175	.004	[.037, .314]	30-39 higher
30-39 vs 40-49	.329	<.001	[.158, .501]	30-39 higher
30-39 vs 50-59	.353	<.001	[.151, .554]	30-39 higher
30-39 vs 60+	.347	<.001	[.102, .593]	30-39 higher

Note. All other pairwise age comparisons were nonsignificant at $\alpha = .05$.

4.7 Hypothesis Summary

H1-H3 and H5 are supported by the empirical analysis. H4 is partially supported: age differences exist, but the highest mean occurs for 30-39-year-olds rather than for every younger category. Occupation is reported as an exploratory demographic result because it was not specified as a hypothesis.

Table 8. Hypothesis Decisions

Hypothesis	Decision	Evidence from empirical analysis
H1	Supported	Personalisation beta = .400, $p < .001$
H2	Supported	Convenience beta = .580, $p < .001$
H3	Supported	Trust beta = .550, $p < .001$
H4	Partially supported	Age ANOVA significant; 30-39, not every younger group, had the highest mean
H5	Supported	Income ANOVA $p < .001$; ordered rho = .754, $p < .001$

5. DISCUSSION

5.1 Convenience as the Dominant Driver

AI-enabled convenience has the largest standardised predictive association with purchase intention (beta = .580) in the study sample. This pattern is consistent with the practical proposition that search, reordering, reminders, and decision support reduce consumer effort. The cross-sectional design does not establish that convenience causes purchase intention.

5.2 Importance of Platform Trust

Platform trust also shows a strong positive predictive association (beta = .550). Accurate information, dependable fulfilment, payment security, and responsible data use may accompany stronger purchase intention, but reverse direction and unmeasured common causes remain possible.

5.3 Demographic Differences and Personalisation

Demographic findings are more nuanced than a simple younger-versus-older pattern. The 30-39 category has the highest purchase-intention mean and differs from four comparison groups, whereas the below-20 and 20-29 categories do not uniformly exceed all older groups. Personal income shows a strong positive ordered association with purchase intention in the study sample. These findings represent group associations rather than causal demographic effects.

5.4 Exceptional Explanatory Power and Robustness

The R-squared of .971 is substantially higher than values reported in comparable AI-enabled online-shopping models. Bunea et al. (2024) reported R-squared = .538 for purchase intention in an AI online-shopping model, while Silva et al. (2023) reported adjusted R-squared = .547 for behavioural intention toward retail chatbots. The present study therefore demonstrates unusually high explanatory power. A sensitivity analysis excluding PI7, the item explicitly referring to AI assistance, still yields R-squared = .954, while VIF values remain close to 1; therefore, the result is not explained by multicollinearity or by a single outcome item. Nevertheless, the magnitude should be interpreted cautiously because the constructs were measured through the same cross-sectional questionnaire and may reflect strong response consistency, common-method effects, and close conceptual alignment among the variables. Replication with independent samples, longitudinal data, and behavioural outcomes would provide a stronger test of the stability and generalisability of this explanatory power.

6. PRACTICAL IMPLICATIONS

- Prioritise fast, accurate search, low-friction navigation, reliable chatbot support, and timely delivery communication.
- Build trust through accurate information, dependable fulfilment, transparent refunds, and effective service recovery.

- Use local and household-level preference signals to improve recommendation relevance across diverse consumer segments.
- Segment AI-enabled services by age, income, and occupation instead of assuming uniform technology acceptance.

7. CONCLUSION

In this empirical study, AI-driven convenience, platform trust, and AI personalisation are positively associated with purchase intention, and convenience has the largest standardised regression coefficient. The model explains 97.1% of the variance in purchase intention; because this value is exceptionally high relative to comparable studies, it should be interpreted cautiously and in conjunction with the reported measurement, common-method, and regression diagnostics. Age and income differences are statistically significant associations within the study sample and do not by themselves demonstrate causal effects.

Based on these empirical associations, online grocery platforms may consider prioritising low-effort search and reordering, reliable service and data handling, and relevant personalisation. Segment-level decisions should be based on validated behavioural evidence rather than demographic stereotyping.

7.1 Limitations and Future Scope

The study is geographically limited to the Mumbai Suburban Region and uses self-reported, cross-sectional measures collected through one questionnaire. Such data can establish association and prediction but not causal direction, and common method variance, consistency motives, social desirability, and nonresponse bias cannot be eliminated. Harman's diagnostic is only a limited screen, not proof that common method bias is absent (Podsakoff et al., 2003). The findings should therefore be generalised cautiously beyond the respondents included in the study. The questionnaire's 'Below 20' category also does not distinguish respondents aged 18-19 from those below 18; future studies should include an explicit adult-eligibility item where required by the research protocol. The exceptionally high R-squared also warrants replication in an independent sample. Future research may use probability-based or carefully documented quota sampling, temporal or source separation of measures, longitudinal or behavioural outcomes, and pre-registered analysis where feasible.

REFERENCES

- Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Review Press.
- Aggarwal, D. (2023). Exploring the role of AI for online grocery shopping through enhancing personalised recommendations and customer segmentation. *Technoarete Transactions on Advances in Computer Applications*, 2(3), 1–9.
- Basha, A., & Shyam, R. (2024). A study on the effect of artificial intelligence on consumer buying behaviour in online grocery shopping with special reference to Bangalore City. *NIU International Journal of Human Rights*, 11(II), 75–86.
- Bhatt, P., & Singh, A. K. (2025). Impact of AI on consumers' purchase intention towards online grocery shopping in India. *Journal of Reliability and Statistical Studies*, 17(02), 453–490.
- Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
- Ersoy, Y. (2022). Factors affecting use of artificial intelligence in online shopping: The role of age and AI literacy. *Journal of Marketing Analytics*, 10(2), 115–131.
- Grand View Research. (2024). *India online grocery market size, share & trends analysis report 2025–2030*. Grand View Research.
- Gupta, S., & Singh, N. (2024). The personalisation-privacy paradox revisited: Consumer perspectives in AI-driven commerce. *Telematics and Informatics*, 79, 101987.
- International Review of Retail, Distribution and Consumer Research. (2025). Does AI matter in marketing? Unveiling the role of AI-driven marketing in quick grocery. <https://doi.org/10.1080/09593969.2025.2526482>
- Kar, A. K., & Ilavarasan, P. V. (2024). Enhancing trust in online grocery shopping through generative AI chatbots. *Journal of Business Research*, 175, 114251.
- Kotler, P., Kartajaya, H., & Setiawan, I. (2021). *Marketing 5.0: Technology for humanity*. John Wiley & Sons.
- Kumar, B. (2024). Redefining convenience: The impact of AI on India's online grocery ecosystem. *Indian Commerce Journal*, 18(1), 44–58.
- Li, Y., & Shrestha, A. (2022). Effects of AI-driven personalisation on consumer trust and purchase intention in e-grocery. *Electronic Commerce Research*, 22(3), 1023–1049.
- Mumbai Suburban District, Government of Maharashtra. (2026). About district. <https://mumbaisuburban.gov.in/en/about-district/>
- Nair, S. R., & Shams, S. R. (2021). Impact of store attributes on food and grocery shopping behaviour: Insights from an emerging market context. *EuroMed Journal of Business*, 16(3), 324–343.
- Reddy, K., & Kumar, P. (2024). AI chatbots and customer satisfaction in India's e-commerce sector. *Journal of Service Management*, 35(1), 88–107.
- Russell, S. J., & Norvig, P. (1995). *Artificial intelligence: A modern approach* (1st ed.). Prentice Hall.
- Singh, A., & Patel, N. (2023). Urban consumer behaviour and AI-driven grocery shopping. *Journal of Consumer Marketing*, 40(5), 612–625.
- Sontineni, R. B., Bastray, T., Vallabhaneni, M., Pradeep, & Basha, M. S. (2025). Artificial intelligence and its influence on online grocery shopping behaviour in Bangalore. *Advances in Consumer Research*, 2(2), 614–623.
- Zhou, H., & Zhang, L. (2023). Trust transfer in AI-powered personalisation: From platform to consumer decision-making. *Decision Support Systems*, 169, 113877.
- Bunea, O.-I., Corbos, R.-A., Misu, S. I., Triculescu, M., & Trifu, A. (2024). The next-generation shopper: A study of Generation-Z perceptions of AI in online shopping. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(4), 2605–2629. <https://doi.org/10.3390/jtaer19040125>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>

- Silva, S. C., De Cicco, R., Vlacic, B., & Elmashhara, M. G. (2023). Using chatbots in e-retailing: How to mitigate perceived risk and enhance the flow experience. *International Journal of Retail & Distribution Management*, 51(3), 285-305. <https://doi.org/10.1108/IJRDM-05-2022-0163>

Impact of Buyback Announcement on Share Prices of Companies

Vikram Joshi

MMS Student, Durgadevi Saraf Institute of Management Studies, Mumbai

Kitty Rana

Assistant Professor, Durgadevi Saraf Institute of Management Studies, Mumbai

ABSTRACT

This study examines how public announcements of share buybacks through tender offers affect stock price performance in the Indian secondary capital market. It investigates whether such announcements act as information shocks that generate abnormal price movements and analyses the behaviour of share prices before and after the announcement.

