


Research Article

From Automation to Intelligence: The Transformative Role of AI in India's Financial Services Sector

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DOI: <https://doi.org/10.5281/zenodo.23212065>

Abstract

India's financial services sector has moved from branch-centred and rule-based processing toward digitally mediated, data-intensive services in which artificial intelligence (AI) and machine learning (ML) increasingly support detection, prediction, personalisation and decision-making. The research problem is that public discussion often treats digitalisation, automation and AI adoption as interchangeable, while nationally comparable measures of institution-level AI adoption remain limited. This study addresses that gap by examining the transition from conventional automation to AI-enabled intelligence using verifiable secondary data and documented Indian financial-sector use cases. The study adopts a quantitative, descriptive and analytical design based on official data from the Reserve Bank of India (RBI), the National Payments Corporation of India (NPCI) and regulatory material from securities-market authorities, supplemented by peer-reviewed academic literature. The principal quantitative series covers FY 2017-18 to FY 2024-25 for Unified Payments Interface (UPI) transaction volume and value, with the RBI Digital Payments Index (DPI) used for the comparable March 2018-March 2024 period and the RBI Financial Inclusion Index used where observations are available. Growth rates and compound annual growth rates (CAGR) are calculated, and Pearson correlation is used only for the overlapping UPI-volume and RBI-DPI observations. UPI volume increased from 915.2 million transactions in FY 2017-18 to 185.866 billion in FY 2024-25, while transaction value increased from ₹1,098.32 billion to ₹260,570 billion; the corresponding seven-year CAGRs are 113.6% and 118.4%. The correlation between UPI volume and the RBI-DPI over FY 2017-18-FY 2023-24 is 0.920, indicating strong positive association, although the relationship is not interpreted causally. The review also finds that Indian authorities explicitly document AI/ML applications in fraud detection, credit assessment, customer service, surveillance, risk management, recommendation, advisory and related functions, while stressing privacy, explainability, accountability, cybersecurity and human oversight. The study concludes that India's transformation is not simply from manual work to automated workflows; it is increasingly toward systems that analyse patterns and generate decision support. The central implication is that future value depends on combining AI capability with data governance, explainability, resilience and responsible regulation.

Manuscript Information

- ISSN No: 2583-7397
- Received: 05-07-2025
- Accepted: 27-08-2025
- Published: 30-08-2025
- IJCRM:4(4); 2025: 814-823
- ©2025, All Rights Reserved
- Plagiarism Checked: Yes
- Peer Review Process: Yes

How to Cite this Article

K K K. From Automation to Intelligence: The Transformative Role of AI in India's Financial Services Sector. Int J Contemp Res Multidiscip. 2025;4(4):814-823.

Access this Article Online


www.multiarticlesjournal.com

KEYWORDS: Artificial intelligence, machine learning, financial services, digital payments, FinTech, financial inclusion, explainable AI.

I. INTRODUCTION

In the totality of the financial services industry in India, there is no branch based banking or human record keeping with online banking, mobile banking and digital public infrastructure like Aadhaar and UPI. Digital payments are on the increase, as are the usage of financial data and AI-based solutions, offering new possibilities. "UPI is becoming the critical infrastructure for retail payments that can speed up and enable digital payments. AI-powered intelligent systems are more than simply automation. Older systems may automate tasks like transaction verification, reconciliation and alerts based on pre-defined criteria. Artificial intelligence (AI) systems can learn from data, identify intricate patterns, predict events and support decision making. This implies conventional artificial intelligence may be used to accomplish tasks in finance such as prediction and classification.

Growth in digital transactions, availability of data and improved processing capabilities has made Automation in Banking possible. Financial institutions may employ artificial intelligence and machine learning for risk management, fraud detection, customer profiling, credit scoring and anti-money laundering. Machine learning algorithms may be utilised for risk prediction with credit evaluation using diverse customer attributes and transaction patterns.

Another key use case is fraud detection. But not pre-set regulations, transaction thresholds and black lists. Artificial Intelligence can spot out of pattern behaviour and developing tendencies of fraud. AI is becoming ubiquitous in customer service, with chatbots and virtual assistants providing quick solutions for typical consumer complaints. But in sensitive or severe cases human help may be necessary.

AI enables personalised banking, investing and insurance. Financial organisations may track customer activity, propose products, assist with investment choices and enhance risk assessments. It highlights how AI has grown from a specialist function to an enterprise-wide expertise in financial services.

Specialist enterprises, alternative credit ratings and low-cost internet channels might be ways that artificial intelligence can help financial inclusion. Engagement is not access and use. Problems with data bias, privacy, cyber security, and unjust automated assessments exist with AI based systems. And that is why good design and good human monitoring are so important."

This is especially true in the financial services industry, where explainable artificial intelligence may have a major impact on automated choices around loans, investments and other financial opportunities. Explainability allows institutions to track, assess and debate model results. In India, SEBI and RBI are increasingly paying attention to Responsible AI (transparency, fairness, privacy, cybersecurity, testing, accountability).

