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Artificial Intelligence in Banking and Financial Services: An Analytical Study of Adoption, Impact and Challenges in the Indian Banking Sector

Dr. Sadaf Khan[1]
Associate Professor,
Faculty of Management and Commerce,
SAM Global University, Raisen, Madhya Pradesh, India[1]

Kajal Yadav[2]
Assistant Professor,
Faculty of Management and Commerce,
SAM Global University, Raisen, Madhya Pradesh, India[2]

Bhumi Hedau[3]
MBA (HR)
School of Management,
Faculty of Management and Commerce,
SAM Global University, Raisen (MP)[3]

Muskan Batham[4]
MBA (Banking and Finance + HR) School of Management,
Faculty of Management and Commerce,
SAM Global University, Raisen (MP)[4]

***Abstract* – Artificial Intelligence (AI) has emerged as one of the most transformative forces reshaping the global banking and financial services industry, and India has become one of its most dynamic testing grounds. This paper analytically examines the adoption of AI in the Indian banking sector, its impact on operational efficiency, customer service, fraud management and financial inclusion, and the principal challenges accompanying its diffusion. The study adopts a descriptive and analytical research design based entirely on secondary data drawn from the Reserve Bank of India (RBI) publications, including the FREE-AI Committee Report (2025), RBI Annual Reports (2022- 23 to 2025-26), the RBI Payment Systems Report, National Payments Corporation of India (NPCI) statistics, industry reports and peer-reviewed academic literature. Trend analysis, percentage analysis and comparative tabulation are used to interpret the data. The findings indicate that AI adoption in Indian banking has grown rapidly but unevenly: larger and better-capitalised banks, particularly private sector banks, lead adoption, while customer support, credit underwriting, sales and cybersecurity constitute the dominant use cases. The analysis further shows a steep decline in the number of card, internet and digital payment fraud cases between 2023-24 and 2025-26, coinciding with the expansion of AI-enabled transaction monitoring, even as the value of advances-related frauds remains a concern. The paper concludes that AI can make Indian banking more inclusive, efficient and secure, provided banks invest in data governance, explainability, talent and ethical safeguards consistent with the RBI's FREE-AI framework, and offers recommendations for banks, regulators and researchers.**

***Keywords* – Artificial Intelligence, Indian Banking Sector, Financial Services, Fraud Detection, Digital Payments, Financial Inclusion, FREE-AI Framework.**

I. INTRODUCTION

1. Background of the Study

The banking and financial services industry has always been an early adopter of information technology, moving progressively from ledger-based accounting to core banking solutions, automated teller machines, internet banking, mobile banking and, most recently, intelligent systems powered by Artificial Intelligence (AI). AI denotes computational systems capable of work that would otherwise demand human cognition - learning from data, spotting patterns, parsing natural language, and generating predictions or decisions (Kaplan & Haenlein, 2019). Within banking, AI and its allied technologies, particularly machine learning (ML), natural language processing and, more recently, generative AI, are being applied to credit underwriting, fraud detection, customer service automation, risk management, regulatory compliance, marketing analytics and wealth management (Königstorfer & Thalmann, 2020; Fares, Butt & Lee, 2023).

India presents a particularly compelling context in which to study this transformation. The country has built one of the world's largest digital public infrastructures, anchored by Aadhaar-based identity, the Jan Dhan financial inclusion programme and the Unified Payments Interface (UPI). According to the Reserve Bank of India's Payment Systems Report, digital transaction volumes in India multiplied roughly 33-fold between 2016 and 2025, and by the second half of 2025 UPI alone was carrying 85.5 per cent of all digital payment volumes (RBI, 2026). From just 2 crore transactions in its first full year (2016-17), annual UPI volume climbed past 24,000 crore by 2025-26, with the value transacted rising from Rs. 0.07 lakh crore to about Rs. 314 lakh crore across that decade (PIB, 2026). This explosion of digital transactions has generated enormous volumes of structured and unstructured data, which constitute the essential raw material for AI systems, while simultaneously creating new risks, such as digital fraud, that manual controls cannot address at scale.

The Reserve Bank of India (RBI) has responded both as an enabler and as a prudential regulator.

