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Review Article

Artificial Intelligence Adoption, Algorithmic Risk and Financial Performance in Indian Banking: A Literature Review

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Abstract

Banks are increasingly turning to artificial intelligence (AI) to carry out a range of tasks, including credit evaluation, fraud detection, customer service and risk management. Although adopting AI may enhance a bank's efficiency and decision-making abilities, it also brings a number of risks, such as algorithmic bias, inaccurate predictions, data quality problems and a lack of transparency. These risks give rise to important questions about how AI adoption relates to financial performance in the banking sector, especially in India, where public-sector and private-sector banks may differ considerably in their technological infrastructure and organizational practices. Drawing on 20 studies identified in a preliminary literature matrix, this review synthesizes the literature around four themes: AI adoption in banking, algorithmic risk and bias, explainable AI and governance, and the relationship between AI adoption and financial performance. The literature reviewed shows that AI applications are widely discussed in the areas of credit scoring, fraud detection and customer services. Yet the benefits of AI cannot be assumed to translate automatically into greater profitability, and predictive accuracy on its own does not ensure fair or transparent decisions. The review points to a potential research gap in the integrated examination of AI adoption, algorithmic risk and financial performance across public- and private-sector Indian banks. Additional empirical research is required to explore these relationships using consistent measures of AI adoption, risk governance and financial performance.

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KEYWORDS: Artificial intelligence, algorithmic risk, Indian banking, financial performance, public-sector banks, private-sector banks, explainable artificial intelligence.

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1. INTRODUCTION

Artificial intelligence (AI) has emerged as a significant area of technological development within the banking sector. Banks are increasingly using, developing or exploring AI and machine learning for activities such as credit assessment, fraud detection, customer service, document processing and risk management. Such technologies can assist financial institutions in analyzing large volumes of information, spotting patterns and supporting decision-making. As banking grows increasingly data-driven, the adoption of AI could shape how banks run their operations, serve their customers and evaluate financial risks.

Earlier studies have looked at various ways AI is applied in banking. Based on the literature matrix, Kalyani and Gupta (2023) reviewed how AI and machine learning have developed in banking and pinpointed key application areas, such as customer relationship management, credit scoring and fraud detection. In a similar vein, Fares et al. (2022) grouped banking-related AI research around strategy, processes and customer services. Together, these studies offer a broad picture of how AI can support banking activities. Adoption, however, involves more than simply bringing in new technology. It also calls for suitable data, technical expertise, organizational readiness and effective management.

Even with its potential benefits, AI adoption brings challenges tied to algorithmic risk. Algorithmic systems depend on data, model assumptions and decision rules that may not fit every situation. Inaccurate predictions, biased training data, limited explainability and insufficient monitoring can all undermine the reliability of automated decisions. In banking, such issues can affect credit approvals, fraud alerts, how customers are treated and risk assessment. It is therefore important to consider not only whether banks adopt AI, but also how they identify, manage and monitor the risks connected with these systems.

Explainable artificial intelligence (XAI) has become an important research area, as it aims to make decisions generated by AI easier to understand. Research reviewed by Černevičienė and Kabašinskas (2024) and Weber et al. (2023) points to the growing attention paid to explainability in financial applications. Approaches such as SHAP and LIME can help clarify which variables contribute to a model's prediction. An explanation, however, does not in itself show that a model is accurate, fair or appropriate. Effective AI governance thus requires more than technical explanations; it also involves model validation, monitoring, accountability and suitable human oversight.

The relationship between AI adoption and financial performance is another key issue. AI can enhance efficiency, help identify credit risk early and improve fraud detection. Yet putting AI into practice may demand considerable investment in technology, data infrastructure, skilled staff and risk-control systems. These costs can influence short-term profitability, while the operational benefits that may arise could take time to materialize. Financial performance should thus be assessed empirically, rather than presuming that greater AI adoption automatically results in higher profits.

The Indian banking sector offers a pertinent setting in which to explore these questions. Public-sector and private-sector banks may vary in their organizational structures, technology investments, operational priorities and reporting practices. Such differences may shape both the adoption of AI and the manner in which its benefits and risks are handled. Comparing the two categories can help establish whether the relationships among AI adoption, algorithmic risk and financial performance are alike or different across bank ownership types.