Digitalisation is catching up but there are no public domain numbers on the quantum of AI used by Indian financial institutions and its quantitative impact. Literature describes specialised usage. Sources on the usage and regulation of AI in government. Therefore, our research links the digital financial

metrics with the respective AI technique and the current AI applications.

The research is aimed at: Trace the evolution of automation in banking from conventional to AI-powered solutions. Explore the evolution to digital finance Explore AI for risk management, customer service, credit scoring and fraud detection. Correlation Analysis of RBI Digital Payment Index and UPI Growth Spot the data and governance challenges of AI deployment.

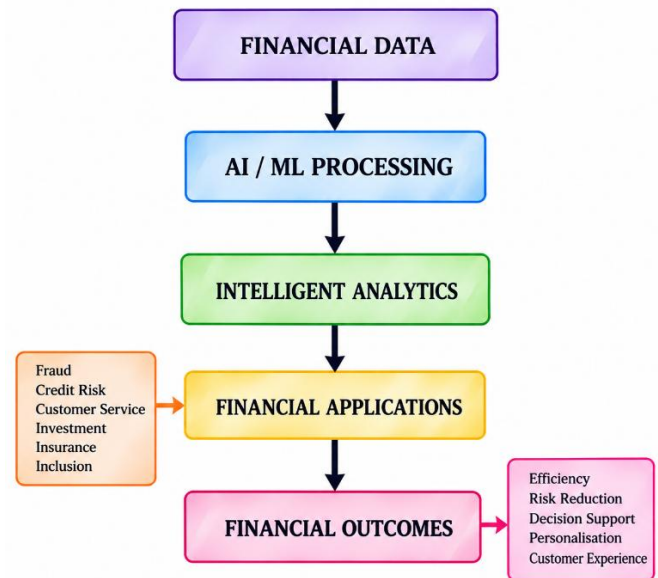


Figure 1: AI-Generated Conceptual Architecture For Intelligent Financial Services.

Figure 1 shows the conceptual architecture of the research. The raw records are processed by AI/ML at the input layer to turn them into predictive, classificatory or pattern-recognition outputs. The results are then translated by intelligent analytics into application-level functions such as fraud detection, credit-risk assessment, customer service, investment analytics, insurance analytics and financial inclusion. The third layer is around objectives like efficiency, risk reduction, decision support, customisation and customer experience. The architecture intentionally decouples the data and processing from the applications and results so that the AI capacity is not conflated with a particular financial product.

II. REVIEW OF LITERATURE

Research on artificial intelligence and machine learning in banking has developed from first-generation expert systems and statistical decision aids to large-scale applications of machine learning, natural language processing, deep learning and big-data analytics. Kalyani and Gupta have conducted an exhaustive study and meta-analysis on the impact of AI/ML in the banking industry via applications supporting operational procedures, customer engagement, trust and digitisation. A wider-scale bibliometric analysis of the Banking, Financial

Services and Insurance sector reveals that there are significant research clusters related to FinTech, risk management, anti-money laundering and actuarial science, showing that AI research in finance is dispersed across different banking activities. The study indicates that AI has advantages in circumstances where the main work requires complex categorisation or prediction, assessment of massive data sets on a recurring basis, and the capacity to feed results into institutional procedures. So the recurring topics are fraud detection, credit scoring, client segmentation, recommendation, compliance monitoring and algorithmic trading. However, there is a distinction in the literature between organisational usefulness and technical model performance. Even the highest performing model provides no value if the data it is based on is dubious, its output cannot be operationalised, value if the data it is based on is dubious, its output cannot be operationalised or the reasoning behind its conclusions cannot be managed. It is particularly pertinent in the financial industry, where errors may have dire consequences for customers, companies and market stability. AI also changes the jobs of the labour force. Intelligent technology means people move to exception handling, judgement, model monitoring and relationship management rather than replacing all manual tasks. Consequently, the study aligns with the outlook of AI as a tool for decision assistance and augmentation in digital financial infrastructure. This is particularly relevant in the Indian context, where the rapid digitisation of payments has created a vast and diverse data landscape on which analytical and predictive approaches may be used. But the study also implies that the implementation of technology should be judged by operational outcomes and governance conditions, not only the monitoring of digital transactions.