An RBI staff study based on text-mining of bank annual reports found that Indian banks' emphasis on AI and related technologies increased sharply between 2015-16 and 2022-23, with private sector banks leading adoption and public sector banks accelerating in recent years (Goel, Raut, Kumar & Sharma, 2024). In December 2024, the RBI constituted a committee to develop a Framework for Responsible and Ethical Enablement of Artificial Intelligence (FREE-AI), whose report, released in August 2025, provides the first comprehensive survey-based evidence of AI adoption across Indian banks, non-banking financial companies (NBFCs) and fintechs, along with principles for responsible use (RBI, 2025a). These developments make the present moment especially appropriate for an analytical stock-taking of AI in Indian banking.

2. Problem Statement

Although the promiseofAI in banking is widely discussed in industry commentary, systematic academic analysis grounded in authoritative Indian data remains comparatively limited. Much of the existing Indian literature is conceptual or opinion-based, and rigorous evidence on the actual extent of adoption, the dominant use cases, the measurable outcomes and the constraints faced by banks is dispersed across regulatory reports, surveys and news sources. There is, therefore, a need to consolidate and analyse the most recent authoritative secondary data, particularly the RBI FREE-AI survey findings, RBI Annual Report fraud statistics and payment system data, in order to develop a coherent, evidence-based picture of how AI is transforming Indian banking, what benefits are materialising, and which challenges demand attention from bankers, regulators and policymakers.

3. Research Objectives

Thestudypursues the following objectives: (1) to examine the extent and pattern of AI adoption in the Indian banking and financial services sector; (2) to identify the principal use cases of AI in Indian banking, including customer service, credit underwriting, fraud detection and cybersecurity; (3) to analyse the impact of AI-enabled digitalisation on fraud trends and payment system performance using RBI data; (4) to evaluate the major challenges, risks and regulatory concerns associated with AI adoption in banking; and (5) to offer suggestions for banks, regulators and future researchers for the responsible and effective deployment of AI.

4. Scope of the Study

The studyis confined tothe Indian banking and financial services sector, with primary emphasis on scheduled commercial banks, and covers the period from 2015-16 to 2025-26, for which authoritative RBI and NPCI data are available. The analysis relies exclusively on secondary data. Global evidence is referred to only for comparative and theoretical context. The study does not attempt econometric causal estimation; rather, it undertakes descriptive and analytical interpretation of trends, shares and growth rates, and it explicitly acknowledges that observed associations, for example between AI adoption and declining digital payment fraud counts, cannot by themselves establish causality.

II. LITERATURE REVIEW

1. Theoretical Foundations

Severalestablished theories inform the study of technology adoption in banking. The Technology Acceptance Model holds that perceived usefulness and perceived ease of use determine users' acceptance of new technologies (Davis, 1989), while the Unified Theory of Acceptance and Use of Technology integrates performance expectancy, effort expectancy, social influence and facilitating conditions as determinants of adoption (Venkatesh, Morris, Davis & Davis, 2003). Diffusion of Innovations theory explains why adoption spreads unevenly across organisations and over time, with innovators and early adopters preceding the majority (Rogers, 2003). At the organisational level, the resource-based view argues that firms with superior resources, financial, technological and human, are better positioned to invest in innovation and derive sustained advantage from it (Barney, 1991). Notably, the RBI's own empirical study of Indian banks found that AI adoption intensity is positively associated with bank asset size and capital adequacy, a result the authors interpret through the lens of resource-based theory and economies of scale (Goel et al., 2024).

2. Artificial Intelligence in Banking: Global Evidence

Asubstantial international literature documentsthe applications and effects of AI in financial services. Brynjolfsson and McAfee (2014) situate AI within a broader 'second machine age' in which digital technologies transform cognitive work, while Agrawal, Gans and Goldfarb (2018) conceptualise AI economically as a dramatic fall in the cost of prediction, which is precisely the core activity of banking functions such as credit scoring, fraud detection and risk management. Khandani, Kim and Lo (2010) demonstrated early that machine-

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learning models applied to consumer credit data could materially improve default forecasting relative to traditional methods, and Lessmann, Baesens, Seow and Thomas (2015) benchmarked dozens of classification algorithms for credit scoring, finding that modern ensemble methods significantly outperform classical logistic regression. In the fraud domain, Ngai, Hu, Wong, Chen and Sun (2011) provided a classification framework for data-mining applications in financial fraud detection, and West and Bhattacharya (2016) reviewed intelligent fraud detection methods, concluding that adaptive machine-learning systems are better suited than static rules to evolving fraud patterns.