With this in mind, the present literature review examines existing research on AI adoption, algorithmic risk and financial performance, paying particular attention to public- and private-sector banks in India. Its purpose is to synthesize the main findings, pinpoint limitations in existing research and lay a foundation for further empirical investigation.

2. REVIEW OF LITERATURE METHODOLOGY

This review draws on a preliminary literature matrix comprising 20 studies related to AI adoption, algorithmic risk, explainable AI and banking performance. The studies employ a range of research designs, including systematic literature reviews, bibliometric analyses, empirical machine-learning studies, survey-based investigations, annual-report content analyses and panel-data analyses.

The studies were grouped into four themes based on their primary research focus. The first theme addresses AI adoption and applications in banking. The second examines algorithmic risk, predictive accuracy and bias. The third concentrates on explainable AI and governance. The fourth considers financial performance and the differences between public- and private-sector banks.

The literature matrix was used to compare the objectives, methodologies, reported findings and research gaps of the selected studies. This thematic approach allows common findings and differences across research contexts to be identified, rather than presenting each study as an isolated summary.

Nevertheless, the present review should be regarded as a preliminary thematic synthesis. A full systematic review would call for a documented search strategy, the databases searched, search terms, inclusion and exclusion criteria, a screening procedure, and a final list of eligible studies. Before the review is finalized, the bibliographic details and reported results of all 20 studies must also be checked against the original publications.

3. REVIEW OF EXISTING LITERATURE

3.1 AI Adoption and Applications in Banking

Research on AI adoption in banking has addressed operational processes, customer services, credit assessment, fraud detection and risk management. These applications show that AI can be used across a range of banking functions, not just in one activity.

Kalyani and Gupta (2023) offer a broad overview of AI and machine-learning applications in banking. According to the matrix, the literature these authors reviewed focused on customer relationship management, credit scoring and fraud detection. The study also points to factors such as data quality, technological feasibility and concerns about algorithmic bias as relevant to implementing AI. This implies that AI adoption hinges not only on technology being available but also on

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whether banks have the necessary organizational and technical capabilities.

Fares et al. (2022) explored AI research in banking through the themes of strategy, processes and customers. Their approach suggests that AI adoption should be viewed as an organizational matter as much as a technological one. For instance, AI-based customer services may alter how banks interact with customers, while automated credit assessment may affect internal lending procedures and risk-management practices. The implications of adoption can thus vary depending on the banking activity in which AI is implemented.

The Indian banking context is covered in the matrix through Kumar et al. (2024), whose review of institutional reports and case studies discusses applications such as automation, revenue generation and fraud control. The examples recorded in the matrix include SBI's SIA and HDFC Bank's EVA. These examples show how AI-related systems are used in customer interaction and banking services. Yet the mere existence of an AI application does not by itself prove its contribution to profitability or risk reduction.

Goyal et al. (2025) examined the factors linked to the adoption of AI-based credit-risk assessment and fraud-detection systems among banking professionals in India. The matrix indicates that technological knowledge and perceived usefulness were key factors linked to adoption. This result highlights the importance of employee capability and organizational readiness. Banks may invest in AI systems, yet how effectively these are used can hinge on whether employees understand the technology and are able to integrate it into existing processes.

On the whole, the literature indicates that AI adoption in banking is shaped by technological, organizational and human factors. However, the studies vary in their emphasis: some look at general banking applications, others examine employee adoption, and still others focus on individual AI systems. This makes it important to separate the adoption of AI, the actual use of AI in banking decisions, and the measurable outcomes linked to its use.

Another concern is how adoption is measured. Public disclosures about AI may show that a bank has introduced or explored a technology, but they do not necessarily reveal how extensively it is used or how well it performs. Research that compares public- and private-sector banks therefore requires clear and consistent measures of AI adoption.

3.2 Algorithmic Risk, Credit Assessment and Bias

Algorithmic risk is a central concern in AI-enabled banking, since automated systems can shape decisions involving lending, fraud detection and customer treatment. While machine-learning models may detect complex patterns in large datasets, their outputs can be influenced by data limitations, unsuitable model assumptions and shifting economic conditions.