Some of the most sophisticated research in AI has been in the areas of credit risk assessment, fraud detection and financial risk management more generally. After all, the question of credit rating is one of predictions. Machine learning may capture non-linear relationships between borrower factors that conventional scorecards may overlook. Bussmann et al. suggested an explainable machine learning approach in credit-risk management using Shapley-value explanations and demonstrated how explanations may be used to cluster borrowers according to the qualities that influence their risk categorisation. More recent systematic research on machine learning-based credit scoring points to the continuous usefulness of prediction models but also questions data quality, interpretability and model governance. Fraud detection is a comparable but distinct kind of challenge. Fraud is infrequent. Fraud is adaptive. Fraudulent conduct is intended to bypass current restrictions. Explainability, anomaly detection and ensemble learning are increasingly combined for financial fraud detection research, to explore suspicious outputs instead of treating them as inexplicable alerts. Risk management includes early warning systems, transaction monitoring, stress analysis and anti-money laundering. However, there exists a substantial literature on class imbalance, concept drift, false positives, biased training data and rising adversarial behaviour. This is

why explainable AI is such a hot area. SHAP, feature-importance methods and rule-based explanations were extensively used for the most typical tasks: Stock price prediction, fraud detection and credit management Survey on XAI in finance. The findings imply that AI-based risk management is most successful when prediction is embedded within a bigger control system including human validation, monitoring, recording and supervision. As India's digital loans and transactions are growing rapidly, financial behaviour is becoming more transparent and the potential for more automated decisions at scale is increasing. But there is a stronger public evidence basis for certain technology applications than a cohesive national look at AI for incremental effect on default, fraud loss or operational risk.

Another aspect of the automation-to-intelligence movement is the literature on FinTech and customer experience. "Digital banking has always been about access to self-service. No longer did customers have to go to a bank to check accounts, transfer money and download statements. Artificial Intelligence (AI) enhances the level of self-service by interpreting natural language requests, identifying customer behaviours, recommending things, and allowing for contextual interactions. The latest research on banking chatbots reveals that ease, rapidity and constant availability are major factors influencing perceived value. But it's complex situations that need human escalation based on constraints on accuracy and reliability. An Indian study on hurdles and variables related to the adoption of banking chatbots has underlined the importance of trust, risk perception, technological anxiety and organisational preparedness. FinTech research adds to this discussion by framing technology not only as a delivery mechanism but also as a source of new business models, data-driven commodities and other types of intermediations. Digital platforms might knit together previously separate financial services such as payments, loans, insurance, asset management and customer analytics. Personalisation is a significant method since AI is able to use transactional and behavioural data to score encounters, identify future needs and change recommendations. Literature also talks on the organisational and technical elements of the digital shift. Banks will have to build new governance, integrate legacy systems, expand data capacity and rethink operations. This is similar to the situation in India where FinTech platforms, digital identity, mobile banking and UPI all have assisted in building a common base to allow more difficult services to be established. But customer experience research warns us not to assume that more automation would necessarily provide better outcomes. Clients may desire speed for day-to-day operations but in disputes, financial problems, big investment decisions or sensitive circumstances they still prefer to meet face to face. The most value comes when AI's machine speed is combined with the correct human interaction. The results are consistent with an augmentation paradigm where humans are still responsible for exceptions, empathy, judgement, critical decisions and AI is responsible for scale and pattern recognition.

The fourth major strand of literature studies financial inclusion, explainability, privacy, ethics and regulation. Ozili's work on digital finance reveals that digital channels may increase access and decrease the cost of intermediation but also present risks that must be controlled to guarantee the sustainability of digital financial inclusion. This disparity in access and use is further aggravated by the World Bank numbers for India. "While 78% of Indians had an account in 2021, fewer were using electronic payments, which shows financial inclusion is about meaningful and active participation and not just the existence of accounts. While artificial intelligence can embed bias at scale via data or opaque models, it may also enable inclusion through lower cost service delivery, alternative risk assessment and personalised solutions. In explainability research, openness is thus linked to accountability, trust and regulatory compliance. Privacy is another worry, with artificial intelligence generally needing a lot of behavioural and transactional data. Emerging issues in the literature and legislative debate include data minimisation, purpose restriction, consent, cyber security and third-party risk. The policy environment in India is likewise seeing an analogous evolution. Safety and reliability, equality, inclusivity, privacy and security, transparency, accountability and human values are the core elements of NITI Aayog's responsible-AI architecture. SEBI's 2025 consultation paper points to similar problems that should be addressed in financial markets, including model governance, transparency, testing, fairness and bias, data privacy and cybersecurity. The BIS and Financial Stability Board have highlighted certain ways in which the widespread deployment of AI might endanger global financial stability, including model risk, data governance, cyber vulnerabilities, third-party concentration and market correlation. These correlations point to a major research gap. There is not a single longitudinal measure of AI adoption in banking, insurance, securities and FinTech in the public Indian data, but there is a wealth of conceptual and technical evidence on AI applications in the literature. The present methodology successfully distinguishes evidence of digital transformation from evidence of AI-specific adoption by integrating quantitative digital-financial indicators with validated AI use cases.

III. Artificial Intelligence Adoption and Digital Transformation in India's Financial Services Industry

The use of AI in India's financial services company must be seen as part of a larger digital revolution. The first phase was the digitisation of papers and key financial operations. The second was via networked channels of ATMs, Internet and mobile banking. The third saw the introduction of interoperable platforms and digital public infrastructure, including UPI, Aadhaar-enabled services and consent-based data systems. The fourth step of development is the addition of AI/ML capabilities to assess the data generated by these systems and transform it into predictions, recommendations, and alerts for anomalies and decision aid. The stages overlap; they do not substitute for each other. Banks may merge machine learning algorithms with

robotic process automation, statistical scorecards and rule-based procedures.