On the customer-facing side, Huang and Rust (2018) theorised the progressive substitution of AI for human service tasks, moving from mechanical to analytical to intuitive intelligence, and Wirtz et al. (2018) examined the deployment of service robots and conversational agents at the customer frontline. Adamopoulou and Moussiades (2020) traced the technological evolution of chatbots, which have become the most visible AI application in retail banking. Jakšič and Marinč (2019) cautioned, however, that while AI and fintech enhance transactional efficiency, relationship banking and human judgment retain importance for soft-information-intensive lending. Königstorfer and Thalmann (2020) synthesised the literature on AI in commercial banks and identified an agenda focused on adoption barriers, trust and organisational integration, while Fares et al. (2023) offered a systematic review that groups banking AI research into strategy, processes and customer domains. At the policy level, the Financial Stability Board (2017) and the OECD (2021) analysed the systemic implications of AI and machine learning in finance, flagging model risk, opacity, third-party dependence and potential procyclicality, and Buchanan (2019) surveyed AI in finance with attention to both innovation and regulation. Concerns regarding fairness and bias in algorithmic decision-making are addressed in the broader machine-learning literature (Mehrabi et al., 2021), and Floridi and Cowls (2019) proposed a five-principle framework, beneficence, non-maleficence, autonomy, justice and explicability, for ethical AI in society, which has influenced regulatory thinking in finance. Dwivedi et al. (2021) provided a multidisciplinary agenda emphasising that AI's organisational value depends on governance, skills and change management, not merely on algorithms.

3. Artificial Intelligence in Indian Banking

Indian scholarship on AI in banking has grown quickly, albeit with a predominance of conceptual studies. Vijai (2019) surveyed the opportunities and challenges of AI in the Indian banking sector, highlighting chatbots, fraud detection and personalised services as key applications and identifying skill shortages and data issues as constraints. Malali and Gopalakrishnan (2020) reviewed AI-powered technologies in Indian banking and financial services, noting early deployments such as SBI's YONO platform and conversational assistants in private banks. Mhlanga (2020) examined AI's role in digital financial inclusion in emerging economies, arguing that AI-driven credit scoring using alternative data can extend formal credit to 'thin-file' and 'new-to-credit' customers, an argument of direct relevance to India, where the World Bank's Global Findex documents rapid but incomplete progress in account ownership and usage (Demirgüç-Kunt et al., 2022). Sadok, Sakka and El Maknouzi (2022) reviewed AI in bank credit analysis, and Payne, Peltier and Barger (2018) studied consumer attitudes toward AI-enabled mobile banking services, finding that perceived benefits and trust drive usage intentions.

The most authoritative recent Indian evidence comes from official sources. The RBI staff study by Goel et al. (2024), using text-mining of the annual reports of 32 commercial banks from 2015-16 to 2022-23, found that references to AI and related technologies rose sharply, that private banks led adoption, and that the emphasis on such technologies in public sector banks' annual reports increased more than three times over the period. The RBI FREE-AI Committee Report (RBI, 2025a) supplemented this with two structured surveys of banks, NBFCs and fintechs, finding that roughly a fifth (20.8 per cent) of surveyed entities had AI either in production or under construction, clustered in customer-facing support, loan underwriting, marketing analytics and cyber defence, alongside widespread generative-AI experimentation. Complementing these, the RBI's Report on Currency and Finance 2023-24 and subsequent bulletins projected substantial macroeconomic gains from AI, with estimates placing the potential contribution of generative AI to Indian GDP in the range of USD 359-438 billion by the close of the decade (Patra, 2024). The NITI Aayog's National Strategy for Artificial Intelligence had earlier identified banking and finance among the priority sectors for AI-led transformation in India (NITI Aayog, 2018).

4. Research Gap

The review reveals three gaps. First, few Indian studies integrate the newest authoritative datasets, the FREE-AI survey (2025), the RBI Annual Report 2025-26 fraud statistics and the RBI Payment Systems Report covering H2 2025, into a single analytical narrative. Second, the relationship between AI-enabled monitoring and the observed trends in digital payment fraud has been discussed journalistically but rarely analysed systematically in academic work. Third, the implications of the RBI's FREE-AI principles for bank strategy and management practice remain underexplored. The present study addresses these gaps through a consolidated secondary-data analysis.