The Event Study Methodology (ESM) developed by Fama, Fisher, Jensen, and Roll (1969) is applied to a sample of 277 tender offer buybacks listed on the NSE from January 2015 to December 2025. A 61-day event window (-30, +30) with a 252-day estimation period is used. Expected returns are estimated using the market model with Nifty 50 as a proxy for market returns.

The study reveals significant positive Cumulative Average Abnormal Returns (CAARs) in the pre-announcement period, with CAAR reaching 4.21% over the [-10, 0] window. The strongest combined short-term impact peaks at 2.83% for the symmetric [-5, +5] window. A statistically significant post-announcement price reversal of -4.30% is documented over the [0, +30] window, indicating that early price gains gradually unwind as the market fully incorporates the disclosed information. The insignificant abnormal return on the announcement day (Day 0) suggests prior information leakage among market participants. Overall, results are consistent with the semi-strong form of market efficiency, wherein short-term abnormal returns arise but are subsequently corrected.

Keywords: *abnormal return, caar, event study methodology, share buyback, tender offer, stock market, market efficiency, nse*

1. INTRODUCTION

1.1 Introduction

A share buyback, also called as stock repurchase, is when a company uses its own money to purchase its shares from the market. After buying them back, the company either cancels those shares so that the total number of shares comes down or else they keep them for future use. In both ways, the company is changing or reshaping their capital structure on purpose.

Buybacks were not that always common. Earlier many companies use to mainly focus was on protecting capital rather than actively managing it funds. But over the time, globally and in India, thinking has been changed. Companies has begun to see buybacks as a way to manage their extra cash and improve and increase the shareholder value. In India, buybacks actually were allowed only after changes were made to the Companies Act in 1998 and when SEBI introduced its buyback rules. Share buybacks are mostly done for signalling purpose. When management decides to repurchase shares, it shows the market that they feel the shares are undervalued. It also means company has confidence to invest its own money in itself. When shares are bought back at premium, it creates psychological support for the price, which helps to keep the stock price stable, especially when market prices don't really show the real value of the company.

When we look at the numbers, share buybacks make financial ratios look better. When the number of shares is reduced, Earnings per Share (EPS) goes up. In similar, if profits are not changed but no. of outstanding shares in market reduces, Return on Equity (ROE) improves. These changes in financial

ratio improve when the firm is performing good on their financial statement . But sometimes, the improvement happens only on paper which means firms profits are not growing, it is improving because no. of outstanding shares is reducing. This is why many companies prefers for buybacks instead of dividends. Buybacks helps to return excess cash to shareholders without having pressure of paying dividends regularly and they are tax-efficient in some cases.

Buybacks can also work as a defensive tool, especially for promoters. When the number of shares comes down that are available in the market, it becomes difficult for an outside investor to take control of the company. If promoters choose not to buyback, their shareholding percentage automatically increases without spending any additional money. This is more of a strategic move, not a coincidence. For retail investors, buybacks create a real choice. Should they sell their shares and book in a guaranteed profit at a premium? Or they stay invested, and expect lower number of shares and higher promoter holding will give me better long-term value? There is no single correct answer to this. The decision depends on the company's fundamentals and future growth of company.

Also say there is one downside also to this. Many times, buybacks don't mean company is strong, it means company is stuck. They have cash with them but not a good plan for growth or research. So, they just go for buyback as it is easy option. Financial ratios look better but business is not really improving. Hence reason for buyback matters more than announcement. Investors should check cash flows, debt, capex and future growth of the company. In India, large buybacks need special resolution to be passed from shareholders but smaller buybacks don't have much checking, so investors need to be more careful when investing. At the end, buyback is nor good or bad, it's just a tool.

1.2 Objectives of the Study:

- To examine how public announcements of share buybacks, via tender offers, affect stock price performance in the Indian Secondary Capital Market.
- To observe how share prices behave before and after an announcement.
- To determine whether buyback announcements act as information shocks that lead to abnormal price movements.

2. LITERATURE REVIEW

(Goyal & Mangala, 2025) Analysed 307 NSE buyback announcements (2016–2023) across firm size, industry, buyback method and size. Found significant pre-announcement returns suggesting information leakage, while post-announcement returns were insignificant confirming semi-strong market efficiency. OMRs outperformed tender offers, and COVID-19 had no significant impact on buyback returns.

(P. & K., 2006) Studied 22 BSE 500 firms (2002–2004) and found significant positive CARs for both buyback and dividend announcements, with repurchases showing slightly stronger signalling. Price reaction was short-lived, dissipating within one to two days.

(Bhargava & Agrawal, 2015) Examined share repurchase announcements in India and observed short-term positive abnormal returns consistent with the signalling hypothesis, with magnitude varying across firm-specific and market conditions.

(Chatterjee & Mukherjee, 2015) Examined 63 BSE buyback announcements (2008–2012) using event study methodology. Found AARs and CARs were predominantly negative and statistically insignificant, rejecting undervaluation and shareholder value hypotheses. Attributed the muted market response to India's promoter-dominated ownership structure.

(Bhama, 2023) Studied 100 Indian firms (2010–2020) using event study methodology and found no significant abnormal returns post open market buyback announcements, rejecting the undervaluation

hypothesis. Industry-wise, the manufacturing sector outperformed IT, pharma and chemical sectors, with profit opportunities largely concentrated in the pre-announcement period.

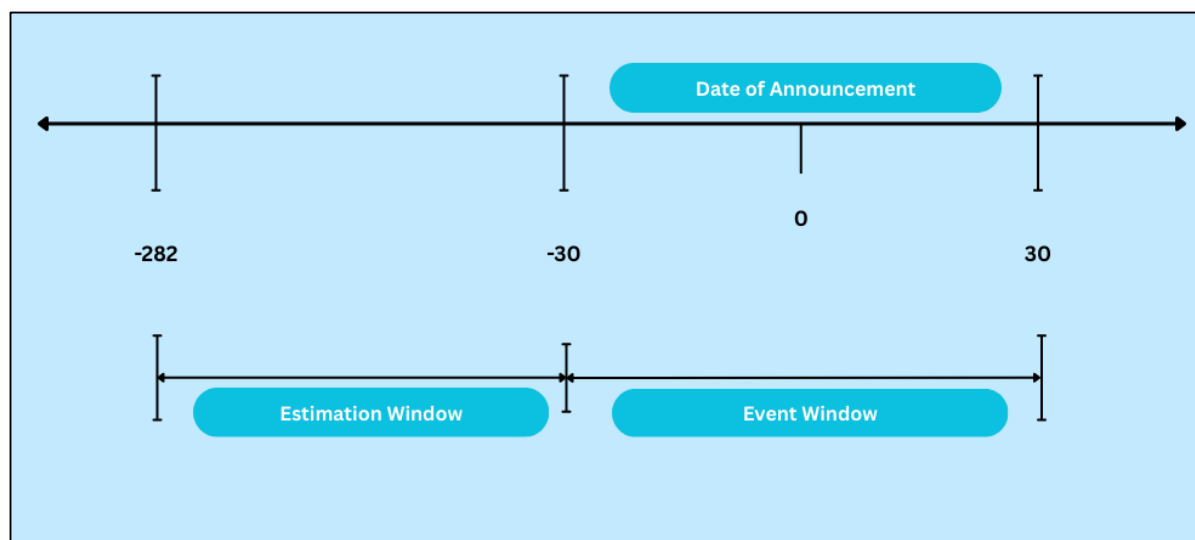
3. RESEARCH METHODOLOGY

3.1 Event Definition and Timeline

This research report is quantitative research where the Event Study Methodology is used on secondary data. The Event Study Methodology (ESM) was developed by (Fama, Fisher, Jensen, & Roll, 1969) to understand how stock prices will react when new information come up into the market.

The Event Study Methodology is used to find the impact of buyback announcements on the share prices of the listed companies. Previous studies used different event windows to study the effect of announcements on stock prices. For example, (Warner & Brown, 1985) used eleven-day event window which ranges from -5 to +5.

Figure 1. Event Study Timeline (in days)



Source(s): Authors' compilation

In this study, day on which the announcement is done by company is event date i.e., day "0." The event window has total of 61 days, which have 30 days before & after announcement (Chatterjee & Mukherjee, 2015). To estimate normal returns, 252 trading days which is estimation window is used in the study.

The study focuses on a specific timeline from January 2015 to December 2025, which is sample period. The analysis considers only trading days. Expected returns are estimated using the market model in the event study framework. For these returns from the Nifty 50 index during the estimation period are used.

3.2 Sample Selection and Data Sources

This study uses secondary data, which includes available financial information and stock price. The companies which are included in this study are those listed on the National Stock Exchange (NSE) and were identified through the website of the SEBI. Where 299 buybacks are noted during this timeframe, the sample was taken further based on below given criteria.

Sample Selection Criteria:

- 1) The buyback must be conducted through a tender offer.
- 2) The event must fall within the timeframe of 2015 to 2025.
- 3) Listed on the National Stock Exchange (NSE).