India's UPI ecosystem reflects how digital the foundation is. Annual UPI transactions have risen from 915.2 million in FY 2017-18 to 185.866 billion in FY 2024-25 (data from the Reserve Bank of India (RBI) and the National Payments Corporation of India (NPCI)). The value of transactions rose from ₹1,098.32 billion to ₹260,570 billion in the same period. This size matters to AI because larger digital ecosystems imply more transaction data, richer behavioural histories and greater possibility for real-time analytics. But just the availability of such data doesn't guarantee AI is being used. Hence, in this study, UPI growth is considered as a measure of digital transformation facilitator and not an indicator of AI adoption.

The connection between FinTech and the changing face of banking is growing. Banks offer regulated accounts, settlement infrastructure and balance sheet capacity, but fintechs may specialise on payments, digital lending, wealth technology, insurance technology, fraud analytics or client interface. This results in a comparable ecosystem of modular services and API-based integration. The RBI has indicated the relevance of FinTech in personalisation, digital financial inclusion and digital public infrastructure and the use of AI and big-data analytics as technologies for more efficient and tailored financial solutions. Digital lending and consent-based data platforms may minimise information flows, but AI might be used for underwriting, fraud detection and customer segmentation. Business value is achieved by combining data, models, infrastructure and better processes.

AI-powered financial solutions are also becoming more contextual. "Predictive models can be useful for credit rating and early warning systems in lending. Artificial intelligence may assist in preventing fraud by identifying strange payment patterns. Conversational A.I. can handle complex problems and respond to routine customer care enquiries. AI/ML has been used in the securities sector for surveillance, pattern recognition, customer identification and monitoring, advisory aid and compliance activities. Data analytics and information from connected devices may have the ability to provide risk profiling and tailored services in the insurance arena. The idea that governs all these use cases is the same: the system evaluates data, detects a pattern or probability and then reaches an actionable decision.

But moving from automation to intelligence introduces new operational requirements. AI models need training data, validation, monitoring, version control, and metrics for performance. "Fraudsters and consumer behaviour are constantly changing, so models can degrade. There are issues about concentration and reliance on third-party AI services. There is a larger risk of hallucinations and synthetic content with generative AI. Governance is hard. It's about creating a lifetime, not a one-time approval procedure. Some of the key issues being discussed within the framework of RBI, SEBI and international authorities include monitoring, explainability, supervision by humans, cyber security and accountability.

The adoption of AI in India may depend upon the capacity of institutions to integrate AI into a robust digital infrastructure. Beyond chatbots and automation, some of the most fascinating possibilities lie in real-time risk analytics, fraud prevention, personalised financial products, supervisory technologies, intelligent compliance, and decision assistance. “Meanwhile, the public measurement has to get better.” It is hard to assess the relative effect of AI to a bank’s increase in performance against digitisation, size, process reform or macro-economic factors without precise reporting standards. Future legislation and research should thus support standard inventories of AI use, result reporting, model-risk disclosures and comparable metrics across banks, insurers, securities intermediaries and FinTech enterprises.

IV. RESEARCH METHODOLOGY

The present study is quantitative, descriptive, and analytical and relies solely on secondary data. This choice of methodology aligns with the need for data integrity in this study, as the objective is to measure quantifiable changes in India’s financial services sector without relying on institution-level AI adoption percentages, which lack accurate public statistics. The main UPI series is researched from FY 2017–18 to FY 2024–25, since comparable annual data is accessible during this whole period. The data used for the study have been confirmed to March 2024 (RBI Digital Payments Index, RBI-DPI), and the common timeframe for observing the association is from FY 2017–18 to FY 2023–24. When precise figures are available for March of each year, the RBI Financial Inclusion Index is used. Primary data gathering was not undertaken. RBI and NPCI are the main quantitative sources. The RBI annual reports, RBI Bulletin payment-system tables and RBI-DPI releases are sources for payment-system and financial-inclusion measures. NPCI provides UPI product data. Other sources of reliability include World Bank Global Findex data (for financial inclusion context), MeitY material on responsible AI, RBI information on AI/ML and responsible adoption, and SEBI material on AI/ML usage in Indian securities markets. Peer-reviewed scholarly studies analyse AI applications in credit risk, fraud detection, explainability, customer service and digital finance. The source hierarchy in terms of national numeric indicators favours the official Indian regulators and payment system operators. The international organisations and peer-reviewed studies follow contextual and conceptual evidence.