III. RESEARCH METHODOLOGY

1. Type of Research

The study employs a descriptive and analytical research design. It is descriptive in that it profiles the current state

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of AI adoption in Indian banking, and analytical in that it interprets trends, shares, growth rates and inter-relationships in the data to draw inferences about impact and challenges.

2. Data Collection Method

Thestudyis basedentirely on secondary data. The principal sources are: (i) Reserve Bank of India publications, including the Report of the Committee on the Framework for Responsible and Ethical Enablement of Artificial Intelligence (FREE-AI, August 2025), the Annual Reports for 2022-23 through 2025-26, the half-yearly Payment Systems Report, the October 2024 Monthly Bulletin study 'How Indian Banks are Adopting Artificial Intelligence?', and speeches of senior RBI officials; (ii) National Payments Corporation of India (NPCI) product statistics and Press Information Bureau releases on UPI; (iii) industry reports, including the Worldline India Digital Payments Report (1H 2025); and (iv) peer-reviewed journal articles, books and reports of international bodies such as the Financial Stability Board, the OECD and the World Bank. All data points used in the analysis are cited to their sources in the references.

3. Sample and Period of Study

Sincethe study uses secondary data, the 'sample' corresponds to the coverage of the underlying official datasets: the RBI text-mining study covers 32 scheduled commercial banks (2015-16 to 2022-23); the FREE-AI surveys cover banks, NBFCs, fintechs and technology firms surveyed by the RBI in 2025; the fraud statistics cover all frauds of Rs. 1 lakh and above reported by banks and financial institutions to the RBI from 2022-23 to 2025-26; and the payment statistics cover the universe of retail and wholesale payment systems in India up to 2025-26.

4. Tools and Techniques of Analysis

Theanalysis employs trend analysis(year-on-year changes in fraud cases and amounts, and decade-long growth of UPI), percentage and share analysis (composition of AI use cases; shares of payment systems in volume and value), simple growth multiples and compound annual growth rate (CAGR) interpretation as reported by the RBI, and comparative tabulation across bank groups (public versus private sector banks). Findings are presented through tables and figures prepared by the researcher from the cited data. Given the secondary and aggregative nature of the data, no inferential statistical tests are applied; the interpretation is analytical and contextual, and limitations are acknowledged in Section 7.

5. Limitations of the Study

The study is limited by its reliance on secondary data, which constrains the analysis to the variables and periods reported by official sources. Fraud statistics reflect the year of reporting rather than the year of occurrence, and reclassifications, such as those following the Supreme Court judgment of March 2023, affect year-to-year comparability. Associations observed in the data, for instance between AI-enabled monitoring and declining digital payment fraud counts, are suggestive rather than causal. Finally, the fast-moving nature of AI means that some figures may be superseded by later releases.

IV. DATA ANALYSIS AND INTERPRETATION

1. The Digital Foundation: Growth of Digital Payments and UPI

AI adoption in banking cannot be understood in isolation from the digital payments revolution that supplies the data on which AI systems learn. Table 1 summarises the growth of UPI, the flagship of India's digital public infrastructure.

Table 1: Growth of UPI Transactions in India (Selected Years)

Year	Transaction Volume	Transaction Value
FY 2016-17	2 crore transactions	Rs. 0.07 lakh crore
FY 2023-24	Approx. 13,100 crore transactions	Approx. Rs. 200 lakh crore
Calendar Year 2025	228.3 billion (22,830 crore) transactions	Approx. Rs. 300 lakh crore
FY 2025-26	Over 24,162 crore transactions	Approx. Rs. 314 lakh crore

The interpretation of Table 1 is striking. In a single decade, UPI transaction volume expanded almost twelve-thousand-fold and transaction value more than four-thousand-fold, a platform that now processes more real-time retail transactions than any other payment system globally (PIB, 2026). The RBI's Payment Systems Report records a roughly 33-fold expansion in total digital transaction volumes between 2016 and 2025, compounding at about 43 per cent annually in volume over the most recent five years (RBI, 2026). Worldline's India Digital Payments Report tells the same story from industry data: 106.36 billion UPI transactions (Rs. 143.34 lakh crore) in the first half of 2025 alone, volume up 35 per cent on a year earlier, even as the typical transaction shrank from Rs. 1,478 to Rs. 1,348 - evidence that UPI is being reached for in ever-smaller everyday purchases (Worldline, 2025).