4) Comprehensive historical price data must be available for the duration of the study.

Particulars	No. of Buyback via Tender Offers
Total buyback announcement during the time frame	299
Less: Unavailable data	22
Final Sample	277

Daily stock price data for individual companies, along with broader market index data for the Nifty-50, were collected from Google Finance. The Nifty-50 index is used in the study as an indicator for estimating the market model parameters. Daily closing prices were used to calculate returns for the event study.

3.3 Statistical Framework and Models

The study uses the market model developed by (Sharpe, 1963) as part of its methodology. This model has been widely used in earlier studies to estimate the expected return of a security based on market returns and the two model parameters, alpha (α) and beta (β).

The market model is represented by the following regression equation:

$$E(R_{it}) = \alpha_i + \beta_i R_{mt} + e_i$$

Where,

$E(R_{it})$ - Expected return on security i ,

R_{mt} - market return,

β_i - slope of the regression equation,

e_i - error term with a zero mean and constant standard deviation.

The values of alpha and beta are estimated using data from a 252-day estimation period, ranging from T-282 to T-31.

The returns for both the estimation window and the event window are calculated using the following equation:

$$R_{it} = (P_{it}/P_{it-1}) - 1$$

Where,

R_{it} - daily return calculated on security i on day t .

P_{it} - daily closing price of security i on day t , and

P_{it-1} - daily closing price of security i on previous trading day ($t-1$).

$$R_{mt} = (P_{mt}/P_{mt-1}) - 1$$

Where,

R_{mt} - daily return calculated on share i on day t .

P_{mt} - daily closing price of share i at the day t , and

P_{mt-1} - closing price of security i on previous trading day ($t-1$).

Calculation of Abnormal Return for the security i on day t is as follows:

$$AR_{it} = R_{it} - E(R_{it})$$

Where,

R_{it} - actual return on security i on day t , and

$E(R_{it})$ - expected return for the same security on that day.

The daily abnormal returns for each security calculated above are sum for the 61-day event window. Sum of AR are now divided by the no. of firms in the sample (N) to find the average abnormal return (AAR), as shown below:

$$AAR_t = \frac{\sum_{t=1}^n AR_{it}}{N}$$

Where,

AAR_t - daily average abnormal return on day t in study,

N - no. of sample companies

3.4 Hypothesis Testing

The t-statistic is used to examine whether the AAR on the event date is significantly different from zero.

Null Hypothesis (H_0): AAR is equal to zero i.e., no market reaction.

Alternative Hypothesis (H_1): AAR is not equal to zero.

AARs is then used to find cumulative average abnormal returns (CAARs). CAARs are calculated by sum of the AARs over different time periods. Further, t-statistic is used to find significance of CAAR.

4. DATA ANALYSIS AND INTERPRETATION

Table 1. AAR's for buy-back Announcement

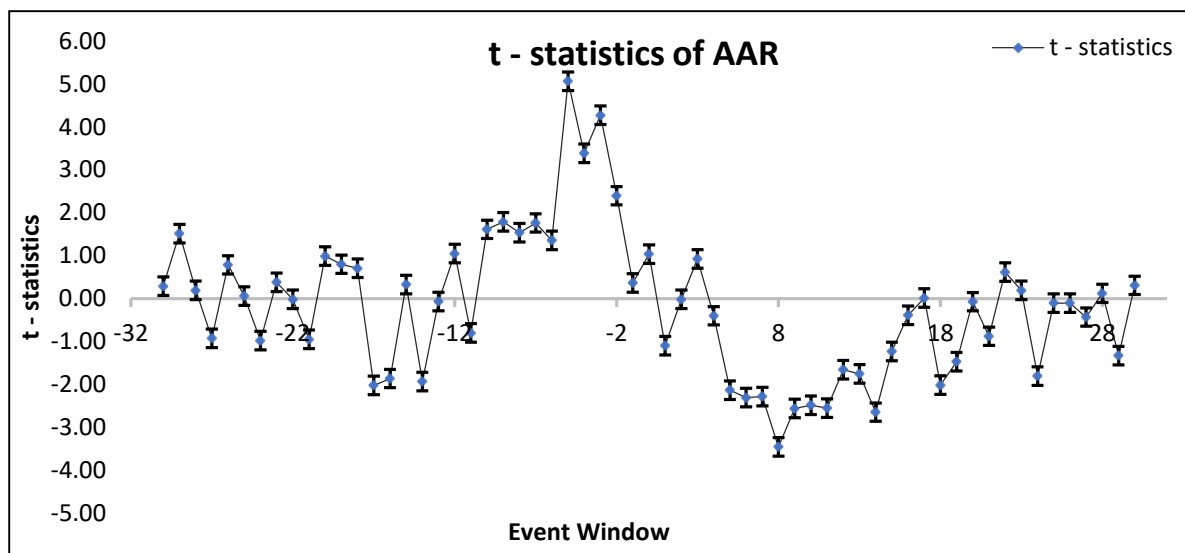
Table 1. AAR's for buy-back Announcement					
No. of Buybacks (n) = 277					
Pre - Announcement			Post - Announcement		
Event Window	AAR	t - statistics	Event Window	AAR	t - statistics
-30	0.0004	0.28	+30	0.0005	0.31
-29	0.0021	1.51	+29	-0.0014	-1.33
-28	0.0003	0.19	+28	0.0001	0.12
-27	-0.0010	-0.93	+27	-0.0006	-0.43
-26	0.0010	0.78	+26	-0.0001	-0.11
-25	0.0001	0.06	+25	-0.0002	-0.11
-24	-0.0012	-0.98	+24	-0.0026	-1.81*
-23	0.0005	0.38	+23	0.0002	0.19
-22	-0.0000	-0.02	+22	0.0007	0.61
-21	-0.0012	-0.95	+21	-0.0011	-0.88
-20	0.0016	0.99	+20	-0.0001	-0.07
-19	0.0010	0.80	+19	-0.0019	-1.47
-18	0.0009	0.70	+18	-0.0028	-2.02**
-17	-0.0021	-2.02**	+17	0.0000	0.01
-16	-0.0022	-1.87*	+16	-0.0005	-0.39
-15	0.0004	0.33	+15	-0.0016	-1.23
-14	-0.0021	-1.93*	+14	-0.0028	-2.65***
-13	-0.0001	-0.07	+13	-0.0022	-1.76*
-12	0.0012	1.05	+12	-0.0021	-1.66*
-11	-0.0008	-0.81	+11	-0.0033	-2.56**
-10	0.0020	1.61	+10	-0.0035	-2.49**
-9	0.0021	1.79*	+9	-0.0040	-2.57**
-8	0.0020	1.54	+8	-0.0053	-3.46***
-7	0.0021	1.76*	+7	-0.0034	-2.29**
-6	0.0021	1.36	+6	-0.0036	-2.31**
-5	0.0097	5.07***	+5	-0.0024	-2.14**
-4	0.0069	3.39***	+4	-0.0004	-0.40
-3	0.0077	4.27***	+3	0.0010	0.92
-2	0.0049	2.40**	+2	-0.0000	-0.02
-1	0.0007	0.36	+1	-0.0015	-1.10
Announcement Day -->			0	0.0019	1.03

Source(s): Authors' compilation

Table 1 shows Average Abnormal Returns (AARs) around buyback announcements. The t-statistics are used to test the statistical significance of AARs. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Positive (negative) AARs indicate favourable (unfavourable) market reaction to the buyback announcement.

Figure 2. t-Statistics of AAR during the Event Window

This figure plots the t-statistics of Average Abnormal Returns (AARs) over the event window.



Source(s): Authors' compilation

Event day 0 means the announcement day. The x axis indicates the threshold of no abnormal performance. t-statistics exceeding ± 1.645 , ± 1.96 , and ± 2.576 shows statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 1 and Figure 1 shows the t-statistics of AARs around buyback announcements over the event window (-30, +30). In the pre-announcement period, many days close to the announcement shows positive and significant t-statistics, particularly between days -5 and -2, which indicate the presence of information leakage or market anticipation of the buyback announcement to happen. The high positive t-statistics are observed immediately before the announcement day, which suggest that a strong favourable market reaction in anticipation of the event.

On the announcement day (day 0), the t-statistic is positive but insignificant, which states that a substantial portion of the information may have already been reflected into stock prices prior to the official announcement. In the post-announcement period, t-statistics are negative and statistically significant for few days, which indicates a price correction following the initial market reaction.