The major criteria include the RBI-DPI, the RBI Financial Inclusion Index, established AI application domains, and the volume and value of UPI transactions. UPI value is indicated in ₹ billion. UPI volume is expressed in millions of transactions. 100 is the basis for the RBI-DPI index for the month of March 2018. The Financial Inclusion Index assesses access, use and quality and scores from 0 to 100. The application variables of AI are not estimated rates of adoption but validated categorical evidence. This distinction matters because public sources point to use cases like chatbots, fraud detection, credit scoring, monitoring and recommendations, but they do not offer a consistent countrywide share of institutions that use each of the

technologies. So the study does not explicitly relate the surge in payments to the use of AI. The growth rate is calculated as:

$$\text{Growth Rate (\%)} = \left[\frac{X_t - X_{t-1}}{X_{t-1}} \right] \times 100$$

CAGR is calculated as:

$$\text{CAGR (\%)} = \left[\left(\frac{X_n}{X_0} \right)^{\frac{1}{n}} - 1 \right] \times 100$$

Descriptive statistics use the arithmetic mean, $\text{Mean} = \frac{\sum X}{N}$, and sample standard deviation:

$$\text{SD} = \sqrt{\frac{\sum (X - \bar{X})^2}{N - 1}}$$

Pearson correlation is used for UPI volume and RBI-DPI because both series are numeric and have seven aligned annual observations. The correlation coefficient is:

$$r = \frac{N \sum XY - (\sum X)(\sum Y)}{\sqrt{[N \sum X^2 - (\sum X)^2][N \sum Y^2 - (\sum Y)^2]}}$$

The main approach does not contemplate a regression model, since the regular increasing trend of the time series and the short annual series would lead to the wrong causal conclusion.

The data processing approach included checking units, aligning financial years, calculating growth rates and CAGR using the reported base and end values and comparing the March-ending financial year with the corresponding RBI-DPI observation. In the application-comparison table, a clear evidence-coding rule is used: a value of 1 means that the application domain is explicitly documented in the assessed source whereas a value of 0 means that there is no explicit documentation. The evidence streams include peer reviewed literature, SEBI’s consultation paper dated 2025 and RBI’s financial sector speech dated 2024. The statistics obtained are descriptive content-analysis metrics, not measures of market penetration or performance.

Several limitations are mentioned. First, there is no single, constant, annual national AI-adoption percentage for the whole financial services sector accessible from official sources. Secondly, UPI is not quite an AI solution but a digital payment infrastructure measure. Third, the correlation analysis represents association, not causation, and is based solely on seven data points and is affected by common historical trends. Fourth, performance data at the application level varies widely and is typically institution specific. Fifth, certain regulatory documentation describes planned or current use, not confirmed performance. These constraints are maintained, instead of being replaced with assumed values. In this strategy, then, the bogus statistical completeness is given up in favour of repeatability and source traceability.

V. ANALYSIS AND INTERPRETATION

The research looks at the growth of AI-enabled and digitally enabled financial services in India using many measures, including UPI transactions, the RBI Digital Payments Index (RBI-DPI), the Financial Inclusion Index (FI-Index) and

recorded AI-enabled applications. The data is analysed using descriptive trends, growth rates, comparative evidence, and correlation analysis to understand the evolution of India's digital financial ecosystem. The findings distinguish between measurable digital transformation and tangible proof of AI adoption, since indicators at the national level primarily concern the digital infrastructure and financial-service ecosystem on which artificial intelligence (AI) technologies are installed.

Table 1: AI and Digital Transformation Indicators in India's Financial Services Sector

Fy	UPI Volume (Million)	UPI Value (₹ Billion)	RBI-DPI (March)	Fi-Index (March)
2017-18	915.2	1,098.32	100.00	-
2018-19	5,353.4	8,769.70	153.47	-
2019-20	12,518.6	21,317.30	207.84	-
2020-21	22,330.7	41,036.58	270.59	-
2021-22	45,956.1	84,159.00	349.30	56.4
2022-23	83,714.4	139,149.00	395.57	60.1
2023-24	131,129.0	199,951.00	445.50	64.2
2024-25	185,866.0	260,570.00	-	-

Table 1 shows the measurable digital basis for the development of intelligent financial services. During the study, UPI volume and value increased yearly. The RBI-DPI also showed a broad-based depth of payment digitisation instead of improvement in a single payment method as it rose to 445.50 in March 2024 from 100 in March 2018. All available observations suggest that the Financial Inclusion Index has grown. The data, while they reveal a significant change in the digital environment, does not adequately reflect the use of AI. Regulators and research papers evaluate the deployment of AI subjectively. Quantitative national series largely examine the digital environment for AI.

Table 2: Growth And Trend Analysis of Selected Financial-Service Indicators

Period	UPI volume growth	UPI value growth
2018-19	484.94%	698.46%
2019-20	133.84%	143.08%
2020-21	78.38%	92.50%
2021-22	105.80%	105.08%
2022-23	82.16%	65.34%
2023-24	56.64%	43.70%
2024-25	41.74%	30.32%
FY2017-18 to FY2024-25	113.63%	118.43%

The quick expansion of the initial phases slowed down as the transaction base increased, as seen in Table 2. It was 41.74% in FY 2024-2025 compared to 484.94% for FY 2018-19 and 133.84% for FY 2019-20. The same basic tendency holds for value appreciation. Volume and value have 7-year CAGRs of 113.63% and 118.43%, respectively. The finding is consistent with diffusion from a small starting base to mature broad usage.