Table 2: Share of Payment Systems in Digital Transactions, H2 2025

PaymentSystem	Share in Volume (%)	Share in Value (%)
UPI	85.5	9.5
NEFT	3.6	14.9
Prepaid Payment Instruments (PPIs)	3.6	0.1
RTGS	0.1	68.6

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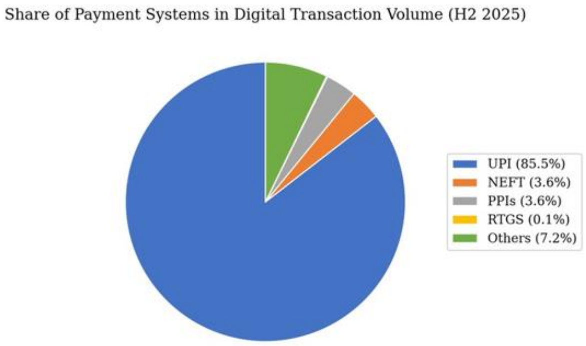

Figure 3: Share of payment systems in digital transaction volume, H2 2025. Source: Prepared by the researcher from RBI Payment Systems Report (2026).

Table 5 and Figure 3 show the complementary structure of India's payment systems in the second half of 2025: UPI carries the overwhelming bulk of transaction counts (85.5 per cent), the signature of everyday retail use, whereas RTGS, with 68.6 per cent of transaction value, is where big wholesale settlements concentrate (RBI, 2026). The analytical significance for this study is twofold. First, the sheer scale, tens of billions of transactions per year, makes manual monitoring of payments impossible and creates a functional necessity for AI-based, real-time transaction monitoring. Second, the granular transaction data generated by UPI and allied systems provides the training data that enables machine-learning models for fraud analytics, credit underwriting using cash-flow data, and hyper-personalised services.

2. Extentand Pattern of AI Adoption in Indian Banking

Two authoritative RBI sources illuminate the extent of AI adoption. The staff study by Goel et al. (2024), which text-mined the annual reports of 32 commercial banks over 2015-16 to 2022-23, established three patterns. First, the salience of AI and related technologies, automation, data analytics, cloud computing and big data, rose steadily across the banking system. Second, private sector banks led adoption, which the authors attribute to their more digitally comfortable and affluent clientele and the cost-effectiveness of AI channels for banks with smaller branch networks; public sector banks, anchored in extensive rural and semi-urban branch networks, entered later but caught up quickly, more than tripling the AI-related emphasis in their annual reports over the period. Third, in the panel-data analysis, a bank's AI score was positively and significantly related to its asset size and capital adequacy, consistent with the resource-based view that larger, healthier institutions can better afford the fixed costs of technological innovation (Goel et al., 2024; Barney, 1991). The FREE-AI Committee's surveys provide the most recent cross-sectional evidence. In 2025, 127 of the 612 supervised entities surveyed (20.8 per cent) had AI in use or under build, with adoption driven mainly by large public and private sector banks and NBFCs, many of which were using comparatively simple rule-based and machine-learning models rather than frontier systems (RBI, 2025a). Table 2 presents the distribution of reported use cases.

Table 2: Principal AI Use Cases Reported by Indian Financial Entities (RBI FREE-AI Survey, 2025)

AI Use Case	Share of Reported Use (%)
Customer support (chatbots, virtual assistants)	15.6
Credit underwriting	13.7
Sales and marketing	11.8
Cybersecurity	10.6
Other uses (operations, compliance, risk and pilots, including generative AI)	Remaining share

The interpretation of Table 2 highlights that customer support is the leading use case, consistent with the global literature on service automation (Huang & Rust, 2018; Adamopoulou & Moussiades, 2020) and with the visibility of Indian banking chatbots and virtual assistants deployed by leading public and private banks. Credit underwriting ranks second, reflecting the migration from purely bureau-score-based lending toward machine-learning models that incorporate transaction and alternative data, which the RBI has noted is instrumental in bringing 'thin-file' and 'new-to-credit' customers into the formal financial system (IBEF, 2025; Mhlanga, 2020). Sales and marketing applications, including customer segmentation, propensity modelling and personalised offers, rank third, while cybersecurity applications, such as anomaly detection and threat intelligence, rank fourth. The survey also found strong interest in generative AI, with a majority of entities running small-scale pilots, most often limited to internal, staff-facing chatbot tools (RBI, 2025a). Industry estimates cited in the academic literature suggest that a majority of leading Indian banks have deployed at least one AI-enabled operational system, and that AI-driven chatbots now handle a substantial share of routine customer interactions in major private banks (Frontiers in Artificial Intelligence, 2025).