The literature matrix contains studies that examine the accuracy of AI-based credit assessment and the possibility of unequal outcomes across borrower groups. As recorded in the matrix, Singh and Mohanty (2026) compared credit-assessment outcomes before and after automation in Indian lending. The matrix reports that the use of machine-learning models enhanced predictive accuracy and was linked to lower levels of non-performing assets. It also reports possible demographic disparities in model outcomes. If confirmed in the original study, these findings illustrate an important distinction: a model may predict repayment risk more accurately overall while still generating unfair outcomes for certain categories of borrowers.

This issue matters for banking because credit decisions affect both the quality of a bank's loan portfolio and access to financial services. An inaccurate prediction may expose a bank to losses, whereas an unfair prediction may shut out creditworthy customers. As a result, model performance should not be assessed solely on overall predictive accuracy. It should likewise be assessed using suitable fairness metrics, error rates across different groups, and the processes applied to review decisions that may be harmful.

As recorded in the matrix, the study by Krey et al. (2026) provides a mapping of research on AI and algorithmic bias in banking and finance. Among the research themes, the matrix identifies responsible AI governance, human–AI interaction, and behavioral considerations. This viewpoint extends the discussion beyond the technical design of models. Organizational practices, the way employees interpret model outputs, and the degree of accountability assigned to automated decisions can also shape algorithmic risk.

Machado et al. (2025) investigated machine-learning methods for identifying commercial clients at risk of financial distress. According to the matrix, their study compared predictive models and applied SHAP to help explain the factors that influence predictions. The matrix further notes limitations related to class imbalance and the short observation period. These issues matter because a model that performs well on a given dataset may not keep the same performance when economic conditions, customer characteristics, or lending practices change.

The literature thus points to a tension between predictive performance and responsible decision-making. Enhancing a model's capacity to identify risk matters, but banks must also weigh fairness, data quality, model stability, and the consequences of incorrect predictions. This supports viewing algorithmic risk as a separate dimension of AI adoption, rather than assuming that all risks are resolved once a bank adopts a more advanced model.

3.3 Explainable Artificial Intelligence and Risk Governance

Explainable artificial intelligence seeks to make the outputs of AI systems easier for users, decision-makers, and reviewers to understand. In banking, explainability can matter when a model supports credit decisions, flags potentially fraudulent transactions, or assesses financial risk. A clearer explanation can help employees review a prediction, investigate errors, and document how a decision was reached.

Černevičienė and Kabašinskas (2024) conducted a review of explainable AI in finance. The matrix shows that credit management and risk management were prominent application areas, and that methods such as SHAP, LIME, and rule-based explanations were frequently discussed. The study also highlights the absence of standardized metrics for evaluating the quality of explanations. This matters because an explanation

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that seems understandable may not be sufficiently accurate, stable, or useful for decision-making.

In a similar vein, Weber et al. (2023) explored explainable AI applications across financial and related research areas. As the matrix shows, their review found growing interest in explainability, especially in risk management and default prediction. Yet the literature also revealed an imbalance between research in information systems and computer science and research aimed directly at finance. This points to a need to link technical methods with the practical requirements of financial institutions.

As listed in the matrix, Khoozani et al. (2026) reviewed graph-learning and explainable methods for credit-risk assessment and fraud detection. The matrix reports that graph-based methods drew attention in fraud detection, whereas their use in retail credit scoring stayed relatively underexplored. This suggests that how suitable an AI technique is may depend on the financial task and on how the data are structured. Using a sophisticated method on its own does not ensure that it will perform effectively in a given banking environment.

According to the matrix, Bairagi and Arora (2026) studied an explainable recommendation system for retail banking. The study applied machine-learning methods and explanation techniques to assess prediction performance and interpretability. The matrix also points out that the work depended on proxy data rather than live core-banking records. This limitation shows why results from experimental or simulated settings should not be automatically generalized to operational banking environments.

Taken together, these studies indicate that explainability can support responsible AI use, but it should be part of a broader governance framework. Effective governance may cover model validation, regular performance monitoring, fairness assessment, documentation, human review and clear accountability. Banks also need to assess whether explanations are understandable and useful to the people responsible for acting on them.

For the present research topic, explainability and governance relate to the algorithmic-risk dimension. They offer a way to examine whether banks are merely adopting AI systems or are also building processes to manage the risks those systems bring.