Table 3: Comparative Analysis of AI-Enabled Financial Applications

AI-enabled application	RBI 2024	SEBI 2025	Academic literature	Evidence streams (n/3)
Fraud detection	1	1	1	3
Credit assessment	1	0	1	2
Customer service	1	1	1	3
Risk management	1	1	1	3
Personalisation	1	1	1	3
Investment / insurance analytics	1	1	1	3

Table 3 shows the combination of risk management, insurance or investment analytics, fraud detection, customer service and customisation. Both in academic research and the RBI, there is substantial concern regarding credit assessment. There is no analogous national denominator, and the table does not convert application evidence into a percentage of Indian universities deliberately. The result is an indication of the breadth of applications rather than market penetration.

Table 4: Statistical / Relationship Analysis of UPI Volume and RBI-DPI

Statistic	UPI Volume (Million)	Rbi-Dpi
Observation Period	Fy2017-18 To Fy2023-24	Fy2017-18 To Fy2023-24
N	7	7
Mean	43,131.06	274.61
Sample Sd	48,266.16	128.49
Pearson R	0.9200	0.9200
Two-Sided P-Value	0.0033	0.0033

Table 4 shows that the Pearson correlation between RBI-DPI and the amount of UPI transactions each year is 0.9200 for seven aligned datasets. The two-sided p-value is 0.0033. Both datasets support the good connection, as they show an increase of digital payments. Due to the limited sample size and the fact that both series are increasing over time, it is inappropriate to consider either series as indicative of AI adoption or as proof of the UPI growth as the reason for the RBI-DPI change.

VI. RESULTS AND DISCUSSION

This section presents and discusses the major findings of India's journey from digital financial automation to AI-enabled intelligence. The results are based on the indicators and comparative data given in Figures 2-5. This study examines documented AI-enabled financial applications, the growth of UPI-based digital transactions, the evolution of the digital payment infrastructure, and the link between UPI operations and the RBI-DPI. The results are discussed within the framework of distinguishing measurable digital transformation from the more general and still-evolving usage of AI in financial services.

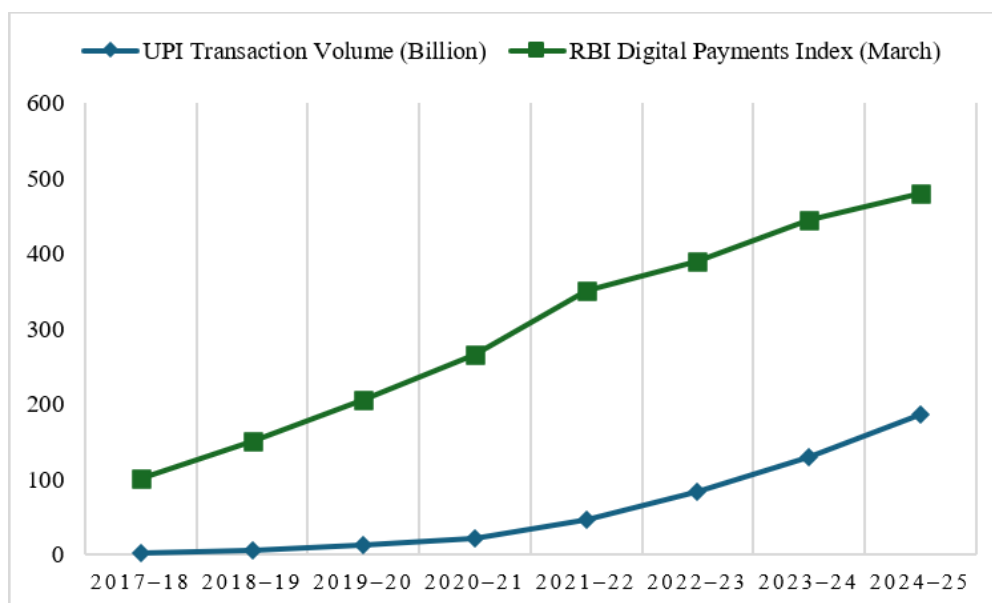


Figure 2: Trend of UPI-Based Digital Financial Transformation Indicators.

The UPI volume has grown significantly from FY 2017-18 to FY 2024-25, as seen in Figure 2. RBI-DPI has also grown throughout the March 2018-March 2024 period. The units are varied; therefore, various axes are used. The increasing number of UPI transactions indicates that digital payment infrastructure is rapidly finding its way into financial activities. The trend of

RBI-DPI, since the index covers several elements of payment digitisation, confirms that the transition was wider than only UPI. The implications for AI are enormous. As financial trades become digital, regular and data-rich, intelligent systems may operate at higher scales. The statistic does not reflect the share of transactions processed or monitored by AI.