3. AI, Fraud Trends and Risk Management

Oneofthemost policy-relevantquestions is whether AI-enabled monitoring is associated with improvements in fraud outcomes. Tables 3 and 4 and Figures 1 and 2 present the RBI's fraud statistics.

Table 3: Frauds Reported by Banks and Financial Institutions (Rs. 1 lakh and above)

Financial Year	Number of Cases	Amount Involved (Rs. crore)
2022-23	13,564	26,127
2023-24	36,075	13,930
2024-25	23,953	36,014
2025-26	10,114	48,021

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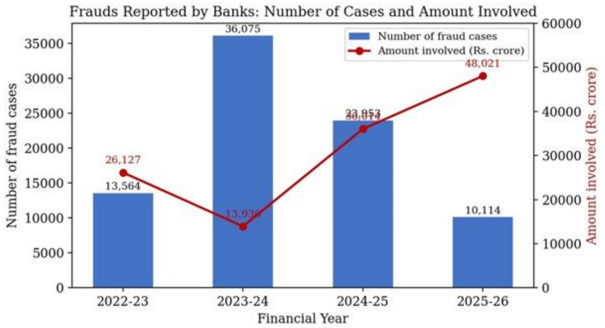

Figure 1: Frauds reported by banks - number of cases and amount involved (2022-23 to 2025-26). Source: Prepared by theresearcher from RBIAnnualReports.

Table 4: Card/Internet/Digital Payment Fraud Cases and Amounts

Financial Year	Number of Cases	Amount Involved (Rs. crore)
2023-24	28,836	1,452
2024-25	13,332	517
2025-26	293	29

Three analytical observations emerge. First, as Table 3 and Figure 1 show, the number of reported fraud cases has fallen sharply, from a peak of 36,075 in 2023-24 to 10,114 in 2025-26, even as the amount involved has risen to Rs. 48,021 crore. Much of this rise, however, is a statistical artefact of how frauds enter the data: a case is recorded in the year a bank reports it rather than the year the fraud actually took place, and the 2025-26 total absorbs 314 older cases worth Rs. 30,199 crore that banks re-classified and re-entered while complying with the Supreme Court's ruling of March 2023 (RBI, 2025b; RBI, 2026b). In value terms, frauds are concentrated in the advances (loan) category, which is a credit-governance problem more than a digital-channel problem.

Second, and most pertinent to this study, Table 4 and Figure 2 document a dramatic collapse in card, internet and digital payment fraud cases: from 28,836 cases involving Rs. 1,452 crore in 2023-24, to 13,332 cases involving Rs. 517 crore in 2024-25, to just 293 cases involving Rs. 29 crore in 2025-26 (RBI, 2026b). This decline occurred while digital transaction volumes continued to grow at double-digit rates, meaning the fraud rate per transaction fell even more steeply than the absolute numbers suggest. The period coincides with the industry-wide rollout of AI- and ML-based real-time fraud monitoring across nearly all large scheduled commercial banks, RBI initiatives such as behavioural analytics for fraud detection, the MuleHunter.AI initiative for identifying money-mule accounts, the operationalisation of the Cyber Range platform for simulated cyber drills, and payee-name-validation measures in payments (RBI, 2026b). While causality cannot be established from aggregate data, and part of the decline may reflect better prevention at the ecosystem level (device binding, tokenisation, customer awareness) as well as reporting changes, the coincidence of large-scale AI deployment in fraud analytics with a steep reduction in digital payment fraud counts is consistent with the international evidence that adaptive machine-learning systems outperform static rule-based controls against evolving fraud (West & Bhattacharya, 2016; Ngai et al., 2011).

Third, the composition shift is itself informative: in 2023-24 and 2024-25 the digital payments category accounted for the largest number of fraud cases, whereas by 2025-26 the advances category dominated both counts and values (RBI, 2026b). This suggests that the frontier of fraud risk in Indian banking is moving from high-volume, small-value digital channel fraud, where AI monitoring is most mature, toward complex credit fraud, where AI applications such as early-warning systems, network analytics and document forensics are still developing.

