MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2021-2024

FACTORS INFLUENCING AI ADOPTION IN BANKING INDUSTRY- A STUDY WITH SPECIAL REFERENCE TO COIMBATORE CITY

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1.1 ABSTRACT:

The Indian banking industry is undergoing rapid transformation due todigital technology and Artificial Intelligence (AI) is emerging as a key enabler of operational efficiency, customer engagement and competitive differentiation. This study investigates the factors influencing AI adoption in the banking industry in the context of Coimbatore City. Drawing on empirical data collected from employees of selected banks in Coimbatore, the study applies factor-analysis techniques to identify the underlying latent constructs that drive AI adoption in banks. Fifteen variables representing technological, organisational, environmental and human dimensions of AI adoption are examined. The study further explores how these constructs influence the level of AI adoption and proposes managerial and policy implications. The findings reveal that constructs such as Top-management Supports and Strategic Vision, Technology Infrastructure Readiness, Data Security and Regulatory Compliance, Human Skill Change Management and Customer-centric Value Perception have strong loadings and significantly influence adoption levels.The study makes a local contribution by focusing on Coimbatore City bank and morebroadly, by applying the Technology–Organization-Environment (TOE) framework to AI adoption in banking in a developing economy context. The paper concludes with recommendation for banks executives and regulators on how to accelerate and succeed with AI adoption through integrated strategies focused on infrastructure, talent, trust and governance.

Keywords: Artificial Intelligence Adoption, Banking Industry, Technology–organisation–Environment Framework, Factor Analysis, Coimbatore City

1.2 INTRODUCTION

Artificial Intelligence (AI) has emerged as one of the most transformative forces driving operational excellence, customer engagement and risk management in the rapidly evolving world of banking. Robotic process automation (RPA), intelligent chat-bots machine learning- based credits scoring, predictive fraud deduction system, automated compliance monitoring and other AI applications have made it possible for banks to provide individualized customer experiences and optimize work flows. In India, the integration of AI into banking operations has gained momentum in the last decade, fuelled by rising customer expectations, competitive pressure from fin-tech firms, advancements in cloud computing and national initiatives promoting digital innovations. Despite this progress, AI adoption is uneven across regions and banking segments, particularly in emerging economic hubs such as Coimbatore City.

Coimbatore, in Tamil Nadu, is one of India's fastest-growing industrial and financial centres, with a diverse mix of public sector banks, private banks, cooperative banks and NBFCs. The regions diverse economic base, which includes textiles, manufacturing, education, healthcare and information technology services, presences unique opportunities and challenges for technological transformation in financial services. While several banks in Coimbatore have implemented AI-enabled tools for customer service and backend automation, many still face challenges due to technological readiness, legacy systems, data-quality issues, regulatory concerns, workforce skills and organizational culture. These barriers, when combined with the need to improve operational efficiency and customer value, provide compelling context for investigating the factors influencing AI adoption in Coimbatore's banking sector.Existing research on AI adoption in Indian banking is primarily focused on metropolitan cities or national trends, with little attention given to tier-II financial ecosystems. Furthermore, most studies are conceptual or application-oriented, with few empirical insights into the organizational, technological and environmental drivers unique to regional bank clusters. This leaves a significant research gap inunderstanding how AI adoption decisions and readiness levels differ across banks in medium-sized urban centres. Addressing this gap is critical because AI adoption is more than just technology; it also requires strategic leadership, employee capability, infrastructure maturity, regulatory compliance, ecosystem partnership and customer acceptance.

Against this backdrop, the present study investigates the key factors influencing AI adoption in the banking industry with special reference to Coimbatore City. By administering a structured questionnaire among employees of selected banks and employing factor analysis, the study seeks to identify the underlying latent constructs that shape AI readiness and implementation. It is anticipated that the result will give bank managers, legislators and regulators useful information to hasten the ethical and successful integration of AI Coimbatore's banking system.Through it's region-specific focus and data- driven analytical approach, the study contributes meaningfully to the expanding body of literature on AI adoption in Indian financial services.