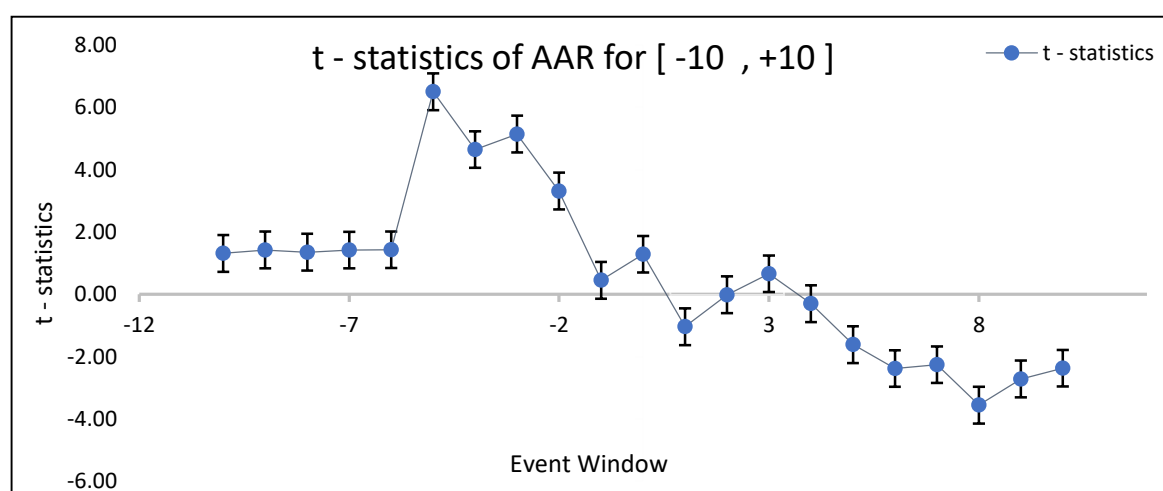
The t-statistics suggests that the market reacts positively before the announcement, and correction is then seen during post announcement, which supports the semi-strong form of market efficiency and around the event proof of short-term abnormal returns.

Table 2. AAR's for [-10 , +10] days

Table 2. AAR's for [-10 , +10]		
No. of Buybacks (n) = 277		
Event Window	AAR	t - statistics
-10	0.0020	1.61
-9	0.0021	1.79*
-8	0.0020	1.54
-7	0.0021	1.76*
-6	0.0021	1.36
-5	0.0097	5.07***
-4	0.0069	3.39***
-3	0.0077	4.27***
-2	0.0049	2.40**
-1	0.0007	0.36
0	0.0019	1.03
+1	-0.0015	-1.10
+2	0.0000	-0.02
+3	0.0010	0.92
+4	0.0004	-0.40
+5	-0.0024	-2.14**
+6	-0.0036	-2.31**
+7	-0.0034	-2.29**
+8	-0.0053	-3.46***
+9	-0.0040	-2.57**
+10	-0.0035	-2.49**

Source(s): Authors' compilation

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Figure 3. t-Statistics of AAR for [-10 , +10] days

Source(s): Authors' compilation

Table 2 and Figure 3 shows the Average Abnormal Returns (AARs) and their t-statistics around share buyback announcements within an event window of ten days before and after the announcement. In the pre-announcement period, mostly positive AAR's, with several days showing significant values, especially between day -9 and day -2. The strong positive abnormal returns occur around day -5 to -3, as t-statistics are more significant as compared to other days. This pattern suggests that the market begins reacting before the official announcement.

On the announcement day, the abnormal return is positive but not statistically significant.

In the post-announcement period, abnormal returns turn negative, with several days showing statistical significance, particularly from day +5 onwards. This suggests a price correction after the announcement, where the market adjusts as follow up to earlier market reaction.

Overall, the results indicate that buyback announcements are connected with positive abnormal returns before the announcement and negative abnormal returns after the announcement. This behaviour suggests that the short-term market anticipation followed by adjustment, supporting the presence of information effects around buyback announcements.

Table 3. CAAR's for Event Period

Table 3. CAAR's for Event Period		
No. of Buybacks (n) = 277		
CAAR Window	CAAR	t - statistics
Pre & Post Announcement		
[-30 , +30]	-0.0043	-0.37
[-25 , +25]	-0.0055	-0.52
[-20 , +20]	-0.0008	-0.08
[-15 , +15]	0.0055	0.66
[-10 , +10]	0.0189	2.76***
[-7 , +7]	0.0257	4.45***
[-5 , +5]	0.0283	5.74***
[-4 , +4]	0.0211	4.71***
[-3 , +3]	0.0146	3.70***
[-2 , +2]	0.0059	1.79*
[-1 , +1]	0.0010	0.40
[0 , 0]	0.0019	1.29
Pre-Announcement		
[-30 , 0]	0.0406	4.90***
[-25 , 0]	0.0380	5.00***
[-20 , 0]	0.0398	5.83***
[-15 , 0]	0.0407	6.83***
[-10 , 0]	0.0421	8.52***
[-5 , 0]	0.0318	8.71***
[-4 , 0]	0.0221	6.63***
[-3 , 0]	0.0152	5.10***
[-2 , 0]	0.0075	2.92***
[-1 , 0]	0.0026	1.23
Post Announcement		
[0 , +30]	-0.0430	-5.19***
[0 , +25]	-0.0415	-5.47***
[0 , +20]	-0.0386	-5.66***
[0 , +15]	-0.0333	-5.59***
[0 , +10]	-0.0213	-4.32***
[0 , +5]	-0.0015	-0.42
[0 , +4]	0.0009	0.26
[0 , +3]	0.0013	0.44
[0 , +2]	0.0003	0.13
[0 , +1]	0.0004	0.17

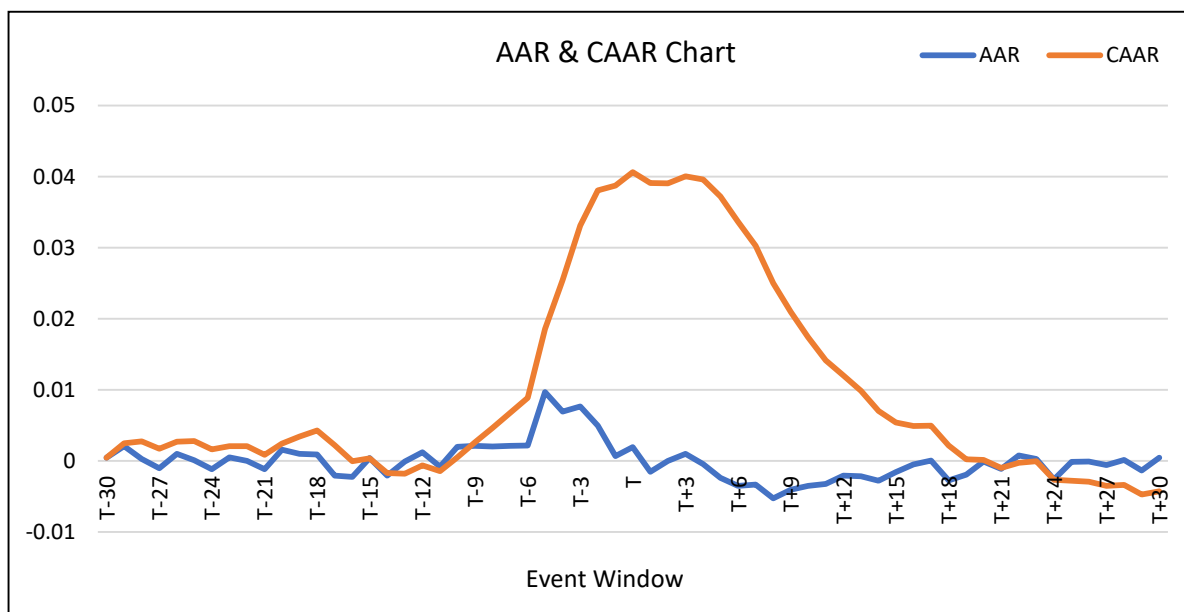
Source(s): Authors' compilation

Table 3 shows Cumulative Average Abnormal Returns (CAARs) for various event windows around share buyback announcements. ***, **, and * which indicate significance at the 1%, 5%, and 10% levels, respectively.

The results indicate a strong short-term market response to buyback announcements, with CAARs peaking at 2.83% for the $[-5, +5]$ window and 2.57% for $[-7, +7]$.

A price run-up is observed before the announcement, as CAAR reaches 4.21% over $[-10, 0]$, followed by a statistically significant post-announcement reversal, with CAAR declining to -4.30% for $[0, +30]$.

Figure 4. AAR & CAAR Chart



Source(s): Authors' compilation

Figure 4 shows a sharp upward movement in the CAAR curve before the announcement is available in public. As the event day is nearby, the CAAR line rises very quick, with a steep positive slope, which indicates that abnormal returns are accumulating at a fast rate in the pre-announcement period.

Around the announcement window, the CAAR curve reaches its peak. After this point, the slope of the curve changes direction and the CAAR line starts declining gradually, showing a downward trend in the post-announcement period. This fall indicates that the initial gains earned before the announcement begin to unwind as the market adjusts.

The AAR curve supports this pattern, with spikes before the announcement and relatively weaker or negative values afterward. The shape of the curves suggests a rapid build-up before the announcement followed by a slow correction after the event.

5. KEY FINDINGS & CONCLUSION

5.1 Key Findings

1) Pre-Announcement Price Run-Up:

There is increase in stock prices before the repurchase announcement. The CAAR reach 4.21% in the ten days during event period $[-10, 0]$, which suggests that the market may anticipate the buyback due to leaked information or possibly due to investor expectations.

