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Artificial Intelligence in Credit Risk Assessment and Credit Scoring: Evidence from the Indian Banking Sector

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ABSTRACT

Purpose. This study examines the role of artificial intelligence (AI) in credit risk assessment and credit scoring in the banking sector, with particular emphasis on underwriting accuracy, loan-processing efficiency, digital lending and credit-risk management.

Design/methodology/approach. The study uses secondary data relating to selected Indian banks and applies descriptive, correlation and cluster analysis to examine associations between AI adoption and selected operational and credit-risk indicators. The source manuscript reports bank-level AI usage and application figures together with turnaround-time reduction, manual-process reduction, digital growth, delinquency impact and AI maturity scores.

Findings. The reported bank-level data indicate that institutions with higher AI usage generally display stronger operational indicators and higher AI-maturity scores. ICICI Bank, HDFC Bank and YES Bank are among the banks with relatively high AI-usage levels, while the reported cluster analysis identifies more advanced AI adopters as a distinct group associated with operational efficiency and stronger risk-control characteristics.

Originality/value. The study brings together AI adoption, credit scoring and credit-risk management in an Indian banking context. It highlights the potential of AI to improve the speed and consistency of credit decisions while recognising the importance of data quality, explainability, model validation and responsible governance.

Keywords: artificial intelligence; credit risk; credit scoring; banking; machine learning; digital lending; underwriting; risk management; India

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1. Introduction

Credit risk assessment is a core banking function because lending decisions influence profitability, asset quality, liquidity and long-term financial stability. Weak borrower assessment can result in credit losses and deterioration in asset quality, making accurate and timely appraisal central to sound banking operations [1,2].

Traditional credit appraisal commonly relies on income, employment, repayment history, existing liabilities and collateral. Although these variables provide an interpretable foundation for lending decisions, conventional rule-based models may have difficulty capturing complex relationships, changing borrower behaviour and non-traditional sources of income. Advances in machine learning and predictive analytics provide opportunities to complement conventional assessment with data-driven approaches [3,4].

AI-based credit models can process large volumes of structured and unstructured data, identify non-linear patterns and update predictions as new information becomes available. Such capabilities may improve underwriting accuracy, reduce processing time and support early identification of borrower stress. At the same time, AI introduces challenges involving data quality, explainability, fairness, model risk and regulatory accountability [5,6].

The present study examines AI adoption in selected Indian banks and considers its relationship with operational and credit-risk indicators. The study focuses on whether greater AI integration is associated with improved credit-decision accuracy, reduced turnaround time, digital growth and stronger risk-control outcomes.

2. Problem Statement

The expansion of digital lending and increasing credit volumes require banks to evaluate borrowers efficiently without compromising risk control. Traditional assessment systems can be slower and may be less capable of recognising complex borrower behaviour. AI offers an alternative through automated analytics and predictive modelling, but its value depends on the quality of data, model governance and the ability to translate predictions into reliable lending decisions.

The research problem is therefore to understand whether greater AI adoption in selected Indian banks is associated with observable improvements in credit-risk assessment and operational efficiency, while identifying the governance limitations that may constrain responsible adoption.

3. Objectives

1. To examine the role of AI in credit risk assessment and credit scoring in the banking sector.

2. To compare AI adoption and selected operational indicators across selected Indian banks.

3. To examine the association between AI usage and indicators such as turnaround-time reduction, digital growth and delinquency impact.

4. To identify groups of banks with similar levels of AI maturity and operational performance.

5. To discuss the benefits, challenges and governance requirements of AI-based credit-risk assessment.

4. Hypotheses

H01: AI-based credit risk assessment models do not significantly improve the accuracy and efficiency of credit scoring compared with traditional methods.

H11: AI-based credit risk assessment models significantly improve the accuracy and efficiency of credit scoring compared with traditional methods.

5. Literature Review

AI and credit-risk assessment. Machine-learning techniques can identify complex relationships among borrower characteristics and repayment outcomes that may not be captured adequately by traditional scoring rules. Research on credit scoring has shown the potential of machine-learning

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methods to improve classification and prediction while also raising questions about interpretability and model governance [3,4].

Alternative data and financial inclusion. AI systems can incorporate transaction behaviour and other non-traditional information, potentially improving the assessment of borrowers who have limited conventional credit histories. This capability is particularly relevant to self-employed and informal-sector borrowers, although alternative data can also introduce privacy and bias concerns [5,7].

AI and banking efficiency. The application of AI across lending can automate document verification, underwriting and monitoring, thereby reducing processing time and allowing human decision-makers to focus on complex cases. Industry evidence also indicates increasing use of AI and advanced analytics across banking operations [6,8].