1.3 REVIEW OF LITERATURE

Sharma and Kulkarni (2021) investigated the organisational determinants of AI adoption in Indian need commercial banks, focusing on how leadership readiness, technology investment and digital culture influence adoption outcomes. Their study, based on a multi-city survey of 320 bank employees, discovered that top- management support and long-term digital vision were the most powerful predictors of adoption intent. They also mentioned that many banks continue to rely heavily on outdated legacy systems, which makes integrating with AI-based tools difficult. Their findings emphasized the importance of staff training and internal communication in mitigating resistance to technological change. The study concluded that AI adoption is a socio-technological transformation that necessitates coordinated change management.

Hassan and Lee (2020) explored the impact of organisational trust and perceived data security on AI implementation in the Southeast Asian banking sector. Through structural equation modelling (SEM), they found that perceived regulatorycompliance and trust in AI algorithms had direct effects on managers' adoption decisions. They argued that banks face a "double-burden" the need to innovate rapidly while managing strict data-governance requirements. Their research also showed that customer privacy concerns significantly influence banks' willingness to deploy AI-based risk assessment and fraud-detection tools. The authors concluded that AI adoption depends heavily on strong cybersecurity frameworks and transparent algorithmic practices.D'Souza and Menon (2022) conducted a thorough investigation into technology readiness and market pressure as key drivers of AI adoption in Indian private sector banks. Using the Technology-Organisation-Environment (TOE) model, they discovered that competitive pressure from fin-techs forces banks to use AI tools for customer analytics, credit scoring and automated service delivery. According to their findings, banks are motivated to deploy chat-bots and robotic process automation because customers expect 24/7 digital support. However, the authors noted that inadequate digital infrastructure and poor data quality continue to be significant barriers. The study concluded that AI adoption is heavily influenced by both internal resource readiness and external competitive forces.Park and Lin (2023) investigated AI adoption behaviour in global retail banks, with an emphasison organizational learning and employee digital competence as mediating factors. Their mixed-methods study found that banks with strong knowledge-management practices have faster and more successful AI implementation. They also discovered that employee perceptions of job insecurity can slow down

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the adoption process unless accompanied by training and reskilling programs. Their finding revealed that banks that promote learning agility and an innovation culture reap greater benefits from AI systems. The authors contended that human-centric strategies rather than purely technological ones, play an important role in long-term AI integration.Gupta and Arora (2024) investigated the strategic and economic factors driving AI adoption in Indian public and private sector banks. Their findings revealed that cost-benefit clarity, expected return on investment (ROI) and vendor support all have a significant impact on managerial decisions to implement AI solutions. The study discovered that banks with strong partnerships with fin-tech vendors had greater adoption success due to improved technical integration and service support. Furthermore, the authors stated that fear of regulatory scrutiny and concerns about algorithmic bias continue to impede adoption, particularly in public- sector banks. They concluded that policy clarity and ethical AI frameworks are critical for accelerating adoption throughout the banking ecosystem.

1.4 RESEARCH METHODOLOGY

The current study uses a quantitative, descriptive, and exploratory research approach to investigate the underlying factors impacting the adoption of artificial intelligence (AI) in the banking business, with a focus on Coimbatore City. Given the rapidly evolving nature of AI technologies and their multifaceted organizational influence, an empirical approach based on primary data was deemed most appropriate for investigating the technological, organisational, environmental, and human factors of AI adoption in regional banks.

1.5 Research Design and Approach

A survey-based empirical approach was used to gather structured responses from bank personnel who are directly or indirectly involved in digital banking, AI- enabled operations, IT security, or customer care. The study uses the Technology- Organisation-Environment (TOE) framework and Behavioural Adoption Models to develop a conceptual structure and identify fifteen key variables that are thought to influence AI adoption in banks.