4. AI, Efficiency, Inclusion and the Macroeconomic Dimension

TheRBI'sassessments indicate that AI, whenappropriately applied, can broaden access, lower service costs and improve the customer experience. Always-on conversational assistants absorb routine queries and release staff for judgment-intensive work, while underwriting models built on alternative data open formal credit to borrowers without credit histories (IBEF, 2025). At the macroeconomic level, RBI Deputy Governor Michael Patra put the prospective GDP contribution of generative AI at USD 359-438 billion by 2029-30, noting also that the share of Indian firms embedding AI in their production had climbed from 8 per cent in 2023 to 25 per cent in 2024 (Patra, 2024). India's generative AI sector has been projected to grow at 28-34 per cent annually, potentially exceeding Rs. 1.02 lakh crore by 2033 (IBEF, 2025). These projections should be read as indicative rather than precise, but they underline the strategic importance that the central bank and industry attach to AI in financial services.

5. Challenges and the FREE-AI Regulatory Response

Thedata and literature converge on a set of challenges. (1) Model risk and explainability: complex models can be opaque, complicating validation, audit and customer redress (FSB, 2017; OECD, 2021). (2) Bias and fairness: models trained on historical data can reproduce or amplify discriminatory patterns in credit and pricing decisions (Mehrabi et al., 2021), a concern the RBI has explicitly flagged (RBI Bulletin, 2024). (3) Data privacy and protection: AI systems depend on personal data, bringing banks within the ambit of the Digital Personal Data Protection Act, 2023, and requiring privacy-by-design. (4) Cybersecurity and AI-enabled fraud: the same technologies that defend banks, such as generative models, also empower attackers through deepfakes and synthetic identities. (5) Uneven adoption capacity: the positive association between AI adoption and bank size implies that smaller banks and cooperative institutions risk falling behind, with possible competitive and inclusion consequences (Goel et al., 2024). (6) Talent and governance: the shortage of AI-skilled personnel and the need for board-level oversight are repeatedly emphasised (Dwivedi et al., 2021; Vijai, 2019). The RBI's FREE-AI framework responds with principles for responsible and ethical enablement, emphasising trust, fairness, accountability, transparency and human oversight, alongside enabling recommendations on infrastructure, capacity building and innovation sandboxes (RBI, 2025a). This dual posture, enabling innovation while containing risk, mirrors the international regulatory consensus (OECD, 2021; Floridi & Cowls, 2019).

V. FINDINGS AND DISCUSSION

The analysis yields the following major findings. First, AI adoption in Indian banking is real, growing and officially measured: about one-fifth of surveyed financial entities had operational or in-development AI by 2025, with large banks and NBFCs in the lead and most deployments concentrated in customer support (15.6 per cent of reported use), credit underwriting (13.7 per cent), sales and marketing (11.8 per cent) and cybersecurity (10.6 per cent) (RBI, 2025a). Generative AI remains largely at the pilot stage. This pattern confirms, for India, the global sequence in which customer-facing automation and prediction-intensive functions are the first to be transformed (Huang & Rust, 2018; Agrawal et al., 2018).

Second, adoption is systematically uneven. Private sector banks led early adoption, and AI intensity rises with bank size and capital strength (Goel et al., 2024). The discussion point here is significant for policy: if economies of scale govern AI adoption, market-led diffusion alone may widen the technological gap between large and small institutions, justifying shared infrastructure, utilities and capacity-building interventions of the kind contemplated in the FREE-AI report.

Third, the digital payments boom is both the enabler of and the justification for AI in Indian banking. With UPI processing over 24,000 crore transactions worth about Rs. 314 lakh crore in 2025-26 and accounting for 85.5 per cent of digital transaction volume, only machine-scale intelligence can monitor, secure and extract value from payment flows of this magnitude (PIB, 2026; RBI, 2026).

Fourth, the fraud data present a nuanced picture. The number of digital payment fraud cases collapsed from 28,836 in 2023-24 to 293 in 2025-26, a period of intensive deployment of AI-based transaction monitoring, behavioural analytics and ecosystem safeguards, while the locus of fraud value shifted decisively to the advances category, inflated in 2025-26 by legacy reclassifications (RBI, 2026b). The discussion must be candid: aggregate coincidence is not proof of causation, and reporting changes complicate comparisons. Nevertheless, the direction and magnitude of the digital-fraud decline, achieved despite rapidly rising transaction volumes, is consistent with the hypothesis, supported by the international literature, that adaptive AI systems materially strengthen fraud defence (West & Bhattacharya, 2016). Simultaneously, the persistence of large-value credit frauds shows that AI's frontier task in India is no longer only payments security but credit-lifecycle surveillance.