Model risk, explainability and fairness. Credit decisions are consequential, and automated systems therefore require governance mechanisms that address model validation, explainability, data quality, bias and accountability. The use of AI should complement rather than eliminate responsible human oversight [5,9].

Research gap. Much of the literature examines AI methods at the model level, while practical evidence comparing AI adoption and operational indicators across Indian banks is less frequently presented in an integrated framework. This study contributes an exploratory bank-level comparison using the indicators reported in the source dataset.

6. Research Methodology

6.1 Research Design

The study adopts a descriptive and exploratory research design based on secondary data. It compares selected Indian banks using indicators reported in the source study and applies descriptive, correlation and cluster analysis.

6.2 Sample and Data Sources

The source dataset covers ten banks: ICICI Bank, State Bank of India, HDFC Bank, Axis Bank, Bank of Baroda, YES Bank, Canara Bank, Federal Bank, Union Bank of India and IndusInd Bank. The manuscript states that secondary information was obtained from institutional, industry and banking sources, including RBI, World Bank, McKinsey, Deloitte, PwC, NITI Aayog, IMF, Harvard Business Review, Statista and official bank websites [10–19].

6.3 Variables

The reported variables are AI usage (%), AI applications (lakhs), turnaround-time reduction (%), manual-process reduction (%), digital growth (%), delinquency impact score and AI maturity score.

6.4 Analytical Methods

Descriptive analysis is used to compare the selected banks. Correlation analysis is used to examine associations between AI usage and selected indicators. Cluster analysis is used to identify groups of banks with similar AI adoption and performance characteristics. The study also states a hypothesis concerning improvement in credit-scoring accuracy and efficiency.

6.5 Important Measurement Limitation

The source manuscript does not provide the complete correlation coefficients, significance levels, cluster solution, clustering method or regression/test statistics. Consequently, the conclusions in this revised paper are limited to the patterns reported in the source and should not be presented as independently verified causal effects.

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7. Results and Analysis

7.1 Bank-level AI Adoption

Bank	AI usage (%)	AI applications (lakhs)	TAT reduction (%)	Manual reduction (%)	Digital growth (%)	Delinquency impact	AI maturity
ICICI Bank	70	200	85	0	20	5	5
SBI	40	60	35	0	15	4	4
HDFC Bank	55	150	90	0	18	4	4
Axis Bank	50	80	40	40	25	4	4
Bank of Baroda	35	30	25	0	20	4	3
YES Bank	65	100	60	0	22	4	5
Canara Bank	30	45	25	30	12	3	3
Federal Bank	45	10	30	0	18	4	3
Union Bank of India	40	40	30	0	15	3	3
IndusInd Bank	50	70	35	0	40	4	4

The dataset shows substantial variation in AI adoption. AI usage ranges from 30% in Canara Bank to 70% in ICICI Bank. AI maturity ranges from 3 to 5, with ICICI Bank and YES Bank receiving a maturity score of 5 in the source data. HDFC Bank reports the highest turnaround-time reduction (90%), while ICICI Bank reports the largest number of AI applications (200 lakhs).

These differences suggest that AI adoption is not uniform across Indian banks. However, the small number of banks and the absence of inferential test statistics mean that the observed differences should be interpreted as descriptive rather than as proof that AI adoption caused the reported operational outcomes.

7.2 Descriptive Interpretation

The source study reports that banks with higher levels of AI integration generally demonstrate improved credit-decision accuracy, reduced turnaround time and lower non-performing-asset levels. The bank-level table supports the broader observation that several higher-adoption banks also report strong operational indicators. Nevertheless, the dataset does not include a directly measured NPA ratio, and therefore the phrase "lower non-performing asset levels" should be treated as a reported interpretation rather than a directly reproduced statistical finding.

7.3 Correlation Analysis

The source manuscript states that correlation analysis confirms a positive relationship between AI usage and key performance indicators. However, the actual correlation matrix and p-values are not included in the document. Therefore, the revised paper reports the direction described by the source but does not assign numerical correlation coefficients or significance levels that are not available in the underlying manuscript.

7.4 Cluster Analysis

The source manuscript reports that cluster analysis identifies institutions with advanced AI implementation as a distinct group characterised by operational efficiency and strong risk-control mechanisms. The exact clustering algorithm, distance measure, number of clusters, cluster centres

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and membership statistics are not provided. The cluster result should therefore be considered exploratory and should be reproduced from the underlying dataset before publication.

7.5 Hypothesis Evaluation

Hypothesis	Evidence available	Decision
H01: AI does not improve accuracy and efficiency	Source reports improved accuracy and efficiency and states that H0 is rejected; detailed inferential output is absent.	Reject H01 as reported, subject to statistical-output verification.
H11: AI improves accuracy and efficiency	Source reports H1 accepted; detailed test statistic and p-value are absent.	Supported as reported, subject to verification.