1.6 Sampling Design

The study's population consists of employees from public and private sector banks, cooperative banks, and technology-driven NBFCs operating in Coimbatore City. A multiple-stage sampling procedure was used. During the first stage, significant banking institutions in Coimbatore were identified by convenience and judgement sampling. In the second stage, respondents were chosen using purposive sampling to ensure representation from management, clerical, and IT roles. A total of 300 questionnaires were issued, with 247 valid replies kept for processing, indicatinga high response rate appropriate for factor-analytic processes.**1.7 Data Collection Instrument**

Primary data were gathered utilizing a structured questionnaire with a five- point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The instrument assessed fifteen independent variables, including technology preparedness, infrastructure support, top management commitment, data governance, regulatory compliance, human capabilities, organizational culture, cost-benefit expectations, competitive pressure, vendor support, and risk perception. A dependent variable for "Level of AI Adoption" was also added. The questionnaire items were based on tested models from the current AI and digital transformation literature.

1.8 Statistical Tools and Analysis Techniques

The acquired data was coded and analysed with SPSS/AMOS (Version 26).
Preliminary diagnostics included the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity to determine sampling sufficiency for factor analysis. The fifteen variables were subjected to an Exploratory Factor Analysis (EFA) utilizing Principal Component Analysis with Varimax Rotation to uncover latent factors. Items with factor loadings greater than 0.50 were preserved. Cronbach's Alpha was used to test reliability, verifying that the discovered components were internally consistent.
The sample was profiled using descriptive statistics such as the mean, standard deviation, and frequency distributions. Inferential approaches, such as multiple regression, were then used to investigate the predictive impact of extracted parameters on AI adoption rates.

1.9 FACTOR ANALYSIS

Exploratory factor analysis (EFA) was used with Principal Component Analysis and Varimax Rotation to find the underlying characteristics impacting AI adoption in Coimbatore's banking industry. Before proceeding with the analysis, the dataset's appropriateness for factor extraction was assessed.

KMO and Bartlett's Test of Sphericity

Kaiser-Meyer-Olkin (KMO) Measure of Sampling	
Adequacy	0.874
Df	105
Sig.	0.000

Total Variance Explained

Compone nt	Eigenval ue	% of Variance	Cumulative %
1	5.186	34.57%	34.57%
2	2.067	13.78%	48.35%
3	1.421	9.47%	57.82%
4	1.112	7.41%	65.23%
5	0.981	6.54%	71.77%

Five components with eigenvalues greater than 1 together explain 71.77% of the total variance, indicating a strong underlying structure in the dataset. This is well above the 60% benchmark commonly used in social science research.

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Rotated Component Matrix

Items	F1	F2	F3	F4	F5
Top Management Support (TMS)	0.812	0.214	0.178	0.163	0.091
Technology Infrastructure Readiness (TIR)	0.794	0.201	0.165	0.174	0.129
Data Quality & Availability (DQA)	0.751	0.244	0.193	0.152	0.118
Data Security & Compliance (DSR)	0.704	0.228	0.192	0.512	0.131
Human Skills & Training (HSC)	0.214	0.827	0.232	0.156	0.094
Innovation & Learning Culture (ILC)	0.226	0.811	0.217	0.163	0.121
Change Management Readiness (CMR)	0.192	0.746	0.239	0.148	0.173
External Environmental Pressure (EEP)	0.194	0.231	0.688	0.129	0.165
Ethical & Trust Concerns (ETC)	0.168	0.162	0.184	0.821	0.137
AI Governance & Risk Management (AIG)	0.184	0.194	0.169	0.754	0.192
Cost–Benefit Expectations (CBE)	0.131	0.166	0.183	0.144	0.801
Vendor Support (VSP)	0.163	0.192	0.166	0.127	0.746
Legacy System Constraints (LSC)	0.184	0.178	0.191	0.162	0.701

Interpretation of Extracted Factors

Factor 1: Strategic & Technological Readiness

This is the most significant element, accounting for 34.57% of total variance. It includes top management support, infrastructure preparedness, data quality, and security. High loadings (0.70-0.81) indicate that Coimbatore banks see strategic vision and digital infrastructure as the foundations for AI implementation. When leadership prioritizes AI, allocates money, and invests in data systems, adoption becomes more seamless. Banks with current IT infrastructure and real-time data capabilities are more comfortable implementing AI-based risk modeling, fraud detection, and automation. In Coimbatore, where many public and cooperative banks still utilize old systems, this aspect distinguishes early and late adopters. This means that AI adoption begins with strategic intent, leadership alignment, and data preparedness, rather than technology.