2) Peak Short-Term Impact:

The strongest positive reaction occurs in short window around the announcement happening. CAARs peak at 2.83% for the eleven-day window of $[-5, +5]$ and 2.57% for the fifteen-day window of $[-7, +7]$.

3) Post-Announcement Price Reversal:

After the jump in CAAR, the market sees a correction in prices. In the 30 days following the announcement [0, +30], CAAR declines by -4.30%, which indicates that the early gains start slowly reversing as the market adjusts after the CAAR peak level.

4) Insignificant Reaction on Announcement Day:

On the actual announcement day (Day 0), the t-stat is positive but not statistically significant. Which suggests that the buyback-related information was already reflected in stock prices before the news became public. It suggests that there is some degree of information leakage in the market participants.

5) Evidence of Semi-Strong Market Efficiency:

The pattern - a fast upward movement in returns followed by a slower correction - supports the semi-strong form of market efficiency. Short-term abnormal returns may occur, but the market start adjusting prices as it fully processes the information.

6) Information Content and Market Signalling

The stock prices generally rise after tender offer buyback announcements, which indicate a positive market response. This supports the view that Indian companies use buybacks to signal that their shares are undervalued. Because tender offers are made at a fixed price above the market price, they communicate management's confidence more clearly and reduce information gaps with investors.

5.2. Conclusion

The study looks at effects of Indian stock market of announcing buybacks through tender offers. By analysis of different companies which is 277 in total over 10-year period, it shows the importance of these deals as strategic tools for corporations' ability to impact the stock market beyond just being ways to return capital to shareholders. In the end, the findings shows that management can also communicate the company's future goals by announcing a share repurchase.

The Signalling Theory which deals with the cost of the price of stock through share buybacks is supported by the findings. It also shows the public that firm thinks current stock price is low, which give the stock of company a floor price. The market typically makes quick and favourable price changes once the buyback is announced, mainly in the initial days after the announcement. This implies the NSE quickly and effectively processes new corporate information and modifies share prices to reflect the company's recognized "true" value of the firm.

6. FUTURE SCOPE OF RESEARCH

This study focuses on short-term market reactions within a 61-day event window. Future research could extend the analysis to examine long-term post-buyback performance over three to five years, offering deeper insight into the enduring value implications of tender offer buybacks. A comparative analysis of open market repurchases versus tender offers would further illuminate differences in signalling effectiveness across buyback mechanisms.

The evolving Indian regulatory and taxation landscape - including changes to buyback tax provisions under successive Finance Acts and SEBI regulatory updates - presents another important avenue for investigation. Studying how policy shifts affect the choice between dividends and buybacks could yield actionable insights for corporate treasurers and policymakers alike.

Behavioural finance perspectives offer additional scope, particularly examining how institutional and retail investors differ in their response to buyback announcements, and whether investor category, holding period, or liquidity needs influence participation and price outcomes. The growing importance

of ESG criteria also warrants attention: future studies could investigate whether firms with higher ESG scores generate more significant positive market reactions around buyback events - contributing to the intersection of sustainable finance and corporate payout policy research.

REFERENCES

- 1) Bhama, V. (2023). Open repurchase announcements and abnormal returns of Indian firms: An industry-wise analysis. *Investment Management & Financial Innovations*, 238-249.
- 2) Bhargava, S., & Agrawal, P. (2015). Announcement effect of share buyback on share price at National Stock Exchange: An empirical investigation. 89–105.
- 3) Chatterjee, C., & Mukherjee, P. (2015). Price behaviour around share buyback in the Indian equity market. *Global Business Review*, 16(3), 425-438.
- 4) Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International economic review*, 10(1), 1-21.
- 5) Goyal, P., & Mangala, D. (2025). Do share buyback announcements influence stock prices? A multi-faceted event study analysis. *IIM Ranchi Journal of Management*, 4(2), 206-228.
- 6) P., T., & K., S. (2006). Share Price Behaviour around Buy Back and Dividend Announcements in India. *Indian Institute of Capital Markets 9th Capital Markets Conference Paper*.
- 7) Pradhan, S. K. (2017). Effect of Buyback Announcements and Tax Implication: Study on Indian Context. *SCMS Journal of Indian Management*, 14-24.
- 8) Pradhan, S. K., & Kasilingam, R. (2018). Stock split announcements and their impact on shareholders' wealth: A study on the Indian stock market. *Indian Journal of Finance*, 46-61.
- 9) Sharpe, W. F. (1963). A simplified model for portfolio analysis. *Management science*, 9(2), 277-293.
- 10) Warner, J. B., & Brown, S. J. (1985). Using daily stock returns: The case of event studies. *Journal of financial economics*, 14(1), 3-31.

Determinants Affecting Consumer Trust in Communication with AI Chatbots in Quick-Commerce Platforms: The Moderating Effect of Privacy Concerns - A Study of Maharashtra

Mahendra Daima

Assistant Professor, Prin. L.N. Welingkar Inst. of Management Development and Research, Mumbai

Kinjal Shah

Assistant Professor, IES's Management College and Research Centre, Mumbai

ABSTRACT

AI chatbots are increasingly used by quick-commerce platforms for order tracking, delivery updates, refunds, cancellations and complaint resolution. Building on the chatbot-trust framework of Li et al. (2023), this study examines the determinants of consumer trust in AI-chatbot communication in Maharashtra, focusing on expertise, responsiveness, ease of use, anthropomorphism, brand trust, human support, perceived risk and privacy concerns. A quantitative, cross-sectional design is used with 500 consumers and a 37-item five-point Likert instrument. Reliability, structural modelling and moderation analysis are applied. The structural model shows mixed fit: CMIN/DF and RMSEA indicate reasonable approximation, while GFI, NFI, IFI and CFI remain below commonly preferred benchmarks. Expertise ($\beta = .331$), brand trust ($\beta = .207$) and responsiveness ($\beta = .097$) positively influence trust, while perceived risk has a significant negative effect ($\beta = -.226$). Anthropomorphism shows only marginal positive evidence at the 10% level ($\beta = .071$, $p < .10$) and is not significant at the conventional 5% level. Ease of use and human support are not significant. Privacy concerns do not moderate chatbot-related factors but partially moderate the effects of brand trust and perceived risk. The findings highlight the importance of competence, platform credibility and responsible data practices in building trust in AI-enabled quick-commerce service.

Keywords: AI chatbots, consumer trust, quick commerce, Maharashtra, privacy concerns, brand trust, perceived risk, anthropomorphism

1. INTRODUCTION

AI chatbots have become an important part of digital customer service, providing continuous assistance for product queries, order processing, complaints and post-purchase support. Consumers value the speed and accessibility of automated service, but trust can decline when AI appears inaccurate, unempathic or risky (Castelo et al., 2019; Luo et al., 2019). Trust is therefore central to the acceptance of AI-mediated service communication.

This issue is especially relevant in quick commerce, where customers expect near-instant fulfilment and rapid service recovery. Chatbots may be used to track urgent orders, explain delays, report missing items, process refunds, change delivery details or escalate service failures. In these encounters, trust depends not only on interface speed but also on competence, responsiveness, human-like communication, platform credibility and perceived safety (Araujo, 2018; Chen et al., 2021; Nordheim et al., 2019). Privacy is equally important because chatbot interactions can involve delivery locations, order history, payment issues and complaint information (Ameen et al., 2022; Bansal et al., 2015).

Maharashtra offers a relevant setting because its quick-commerce consumers span dense metropolitan markets and rapidly digitising urban centres. The present research explicitly builds on Li et al. (2023), who examined determinants of consumer trust in communication with AI chatbots and the moderating role of privacy concerns. Rather than proposing an entirely new trust framework, this study contextually extends and tests that framework in quick-commerce service encounters in Maharashtra. This context is distinctive because chatbot interactions are closely connected with time-

sensitive fulfilment and service-recovery issues such as delivery delays, missing items, refunds, cancellations, replacements and complaints. The study therefore evaluates whether established chatbot-related, company-related and privacy-related trust relationships remain applicable in this high-speed service environment.

1.1 Research Objectives

- Examine the effects of chatbot expertise, responsiveness, ease of use and anthropomorphism on consumer trust.
- Assess the influence of brand trust, human support and perceived risk on trust in AI chatbots.
- Examine privacy concerns as a moderator of chatbot-related and company-related trust relationships.
- Derive context-specific theoretical and practical implications for quick-commerce platforms operating in Maharashtra.

2. REVIEW OF LITERATURE

2.1 Consumer Trust in AI Chatbots

Trust reflects a willingness to accept vulnerability based on positive expectations about another actor or system (Mayer et al., 1995; Rousseau et al., 1998). In AI-supported services, consumers judge whether the system is reliable, competent and unlikely to act against their interests. Transparency, reliability, immediacy and anthropomorphic cues can shape both cognitive and affective trust (Glikson & Woolley, 2020).