3.4 AI Adoption and Financial Performance

Financial performance is another key theme in the literature, since banks invest in technology expecting to improve their operations, manage risks or strengthen their competitive position. However, the link between AI adoption and financial performance may be neither immediate nor uniform.

The literature matrix documents a study by Dr. N. Mansuri (2026) that examines AI adoption and the performance of Indian banks through fixed-effects panel regression. According to the matrix, AI adoption intensity had no statistically significant direct impact on return on assets (ROA) or return on equity (ROE) within the sample studied. It further observes that internal operational efficiency may affect bank margins. If confirmed, this finding would call into question the assumption that greater AI adoption automatically leads to better financial performance.

One plausible explanation is that the benefits and costs of AI adoption materialize over different time horizons. The initial implementation phase may require spending on infrastructure, data systems, cybersecurity and staff training. Gains from improved processes or risk assessment may only become apparent once systems are embedded in routine operations. As a result, the short-term financial effect may differ from the longer-term one.

As summarized in the matrix, Ni et al. (2026) examined AI innovation and bank performance across CAMEL dimensions using data from large US commercial banks. The matrix reports that AI innovation was linked to better asset quality, but also to higher immediate operating costs and weaker short-term profitability. Since the study focuses on US banks, its findings cannot be assumed to apply directly to Indian banks. It nonetheless offers a useful perspective on why the effects of AI may differ across performance indicators and over time.

Financial performance also needs to be measured carefully. ROA and ROE capture different dimensions of profitability, whereas the net interest margin (NIM) reflects the relationship between interest income and interest expenses. Measures of operating efficiency and asset quality may offer further insight into how AI adoption relates to banking operations. No single indicator can represent every possible benefit or cost of AI.

In addition, financial performance is shaped by many factors beyond technology. Movements in interest rates, loan growth, credit losses, capital adequacy, provisioning, competition and broader economic conditions can all affect bank results. Thus, a rise in profitability occurring alongside AI adoption does not prove that AI caused the improvement. Likewise, a drop in profitability does not necessarily indicate that an AI initiative failed.

The existing literature therefore backs a careful approach when it comes to examining AI and financial performance. It matters to separate AI adoption from AI innovation, reported AI initiatives from real implementation, and short-term results from longer-term effects. These distinctions can support the development of a more balanced analysis of AI adoption in Indian banking.

3.5 Public-Sector and Private-Sector Indian Banks

Comparing public-sector and private-sector banks matters because the two categories may vary in organizational structures, technology strategies, operational priorities and reporting practices. Such differences may shape how far AI is adopted, which types of applications are implemented and the procedures used to manage algorithmic risk.

According to the matrix, Uttam et al. (2026) examined AI-related disclosures in the annual reports of selected Indian banks. The matrix notes that disclosures concentrated more on describing applications than on quantifying financial outcomes. It further documents variations in disclosure levels between public- and private-sector banks. This points to a measurement challenge: the volume of information a bank publishes about AI may not reliably indicate how extensively or effectively it has implemented it.

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A bank that reports more AI initiatives may simply have a more developed reporting process, greater transparency, or a broader set of publicly disclosed projects. It does not automatically mean that the bank uses AI more effectively or achieves stronger financial results. Disclosure-based indicators should therefore be interpreted with caution and, where feasible, combined with other measures of implementation and performance.

The literature matrix also documents a comparative analysis by Dr. N. Mansuri (2026) that examines AI adoption and financial performance across public- and private-sector Indian banks. The reported findings show no statistically significant difference in direct ROA and ROE outcomes that can be attributed to AI adoption alone. This implies that bank ownership may not be enough to explain the financial effects of AI. Organizational execution, the type of technology adopted, and the capacity to integrate AI into existing processes may also play a role.

The matrix includes additional work comparing credit-risk outcomes across public- and private-sector banks. Such research matters because the implications of automated lending decisions may reach beyond profitability to asset quality and fairness in access to credit. However, the findings and publication details of these studies need verification before they can be regarded as established evidence.

Overall, the literature indicates that public- and private-sector banks should not be compared solely on how many AI applications they disclose or how much they invest in technology. A meaningful comparison should examine AI adoption together with risk-management practices and financial indicators. When interpreting results, it should also take into account differences in bank size, business mix, capital structure, and operating conditions.