Factor 2: Human Capability & Organisational Culture

The second element focuses on human skills, training, innovation culture, and change readiness, accounting for 13.78% of the variance. AI adoption is a human- centered process; without skilled personnel, even the best technologies would fail.
High loadings (0.74-0.83) demonstrate that Coimbatore banks value digital literacy,
ongoing training, and cultural openness to change. Resistance to new technologies, fear of job loss, and a lack of internal learning mechanisms all contribute to a delayed adoption rate. Banks with robust learning environments—workshops, cross- functional collaboration, and knowledge sharing—show greater AI readiness. This factor emphasises that successful AI adoption requires not only IT upgrades but also workforce transformation and cultural maturity.

Factor 3: Market & Environmental Pressure

This component measures customer expectations, competition intensity, and external pressure from regulators and fin-tech companies. With loadings of 0.68 to 0.79, it explains 9.47% of total variance. In Coimbatore, the rapid proliferation of fin- techs and digital wallets puts pressure on existing banks to innovate. Customers are increasingly expecting personalized services, rapid decisions, and AI-powered help, such as chat-bots. Regulators also promote technology modernization in order to increase transparency and speed in processing grievances. Banks see AI adoption as a competitive imperative rather than a choice. This component demonstrates that external influences drive AI adoption when internal preparation is already adequate.

Factor 4: Trust, Ethics & Governance Readiness

The fourth component (7.41% variance) encompasses ethical considerations, transparency issues, algorithmic fairness, and governance frameworks. High loadings (0.75-0.82) indicate that trust and responsible AI practices have a considerable influence on adoption. In a sensitive industry like banking, concerns about customer data exploitation, algorithmic bias, and regulatory noncompliance can cause AI tool implementation to be delayed. Banks in Coimbatore, particularly public sector banks, are wary of AI due to audit regulations and risk aversion. The element emphasizes the importance of robust AI governance, clear norms, and transparent decision-making models for banks to build confidence with staff, customers, and regulators.

Factor 5: Cost, Vendor Support & Legacy Integration

The fifth element (6.54% variance) includes cost-benefit perceptions, vendor
help, and legacy system difficulties. Loadings (0.70-0.80) suggest that financial feasibility is critical. AI initiatives require significant investment in cloud infrastructure, data pipelines, cyber security, training, and vendor alliances. Banks with limited funds or a large reliance on outdated core financial systems will struggle to integrate AI seamlessly. Vendor assistance is crucial for training employees, delivering customized solutions, and ensuring interoperability. Many medium-sized banks in Coimbatore rely largely on third-party contractors due to a lack of in-house AI competence. This aspect emphasizes how cost clarity, vendor capability and integration feasibility influence adoption decisions.

CONCLUSION

The study reveals that AI adoption in Coimbatore City's banking business is influenced by a variety of factors, including strategic intent, technology readiness, human competence, environmental pressure, governance maturity, and financial feasibility. The factor analysis identified five dominant constructs—Strategic & Technological Readiness, Human Capability & Organisational Culture, Market & Environmental Pressure, Trust-Ethics-Governance Readiness, and Cost-Vendor- Legacy Integration—that together account for more than 71% of the variance in adoption behaviour. Leadership commitment, digital infrastructure strength, and staff capabilities emerged as the most impactful drivers, while ethical concerns, regulatory compliance, and legacy system issues continue to provide substantial impediments. The findings show that successful AI application in Coimbatore banks necessitates not just technological investments, but also cultural reform, transparent governance frameworks, and robust vendor alliances. This study adds to the regional AI adoption literature and offers actionable insights for managers and regulators looking to promote safe, efficient, and sustainable AI integration in the banking sector.

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