Fifth, AI is contributing to financial inclusion through alternative-data credit underwriting for thin-file customers and low-cost service channels, aligning with the inclusion literature (Mhlanga, 2020; Demirgüç-Kunt et al., 2022) and with the RBI's own assessment that AI can make banking more inclusive and customer-friendly (IBEF, 2025).

Sixth, challenges of explainability, bias, data protection, cybersecurity, talent and governance are recognised at the highest regulatory level, and India has moved early, by emerging-market standards, to articulate a comprehensive responsible-AI framework for finance through FREE-AI (RBI, 2025a). The managerial implication is that AI strategy in Indian banks must now be built around demonstrable governance, model risk management, human oversight and compliance with the Digital Personal Data Protection Act, 2023, rather than around experimentation alone.

VI. CONCLUSION

This study set out to analyse the adoption, impact and challenges of Artificial Intelligence in the Indian banking and financial services sector using the most recent authoritative secondary data. The evidence supports four conclusions. First, AI has moved from rhetoric to measurable reality in Indian banking: adoption is documented by the RBI's own surveys and text-mining studies, is led by large private and public sector banks, and is concentrated in customer support, credit underwriting, sales and cybersecurity. Second, India's world-leading digital payments infrastructure, epitomised by UPI's growth to more than 24,000 crore annual transactions, has created both the necessity and the data foundation for AI at scale. Third, the impact of AI is most visible in digital risk management: the precipitous decline in card, internet and digital payment fraud cases between 2023-24 and 2025-26, against a backdrop of surging transaction volumes, plausibly reflects, at least in part, the maturing of AI-enabled real-time monitoring, even as large-value credit frauds demand the next wave of AI application. Fourth, the challenges of opacity, bias, privacy, security, uneven capacity and skills are substantive but are being addressed proactively through the RBI's FREE-AI framework, which seeks to balance innovation with trust.

The practical implication for bank management is that competitive advantage will accrue to institutions that pair AI investment with strong data governance, explainable models, skilled talent and board-level accountability. For regulators, the priority is to convert FREE-AI principles into supervisory practice while ensuring that smaller institutions are not left behind. For the academy, India's combination of open digital infrastructure, rich official data and rapid AI diffusion offers an exceptional laboratory for future research on technology, finance and development. If these complementary efforts succeed, AI can help Indian banking become simultaneously more efficient, more secure and more inclusive, advancing the larger national goal of broad-based, digitally enabled economic growth.

Suggestions and Recommendations

Based on the findings, the following suggestions are offered. For banks: (1) institutionalise AI governance by adopting board-approved AI policies, model risk management frameworks, explainability standards and human-in-the-loop controls consistent with the FREE-AI principles; (2) extend AI from payments fraud monitoring to the credit lifecycle, deploying early-warning systems, network analytics and document-forensics tools to address the advances-category frauds that now dominate fraud value; (3) invest in data quality, privacy-by-design and compliance with the Digital Personal Data Protection Act, 2023; and (4) build internal AI talent through recruitment, reskilling and partnerships, rather than relying wholly on vendors, to mitigate third- party concentration risk. For regulators and policymakers: (5) operationalise FREE-AI through supervisory guidance, disclosure norms and periodic AI-adoption surveys so that trends can be tracked publicly; (6) support shared AI infrastructure, utilities and sandboxes to help smaller banks, cooperative banks and NBFCs adopt AI affordably, preventing a two-speed banking system; and (7) strengthen ecosystem defences against AI-enabled crime, including deepfake fraud, through initiatives such as MuleHunter.AI, the Cyber Range and coordinated customer- awareness campaigns. For future researchers: (8) undertake bank-level econometric studies linking AI investment to efficiency, profitability and fraud outcomes as more granular data become available; (9) conduct primary surveys of customers and employees to study trust, acceptance and the human impact of AI in Indian banking, applying frameworks such as UTAUT; and (10) evaluate the implementation and effectiveness of the FREE-AI framework over time. The scope of this inquiry can also be extended to insurance, securities markets and cooperative banking, where AI diffusion is at an earlier stage.

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