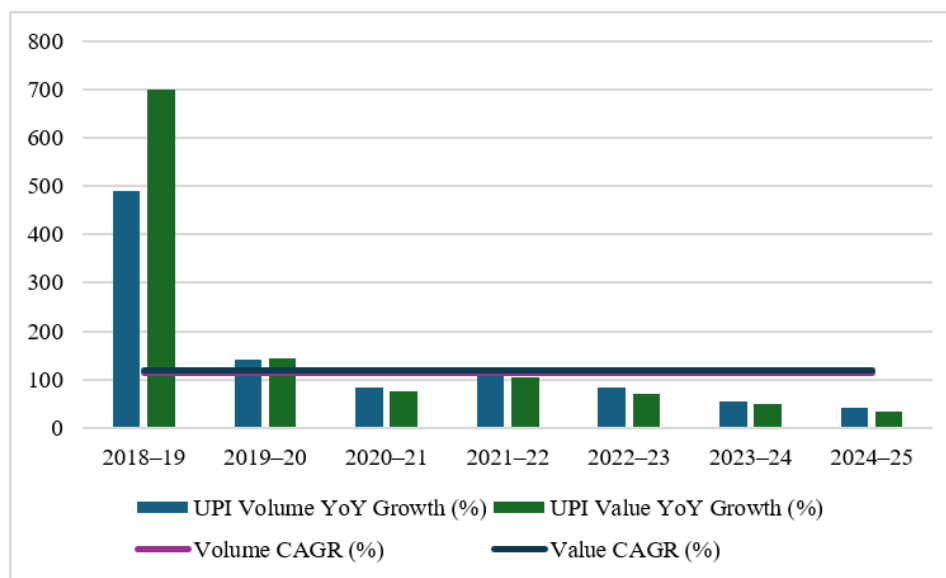


Figure 3: Growth and CAGR Comparison Derived

Figure 3 shows rapid early-stage growth, then a slowdown. Value growth fell to 30.32% from 698.46%, while UPI volume growth fell to 41.74% from 484.94% in FY18-19. The high CAGRs are still mostly driven by the small base at the start.

The pattern suggests that the future of AI value is more likely to be in applying intelligence to an existing digital base than in digitisation alone, and it is consistent with the development of a rapidly accepted digital infrastructure.

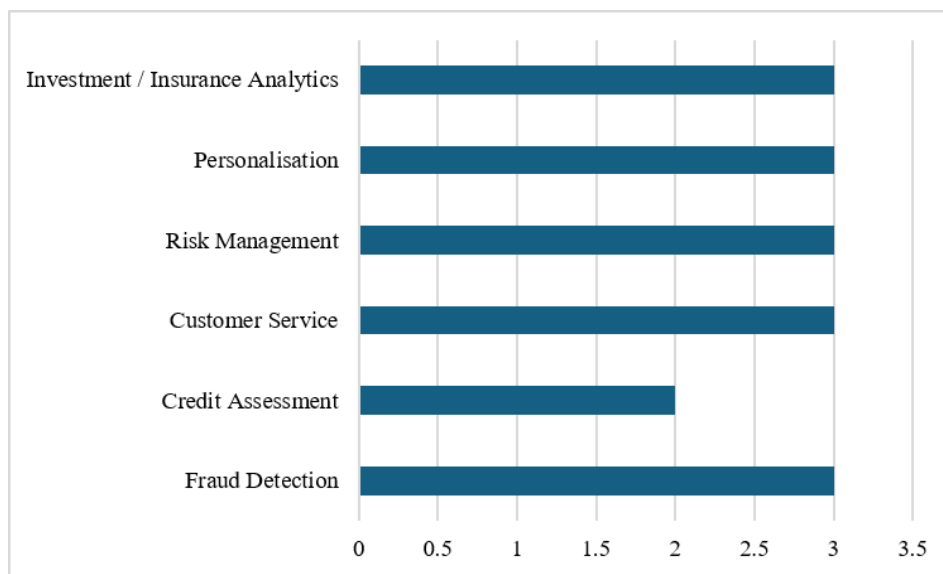


Figure 4: Comparative Evidence of Ai-Enabled Financial Applications

Figure 4 shows the number of evidence streams reviewed that expressly document each application domain. The range of reported applications is consistent with the reported use of AI/ML by SEBI for surveillance, cybersecurity, chatbots, product recommendation, AML, account opening and customer

segmentation and by RBI for fraud detection, credit scoring, chatbots, advisory and algorithmic functions. That indicates AI is becoming a cross-functional competence. A major impediment to evaluating AI's incremental contribution is the absence of consistent national outcome criteria.