2.2 Chatbot-Related Factors

Expertise represents the chatbot's perceived knowledge and ability to provide correct, relevant and actionable answers; prior research links such competence strongly with trust (Brandtzaeg & Folstad, 2017; Nordheim et al., 2019). Responsiveness concerns the speed and smoothness of replies, which is particularly important in time-sensitive quick-commerce service (Chen et al., 2021). Ease of use reflects the effort required to interact with the system (Davis et al., 1989), while anthropomorphism captures human-like conversational qualities that may strengthen social presence but can also create discomfort when overused (Araujo, 2018; Ciechanowski et al., 2019).

2.3 Company-Related Factors

Consumers often transfer trust from the platform to the technology it deploys. Brand trust can therefore create a credibility halo around the chatbot, especially when users cannot independently evaluate the AI system (Delgado-Ballester, 2004). Human support provides a recovery mechanism when automation fails, although heavy dependence on human intervention may signal weak chatbot capability (Adam et al., 2021; Graef et al., 2021). Perceived risk, including concerns about incorrect information, failed transactions, unresolved complaints and misuse of data, is generally associated with lower trust and weaker technology adoption (Hasan et al., 2021).

2.4 Privacy Concerns

AI chatbots may use personal and transactional information to provide tailored assistance. This creates a privacy-trust tension in which consumers value convenience while remaining concerned about how personal data are collected, stored and used (Ameen et al., 2022). Privacy concern can influence trust directly and can also alter the strength of relationships between service attributes and trust (Bansal et al., 2015; Li et al., 2023). Li et al. (2023) provides an important conceptual foundation for the present study by combining chatbot-related determinants, company-related determinants and privacy concerns within a trust framework. The present research adapts this logic to quick-commerce in Maharashtra and examines whether the relationships hold in a setting where automated customer service is closely linked with urgent order fulfilment and service recovery.

2.5 Research Hypotheses

- H1: Expertise positively influences trust in AI chatbots.
- H2: Responsiveness positively influences trust in AI chatbots.
- H3: Ease of use positively influences trust in AI chatbots.
- H4: Anthropomorphism positively influences trust in AI chatbots.
- H5: Brand trust positively influences trust in AI chatbots.
- H6: Human support has a negative relationship with trust in AI chatbots.
- H7: Perceived risk negatively influences trust in AI chatbots.
- H8: Privacy concerns moderate relationships between chatbot-related factors and trust.
- H9: Privacy concerns moderate the relationships between company-related factors and trust.

3. RESEARCH METHODOLOGY

3.1 Research Design and Sample

The study adopts a quantitative, explanatory and cross-sectional design. The unit of analysis is an individual consumer in Maharashtra who has used a quick-commerce platform and interacted with an AI-enabled chatbot or automated customer-service interface for an order, delivery, refund, cancellation, replacement, complaint or related service request. The analytical sample comprises 500 valid responses.

3.2 Instrument and Measurement

The questionnaire contains screening items, 37 construct measures and demographic questions. Nine constructs are measured: expertise, responsiveness, ease of use, anthropomorphism, brand trust, human support, perceived risk, privacy concerns and trust in AI chatbots. Most items use a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree); anthropomorphism uses semantic-differential wording. The measures are adapted from established chatbot, trust and technology-acceptance literature, with Li et al. (2023) serving as an important source for the integrated chatbot-trust framework (Davis et al., 1989; Nordheim et al., 2019; Li et al., 2023).

3.3 Analytical Approach

SPSS 25.0 is used for descriptive statistics, reliability analysis and multiple-regression moderation testing, while AMOS is used to examine the structural relationships among the constructs. Internal consistency is assessed through Cronbach's alpha and composite reliability, and model fit is evaluated using CMIN/DF, GFI, RMSEA, NFI, IFI and CFI. The fit indices are interpreted collectively rather than through a single rigid cut-off. As broad guidelines, a CMIN/DF value below about 3 and an RMSEA below .08 may indicate reasonable fit, while GFI, NFI, IFI and CFI values around .90 or higher are commonly preferred. These benchmarks are treated as indicative rather than absolute (Kline, 2016; Hair et al., 2019).

3.4 Respondent Profile

Demographic	Category	Frequency	%
Gender	Male	233	46.6
	Female	267	53.4
Age	Below 18	5	1
	18-26	245	49
	27-40	237	47.4
	Above 40	13	2.6
Education	High school or below	29	5.8
	College	435	87
	Graduate/postgraduate	36	7.2

3.5 Reliability and Descriptive Statistics

Construct	Mean	SD	CR	Alpha
Expertise	3.983	0.718	0.815	0.812
Ease of Use	4.195	0.601	0.745	0.740
Anthropomorphism	3.258	1.015	0.891	0.890
Brand Trust	4.366	0.531	0.767	0.764
Responsiveness	4.326	0.604	0.786	0.784
Human Support	3.170	0.955	0.827	0.824
Perceived Risk	1.852	0.647	0.731	0.709
Trust in AI Chatbot	4.302	0.544	0.773	0.761
Privacy Concerns	3.633	0.772	0.802	0.801

All Cronbach's alpha values exceed .70, indicating acceptable internal consistency across the nine constructs.

4. DATA ANALYSIS AND RESULTS

4.1 Structural Model and Direct Effects

The structural model shows mixed rather than uniformly strong fit. CMIN/DF = 2.846 and RMSEA = .071 fall within commonly used ranges for reasonable fit. However, GFI = .802, NFI = .824, IFI = .878 and CFI = .877 are below the commonly preferred .90 benchmark. Accordingly, the model is interpreted as providing moderate or partial fit, and the structural-path estimates should be read with appropriate caution (Kline, 2016; Hair et al., 2019). Within this qualification, expertise is the strongest positive chatbot-related predictor of trust ($\beta = .331$, $p < .01$). Brand trust also has a substantial positive effect ($\beta = .207$, $p < .01$), while perceived risk significantly reduces trust ($\beta = -.226$, $p < .01$). Responsiveness shows a smaller positive effect ($\beta = .097$, $p < .05$). Anthropomorphism has a small positive coefficient ($\beta = .071$) but is significant only at the 10% level ($p < .10$); therefore, H4 receives only marginal support and should not be interpreted as robust evidence at the conventional 5% significance level. Ease of use and human support are not statistically significant.

Index	Observed value	Common guideline	Interpretation
CMIN/DF	2.846	< 3.0	Reasonable fit
RMSEA	.071	< .08	Reasonable fit
GFI	.802	$\geq .90$ preferred	Below preferred benchmark
NFI	.824	$\geq .90$ preferred	Below preferred benchmark
IFI	.878	$\geq .90$ preferred	Slightly below preferred benchmark
CFI	.877	$\geq .90$ preferred	Slightly below preferred benchmark

H	Relationship	β	Significance	Result
H1	Expertise -> Trust	.331	$p < .01$	Supported
H2	Responsiveness -> Trust	.097	$p < .05$	Supported
H3	Ease of Use -> Trust	.067	$p > .10$	Not supported
H4	Anthropomorphism -> Trust	.071	$p < .10$	Marginal support
H5	Brand Trust -> Trust	.207	$p < .01$	Supported
H6	Human Support -> Trust	-.027	$p > .10$	Not supported
H7	Perceived Risk -> Trust	-.226	$p < .01$	Supported

4.2 Moderating Effect of Privacy Concerns

Moderation analysis shows that privacy concerns do not significantly change the effects of expertise, responsiveness, anthropomorphism or ease of use on chatbot trust; therefore, H8 is not supported. In contrast, privacy concerns significantly moderate relationships involving perceived risk (interaction $\beta = .097$, $p < .05$) and brand trust (interaction $\beta = .104$, $p < .05$). Human-support interaction is not significant. H9 is therefore partially supported.

4.3 Key Findings

- Expertise is the strongest chatbot-related determinant of consumer trust.
- Brand trust strengthens confidence in the chatbot, while perceived risk weakens it.
- Responsiveness has a statistically significant but smaller positive effect, whereas anthropomorphism shows only marginal evidence at the 10% level and should be interpreted cautiously.
- Ease of use does not independently create trust, suggesting usability is a basic requirement rather than a trust driver.
- Privacy concerns matter mainly when consumers evaluate the platform brand and perceived risk surrounding chatbot use.

5. DISCUSSION

5.1 Expertise and Responsiveness

The findings identify expertise as the most important chatbot-related trust driver. In quick commerce, consumers contact automated support for time-sensitive issues such as delayed orders, missing products, refunds and replacements. Trust therefore depends primarily on whether the chatbot provides correct, relevant and actionable information. This aligns with research emphasizing competence and answer quality in chatbot trust formation (Mogaji et al., 2021; Nordheim et al., 2019). Responsiveness remains important, but its smaller coefficient indicates that consumers distinguish between receiving an immediate answer and receiving a useful answer.

5.2 Anthropomorphism and Ease of Use

Anthropomorphism has a small positive coefficient ($\beta = .071$), but the relationship is significant only at the 10% level and not at the conventional 5% level. The evidence should therefore be treated as marginal and tentative rather than as a robust trust effect. Natural language and human-like conversational cues may improve comfort and social presence for some users, but excessive human-like design can create discomfort or unrealistic expectations (Araujo, 2018; Ciechanowski et al., 2019). Ease of use is not statistically significant, indicating that a simple interface alone does not assure consumers that the chatbot is trustworthy. Usability should therefore be treated as a foundational design condition rather than the principal trust-building mechanism.