4. Critical Synthesis of the Literature

The reviewed studies help to explain AI adoption, algorithmic risk, explainability, and financial performance, but they do not all examine these dimensions together.

First, the literature on AI adoption covers applications in customer services, fraud detection, credit assessment and internal processes. It further highlights the significance of technological knowledge, organizational readiness and data quality. Yet evidence of adoption does not automatically show that a bank's AI systems are used widely or effectively.

Second, research on algorithmic risk underscores the importance of predictive accuracy, fairness, explainability and model monitoring. A model may enhance overall prediction accuracy while still generating unequal error rates across customer groups. This implies that model performance and responsible decision-making should be assessed together.

Third, research on explainable AI offers tools and approaches for understanding model outputs, though challenges remain in evaluating how good and practically useful explanations are. Explainability should thus be viewed as one component of risk governance, not as conclusive proof that an AI system is safe or fair.

Fourth, the evidence on financial performance is not necessarily consistent. AI adoption may be linked to better asset quality or operational processes without causing an immediate rise in ROA or ROE. Implementation costs and the time needed to realize benefits may help explain why findings differ across studies.

Finally, research that compares public- and private-sector banks faces a measurement challenge. Variations in public disclosure do not necessarily reflect variations in actual adoption, risk governance or financial outcomes. Comparative research must therefore rely on consistent definitions and carefully chosen indicators.

The key implication is that AI adoption, algorithmic risk and financial performance should be treated as related but separate dimensions. Examining only one of these dimensions may yield an incomplete picture of how AI affects banking institutions.

5. RESEARCH GAPS

The literature matrix points to several possible research gaps. These should be treated as preliminary gaps until the original studies and the broader body of relevant literature have been verified.

5.1 Limited integration of the three core dimensions

A large number of studies concentrate mainly on AI applications, model accuracy, explainability, or financial outcomes. One possible gap is the need to examine AI adoption, algorithmic risk, and financial performance jointly within a single research framework. Such an approach could offer a fuller understanding of both the opportunities and the limitations that accompany AI adoption.

5.2 Need for stronger comparative evidence from Indian banks

The literature does include studies on Indian banks, yet additional work may be required to compare public- and private-sector banks using consistent measures. Such a comparison should explore whether differences in adoption and risk governance are linked to differences in financial performance, instead of assuming that ownership type determines outcomes.

5.3 Measurement of actual AI adoption

Annual-report disclosures can help identify publicly reported AI initiatives, but they may not offer a complete measure of actual AI use. More consistent indicators are needed to distinguish general digitalization, planned initiatives, pilot projects, and AI systems used in operational decisions.

5.4 Measurement of algorithmic risk and governance

The matrix draws attention to concerns about bias, explainability, data quality, and model reliability. However, these risks may be measured differently from one study to another. Future research could examine whether banks report or demonstrate practices such as model validation, fairness assessment, ongoing monitoring, and human oversight, while acknowledging that public disclosures may not reveal the full internal governance process

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5.5 The relationship between AI adoption and financial performance

The reported findings do not establish that AI adoption consistently improves profitability. Further research could examine multiple performance indicators, including ROA, ROE, NIM, operating efficiency, and asset quality. It could also investigate whether any association varies over time and whether it persists after accounting for other factors that affect bank performance.

5.6 Need for stronger empirical identification

A relationship between AI adoption and financial performance does not, on its own, establish causation. Banks that possess stronger financial resources might be better placed to invest in AI, whereas other organizational and economic factors could affect both adoption and performance. Future empirical studies should therefore adopt suitable research designs and controls before drawing causal conclusions.

5.7 Proposed contribution of the present study

To address these potential gaps, the proposed study intends to examine AI adoption, algorithmic risk and financial performance in Indian banks across both the public and private sectors. Its intended contribution is to integrate these three dimensions into a single comparative framework.

The study should clearly specify how AI adoption and algorithmic risk will be measured, choose appropriate financial-performance indicators, and establish a suitable sample and observation period. The research design should also take into account other factors that may influence bank performance. This would enable the study to assess the relationships among the three dimensions without presuming in advance that AI adoption necessarily improves financial outcomes.

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