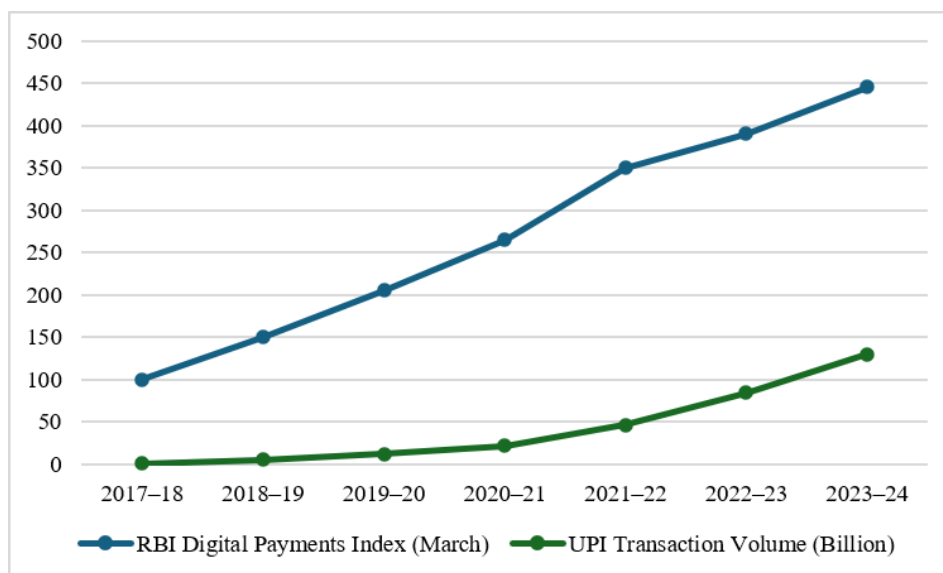


Figure 5: Relationship Between Upi Transaction Volume and Rbi-Dpi, Fy 2017-18 To Fy 2023-24.

Figure 5 shows the seven routine annual measurements. The positive slope and Pearson correlation of 0.920 indicate a strong co-movement between UPI transaction volume and RBI-DPI. This corroborates the broader statistics that as UPI use rose, so did India's payments sector. However, there are just seven data available, and the series shares a major temporal trend; thus, the link is descriptive rather than causative. Hence, the figure does not support a causal claim but co-movement.

Taken together, the data supports a two-level perspective on the shift from automation to intelligence. The Financial Inclusion Index, RBI-DPI, transaction values and UPI volumes are testimony to the fast and continual digitalisation of India's infrastructure. Regulators and academic research have documented the use of AI/ML for fraud detection, credit evaluation, customer service, customisation, surveillance, risk management and investment-related activities. The first level

may be evaluated using long-term national series. The second level is not so well recorded now by standardised national performance data as by inventory, regulatory descriptions and individual studies.

Results also further demonstrate that automation and AI are not the same thing. The ability to forecast, to see patterns, to classify, to suggest or to comprehend context is what we call intelligence. Automation decreases human repetition. That might entail moving from static rules to adaptive anomaly detection for fraud management. It may be adding predictive models to rule-based scorecards in the loan market. It may mean a change from menu-driven self-service to natural language interaction in customer care. In the insurance and investment industries, there may be a requirement to analyse vast and dynamic data sets in support of risk and recommendation evaluations.

Financial firms should not be judged on stand-alone software initiatives but instead look at AI investments with data quality and operational change. Model governance should include development, validation, deployment, monitoring, retraining and retirement. Institutions should also stress-test for bias and robustness, identify dependency on third-party AI and establish escalation processes for high-impact or low-confidence scenarios. These ramifications align with the global banking industry's attention to model risk, data governance, third-party reliance and cyber vulnerabilities.

The consumer also has big effects. Artificial intelligence may make a business more responsive, accessible and personalized - but consumers still want security, transparency and the opportunity to question key choices. A chatbot can handle regular requests, but a contested transaction or a major credit decision may require a person to assess. Ethical financial AI must be a balance of human responsibility + machine efficiency.

The article calls forth the need for greater public measurement. India has solid national data on digital payments and financial inclusion but no one longitudinal indicator on application of AI in banking, insurance, securities and FinTech. Future reports should include AI use cases, model materiality, human supervision procedures, frequency of validation, significant occurrences and quantifiable results. Such reporting would allow future studies to separate the impacts of AI from those of digitization, scalability, process change and macroeconomic trends.

VII. CONCLUSION

The present research examines the transition from traditional automation to AI-based financial products in India's banking business. The value of UPI has increased from ₹ 1,098.32 billion in FY 2017-18 to ₹ 260,570 billion in FY 2024-25 and volume has increased from 915.2 million in FY 2017-18 to 185.866 billion in FY 2024-25. The Financial Inclusion Index and RBI-DPI are rising rapidly, indicating further progress in the digital world.

AI/ML is rapidly being utilised in fraud detection, credit scoring, customer service, risk management and

personalisation. And despite the incredibly excellent link between UPI volume and RBI-DPI, it says nothing about causality and AI adoption.

“Successful AI requires data quality, explainability, cybersecurity, oversight by humans, and governance. The fundamental challenge is the absence of national standardised statistics on the usage and efficacy of AI. Future work should explore the effect of AI on customer satisfaction, availability of loans, financial inclusion and fraud prevention.

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