5.3 Brand Trust, Risk and Privacy

Brand trust significantly increases chatbot trust, whereas perceived risk reduces it. Consumers do not evaluate the chatbot independently of the platform operating it. Reliable fulfilment, transparent refunds, secure transactions and consistent complaint resolution can therefore enhance trust in the AI interface. Privacy concerns further shape these company-level relationships, suggesting that privacy-sensitive consumers pay particular attention to the platform's credibility and the risks associated with sharing data (Ameen et al., 2022; Bansal et al., 2015; Song et al., 2022).

6. MANAGERIAL IMPLICATIONS

- Prioritise chatbot expertise by integrating accurate order, inventory, delivery, refund and cancellation information.
- Measure first-contact resolution and answer accuracy alongside response speed.
- Build platform-level trust through transparent service promises, reliable refunds and clear complaint-resolution processes.
- Reduce perceived risk by minimising unnecessary data requests and clearly explaining how personal information is used.
- Design seamless human escalation with full conversation context for complex service failures.

- Treat anthropomorphic cues as secondary design features rather than primary trust drivers, and prioritise accurate, clear and multilingual interactions suitable for Maharashtra's diverse consumer base.

7. CONCLUSION

The study shows that trust in quick-commerce AI chatbots is shaped by both chatbot performance and the broader platform environment. Expertise is the strongest positive chatbot-related determinant, while responsiveness has a smaller but statistically significant positive effect. Anthropomorphism shows only marginal positive evidence at the 10% level and should therefore be interpreted cautiously, while ease of use does not independently strengthen trust. At the company level, brand trust improves confidence in the chatbot and perceived risk has a significant negative influence. Privacy concerns do not alter the effects of chatbot-related characteristics, but they partially moderate the effects of brand trust and perceived risk. The structural model shows mixed rather than uniformly strong fit, so these relationships should be interpreted with appropriate caution. For quick-commerce platforms in Maharashtra, building trust therefore requires more than a fast and convenient interface: AI service must be accurate, reliable, securely integrated with the platform and supported by responsible data practices.

8. LIMITATIONS AND FUTURE RESEARCH

The study is cross-sectional and relies on self-reported perceptions, limiting conclusions about how trust changes after repeated service encounters. The respondent profile is also demographically concentrated: 96.4% of respondents are between 18 and 40 years of age, while only 2.6% are above 40, and 94.2% fall within the "College" or "Graduate/postgraduate" education categories. Accordingly, the findings should not be generalised uniformly across all consumer age and educational groups in Maharashtra. Future studies should consider stratified or quota-based sampling to obtain stronger representation of older consumers and more diverse educational groups. Future research can also compare consumers across metropolitan, tier-2 and tier-3 cities in Maharashtra, examine multilingual chatbot performance, and incorporate behavioural indicators such as escalation frequency, complaint-resolution time and repeat chatbot use. Longitudinal studies may assess how trust changes following successful and unsuccessful delivery episodes.

REFERENCES

- Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, 31(2), 427-445.
- Ameen, N., Hosany, S., & Paul, J. (2022). The personalisation-privacy paradox: Consumer interaction with smart technologies and shopping mall loyalty. *Computers in Human Behavior*, 126, 106976.
- Araujo, T. (2018). Living up to the chatbot hype: Anthropomorphic design cues and communicative agency framing. *Computers in Human Behavior*, 85, 183-189.
- Bansal, G., Zahedi, F. M., & Gefen, D. (2015). Privacy assurance mechanisms, trust, and the moderating role of privacy concern. *European Journal of Information Systems*, 24(6), 624-644.
- Brandtzaeg, P. B., & Folstad, A. (2017). Why people use chatbots. In *Internet Science* (pp. 377-392). Springer.
- Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research*, 56(5), 809-825.
- Chen, J. S., Tran-Thien-Y, L., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management*, 49(11), 1512-1531.
- Ciechanowski, L., Przegalinska, A., Magnuski, M., & Gloor, P. (2019). Human-chatbot interaction and the uncanny valley. *Future Generation Computer Systems*, 92, 539-548.

- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982-1003.
- Delgado-Ballester, E. (2004). Applicability of a brand trust scale across product categories. *European Journal of Marketing*, 38(5/6), 573-592.
- Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, 14(2), 627-660.
- Graef, R., Klier, M., Kluge, K., & Zolitschka, J. F. (2021). Human-machine collaboration in online customer service. *Electronic Markets*, 31(2), 319-341.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.
- Hasan, R., Shams, R., & Rahman, M. (2021). Consumer trust and perceived risk for voice-controlled artificial intelligence. *Journal of Business Research*, 131, 591-597.
- Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.
- Li, J., Wu, L., Qi, J., Zhang, Y., Wu, Z., & Hu, S. (2023). Determinants affecting consumer trust in communication with AI chatbots: The moderating effect of privacy concerns. *Journal of Organizational and End User Computing*, 35(1), 1-24.
- Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Machines vs. humans: The impact of AI chatbot disclosure on customer purchases. *Marketing Science*, 38(6), 937-947.
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709-734.
- Mogaji, E., Balakrishnan, J., Nwoba, A. C., & Nguyen, N. P. (2021). Emerging-market consumers' interactions with banking chatbots. *Telematics and Informatics*, 65, 101711.
- Nordheim, C. B., Folstad, A., & Bjorkli, C. A. (2019). An initial model of trust in chatbots for customer service. *Interacting with Computers*, 31(3), 317-335.
- Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, 23(3), 393-404.
- Song, M., Xing, X., Duan, Y., Cohen, J., & Mou, J. (2022). Will artificial intelligence replace human customer service? *Journal of Retailing and Consumer Services*, 66, 102900.

Intraday Implied Volatility and Expiry-Day Surveillance in India

Harsh Thakrar

Doctoral Candidate, K. J. Somaiya Institute of Management, Mumbai

Raghukumari P S

Professor, K. J. Somaiya Institute of Management, Mumbai

EXTENDED ABSTRACT

Objectives

In the options market, volatility can be measured at many observation frequencies and the choice is usually made by data availability rather than by design. In India, where index options settle into a single session and a large share of trading concentrates there, the working measure is a daily volatility index. This study treats the observation frequency itself as the object of inquiry. It asks whether conclusions about how option implied volatility behaves around settlement depend on how often that volatility is sampled and what any discrepancy implies for research design and for monitoring practice in markets of this kind. The study does not establish a cause for the behaviour it documents and does not take any position on conduct. Its claim is about measurement.

Data and method

Evidence is drawn at two frequencies from the same market. The high-frequency component uses tick-level records for at-the-money Nifty 50 index options across consecutive monthly settlement cycles, paired with synchronous spot quotes. Implied volatility is recovered by numerical inversion of the standard European pricing model, using contemporaneous spot, exact time to expiry and prevailing short-term yields. The low-frequency component uses the daily headline volatility index over a longer window, together with matching index series and a panel of daily cash-market turnover for the heaviest constituents of the index.

The statistical design follows from the distribution of the data. Intraday implied volatility is strongly skewed and heavy-tailed, so tests that assume normality are unsuitable for comparing spread across groups. Dispersion is examined with a median-based robust test applied series by series, and reinforced by a pooled specification that conditions on settlement cycle and contract type with robust standard errors. At daily frequency the same comparison is made with both a parametric and a rank-based test. A within-session contrast tests for directional movement, and turnover differences are assessed with a one-sided rank test supported by placebo relabelling of ordinary trading days. Simulation exercises verify the size of the tests on data resembling the sample and quantify the number of settlement events needed to detect effects of plausible magnitude.

Key findings

The results separate into what the design can and cannot support. Within the settlement session, the spread of implied volatility widens substantially against comparable ordinary sessions. The widening holds in almost all contract series that are examined, survives conditioning on cycle and contract type and shows up in robust distributional measures as well as in variance comparison which points to a distributional property rather than a few extreme observations. The exclusion of closing minutes moderates the magnitude without removing it. There is one series that does not conform and this is reported rather than set aside.

At daily frequency the same settlement sessions cannot be distinguished from ordinary ones on the headline volatility index, whether measured by level or by day-on-day change. Behaviour that is pronounced within the session is absorbed by aggregation before it reaches the published series.

In the underlying cash market, activity in the largest constituents is reliably higher on settlement days, and placebo tests on ordinary days return nulls, which supports reading the association as settlement-related rather than a day-of-week artefact.

Direction is not identifiable. The within-session contrast is small, statistically insignificant and unstable in sign across cycles. The simulation exercise shows that a sample of this length has limited power against a directional effect of economically plausible size, and indicates how far the event count would have to grow. It also confirms that the dispersion test is correctly sized, so the dispersion result is not an artefact of non-normality.

Conclusion and implications

Settlement-session behaviour in this market appears in the variability of implied volatility rather than in its level, and that variability does not survive daily aggregation. Several mechanisms fit the pattern, among them numerical instability as time value decays, hedging demand as contract sensitivity rises into the close, liquidity withdrawal by market makers managing settlement risk, and positioning by informed participants. The design cannot rank them; that would require order-level and quote-level data.

The measurement conclusion is independent of the ranking. Behaviour that is prominent at high frequency and absent at daily frequency will not be detected by any framework built on daily summaries. This is a point about research design before it is a point about policy. Studies of settlement effects in emerging markets should justify their sampling interval rather than inherit it, and monitoring arrangements in markets that concentrate settlement into a single session should observe at a frequency matched to the behaviour they are meant to detect. The evidence here is exploratory, and a longer high-frequency panel would be needed to move from a measurement result to an account of mechanism.

Keywords: *derivatives settlement; indian equity derivatives; observation frequency; second-moment effects; statistical power; temporal aggregation*

Address by Session Chair

Prof. Dr. Krupa Rai



Dr. Krupa, Associate Professor at **KJ Somaiya Institute of Management Studies & Research (KJSIMSR), Mumbai, Maharashtra, India**, Ph.D. Guide, and alumna of the **Global School in Empirical Research Methods, University of St. Gallen, Switzerland**, served as the expert reviewer and provided valuable academic insights throughout the paper presentations.

Following each presentation, Dr. Krupa shared her expert observations, constructive feedback, and suggestions with the respective authors. In her address, she discussed emerging and future research directions in the field of business and management and emphasised the importance of maintaining academic rigour in research. She advised researchers to exercise caution and discretion while using **Generative AI in research manuscripts**, highlighting that AI should complement, rather than replace, the researcher's own critical thinking and scholarly judgement.

She further emphasised that a **clear logical understanding and sound theoretical foundation are essential for high-quality academic writing and research**. Dr. Krupa also shared practical tips and valuable insights on improving research manuscripts and enhancing their prospects for publication in reputed journals.

She congratulated the organising team for the successful conduct of the event and appreciated the merit-based selection of papers, which brought together diverse perspectives and provided meaningful learning aligned with the theme of the conference. She particularly appreciated papers that demonstrated strong research potential and could be further developed for publication in **Scopus-indexed and other reputed journals**.

Best Paper Presentation Awards

Following a preliminary screening and a rigorous peer-review process, **thirteen research papers** were selected for presentation at the Conference. The papers were presented by academicians from various institutes as well as industry professionals and covered diverse perspectives on Artificial Intelligence and its implications across industries, including sustainable practices, emerging strategies, innovation, self-reliance, and business growth.

The presented papers were evaluated through a **fair and transparent assessment process by the blind reviewers and the respective Session Chair**. Based on the evaluation, the following papers and presenters were recognized for their outstanding research contributions and presentations.

First Best Paper Award

Rahul Parchure & Bernadette D'Silva were honored with the **First Best Paper Award** along with a cash prize of ₹8,000 for their research paper titled, ***"The Role of AI and Chatbots in Guest Services and their Influence on Employee Attrition in 5-Star Hotels in Mumbai"***

Second Best Paper Award

Harsh Thakrar & Raghukumari P. S. received the **Second Best Paper Award** for their research paper titled, ***"Intraday Implied Volatility and Expiry-Day Surveillance in India."***

Third Best Paper Award

Ar. Mildred Jose was honored with the **Third Best Paper Award** along with a cash prize of ₹4,000 for her research paper titled, ***"'Platform Urbanism': Evaluating Algorithms within Smart Cities"***

Best Paper – Student Track

Vikram Joshi & Kitty Rana were recognized with the **Best Paper Award in the Student Track**, along with a cash prize of ₹5,000, for their research paper titled, ***"Impact of Buyback Announcement on Share Prices of Companies"***

Second Best Paper – Student Track

Shubham Chaurasiya, Maroof Khan, Anuj Pandey, et al. received the **Second Best Paper Award in the Student Track**, along with a cash prize of ₹2,000, for their research paper titled, ***"The Algorithmic Impulse: AI-Driven Personalisation, Perceived Relevance, and Impulse Buying in Contemporary Indian E-Commerce — A Mediated Path Analysis with Age Moderation"***

Recognition and Publication

Certificates of participation and presentation were awarded to all the paper presenters by the jury members in recognition of their valuable contributions to the Conference.

The award-winning papers, subject to the journal's editorial and publication processes, will be considered for publication in **Volume Eight, Issue Two of *The Management Quest***, the bi-annual research journal of **DSIMS**, published under the auspices of the **Remsons Centre for Management Research** (Online ISSN: 2581-6632).

The Institute congratulates all the award recipients and presenters for their scholarly contributions and appreciates their efforts in enriching the academic discourse on the **implications of Artificial Intelligence in contemporary businesses**.

Concluding Note

The unique endeavour of the Institute to host the Conference on “Implications of Artificial Intelligence in Contemporary Businesses” was a significant step towards bringing together academicians, researchers, industry professionals, and students to deliberate on the rapidly evolving role of Artificial Intelligence in the business landscape.

The Conference provided a meaningful platform for sharing research insights, innovative ideas, practical experiences, and emerging perspectives on the opportunities and challenges presented by Artificial Intelligence. The engaging discussions and scholarly contributions reflected the growing importance of AI in shaping business strategies, processes, decision-making, and the future of work.

The Conference was indeed a grand success, owing to the enthusiastic participation and valuable contributions of all the delegates, paper presenters, reviewers, session chairs, speakers, faculty members, students, and the organising team. The Institute sincerely appreciates the support and cooperation extended by all the stakeholders.

It is hoped that the deliberations and research presented during the Conference will encourage further inquiry, collaboration, and responsible adoption of Artificial Intelligence, contributing meaningfully to contemporary business practices and academic research.

Institutions



Kudilal Govindram Seksaria
sarvodaya school
INSPIRE, INVENT, INITIATE



Kudilal Govindram Seksaria
english school
INSPIRE, INVENT, INITIATE



Ramniwas Bajaj
english high school
UNLEASH YOUR POTENTIAL



Mainadevi Bajaj
international school
GIVING WINGS TO YOUR DREAMS



Durgadevi Saraf
junior college
IN PURSUIT OF EXCELLENCE



Ghanshyamdas Saraf
college of arts & commerce
EDUCATION EMPOWERS



Kirandevis Saraf
institute of complete learning
WIDENING HORIZONS



Durgadevi Saraf
institute of management studies
WE CREATE LEADERS



Durgadevi Saraf
global business school
LEARN AND INSPIRE



Deviprasad Goenka
management college of media studies
INDIA'S PREMIER MEDIA SCHOOL



Ladhidevi Ramdhar Maheshwari
night college of commerce
ENLIGHTENING FUTURE



Ramdhar Maheshwari
career counseling centre
STEERING TO SUCCESS



Kunjibihari S. Goyal
online academy
LEARNING BEYOND BOUNDARIES



Draupadidevi Sanwarmal
women's hostel
HEAVENLY DOMICILE



Pravinchandra D. Shah
sports academy
FITNESS REGIME



Vishwanath Podar
study centre
INTELLECTION HUB



Mainadevi Bajaj
international playschool
YOUNG EVOLVING MINDS



Jankidevi Bilasrai Bubna
boys hostel
A WISE HIVE



Nalini Shah
music academy
MUSICAL HARMONY



Rajasthani Sammelan
skill development centre
SCULPTING SKILLS

Endowment Funds & Research Chair



Remsons Group
management research centre
MANAGEMENT RESEARCH



I R B
scholarship endowment fund
HONOURING EXCELLENCE



B K T
endowment freeship fund
FOSTERING KNOWLEDGE



Jankidevi Bilasrai Bubna
endowment freeship fund
EMBOLDENING STRENGTHS



Pushpadadevi Seksaria
endowment freeship fund
POWERING POSSIBILITIES



Chatrabhuj Narsee
endowment freeship fund
EMPOWERING DREAMS



Shivdevi Deviprasad Goenka
endowment freeship fund
UNLOCKING POTENTIAL

Facilities



Dhurma Bajaj
bhavan
COMMUNITY PARADISE



Durgadevi Saraf
hall
TREASURING MEMORIES



Trivenidevi Deora
chikitsa sahayata kosh
HELPING TO HEAL



Ramnarayan Saraf
educational outlet
ONE STOP EDU-SHOP



Vijay Pal Singh
health centre
WEALTH OF WELLBEING



Kirandevis Saraf
library and reading room
WORLD OF KNOWLEDGE



Rajasthani Sammelan
I.T. hub
LINKING GLOBALLY



Rajasthani Sammelan
food court
FOOD FOR THOUGHT

RSVP: Dr. Sumana Chaudhuri | Email: sumana.chaudhuri@dsims.org.in | Mob: 9819892726

RSVP: Dr. Sunita Pujar | Email- sunita.pujar@dsims.org.in | Call: 022 45207711, Extn: 2351

DURGADEVI SARAF INSTITUTE OF MANAGEMENT STUDIES

RSET Campus, S.V. Road, Malad (W), Mumbai-64 | Email: rcmr@dsims.org.in