For journal submission, the final manuscript should report the exact statistical test used to compare AI-based and traditional credit-scoring performance, including the test statistic, degrees of freedom, p-value and effect size. Without these values, the hypothesis result remains a reported conclusion rather than a fully reproducible statistical test.

8. Discussion

The study indicates that AI adoption is associated with operational improvements in the selected banking sample, particularly in turnaround time and digital processing. The highest AI-usage banks in the dataset also tend to have relatively high AI-maturity scores, suggesting that adoption depth and organisational maturity may develop together.

The findings are consistent with the broader literature on machine-learning-based credit assessment, which identifies potential improvements in predictive performance and the ability to capture complex borrower relationships [3,4]. AI may also support financial inclusion by incorporating alternative information into credit assessment, although such approaches require careful controls for bias and data quality [5,7].

At the same time, the results should not be interpreted as evidence that AI adoption automatically produces better asset quality. The dataset is cross-sectional, contains only ten banks and does not control for bank size, portfolio composition, macroeconomic conditions, technology investment or differences in credit policy. Higher-performing banks may also have greater resources to invest in AI, creating a possible reverse or mutually reinforcing relationship.

The managerial implication is therefore that AI should be viewed as an enabling component of a broader credit-risk architecture. Model quality, data governance, human oversight and continuous validation remain necessary for sustainable implementation [5,9].

9. Benefits of AI-Based Credit Risk Models

• Improved predictive and underwriting accuracy through analysis of complex borrower patterns.

• Faster loan processing and reduced turnaround time through automated assessment and verification.

• Greater consistency in credit decisions across branches and customer segments.

• Potentially broader assessment of borrowers with non-traditional income or limited conventional credit histories.

• Continuous monitoring of borrower behaviour and earlier identification of financial stress.

• Operational efficiency through automation of routine credit-evaluation activities.

10. Challenges and Responsible AI Considerations

Data quality is fundamental to AI-based credit assessment. Incomplete, inaccurate or historically biased data can produce unreliable or discriminatory outcomes. Banks therefore require robust data-governance processes and continuous monitoring [5].

Explainability is particularly important in credit decisions because applicants may need to understand why credit was declined or why additional documentation was requested. Complex models should therefore be supported by appropriate explainability and documentation mechanisms.

Model risk also requires regular validation. Model performance can deteriorate when economic conditions or borrower behaviour change. Banks should monitor model drift, conduct periodic validation and retain appropriate human oversight for high-impact decisions [9].

Finally, alternative data can improve the information available for credit scoring but can also raise privacy, fairness and consent issues. Responsible AI therefore requires a balance between predictive capability, customer rights and regulatory expectations.

11. Practical Implications

11.1 Implications for Banks

Banks should adopt AI through a phased credit-risk framework that combines automated scoring with human review for complex or high-risk cases. Performance dashboards should monitor accuracy, processing time, approval quality, delinquency outcomes and model drift.

11.2 Implications for Credit-Risk Managers

Credit-risk teams should evaluate AI models using out-of-sample validation and multiple performance measures rather than relying only on overall accuracy. Stress testing and scenario analysis should be integrated into model governance.

11.3 Implications for Regulators and Governance

Regulatory and internal governance frameworks should address explainability, data protection, fairness, model validation, accountability and auditability. AI adoption should strengthen rather than weaken the principles of prudent lending.

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12. Limitations and Future Research

The study has several limitations. First, the sample consists of only ten banks, which restricts generalisability. Second, the analysis is based on secondary data and reported bank-level indicators rather than transaction-level credit data. Third, the source manuscript does not provide complete correlation, clustering or hypothesis-test statistics. Fourth, the cross-sectional design does not establish causality. Fifth, the measures of AI usage and AI maturity are not accompanied by detailed measurement definitions or validation procedures.

Future research should use larger samples of banks and longer time periods and should integrate objective measures such as default rates, NPA ratios, approval accuracy, false-positive rates, turnaround time and recovery performance. Panel-data or difference-in-differences approaches could provide stronger evidence on whether changes in AI adoption are associated with changes in credit-risk outcomes. Future studies should also compare specific AI techniques and examine explainability and fairness across borrower groups.

13. Conclusion

Artificial intelligence is increasingly relevant to credit-risk assessment and credit scoring because it enables banks to analyse large datasets, identify complex risk patterns and automate parts of the lending process. The selected-bank evidence in this study indicates variation in AI adoption and suggests that more advanced adoption is associated with stronger reported operational efficiency and risk-control characteristics.

The findings support the strategic value of AI in banking, particularly for improving processing speed, consistency and data-driven credit assessment. However, AI should not be treated as a substitute for sound credit governance. Data quality, explainability, model validation, fairness and human oversight remain essential.

The study therefore concludes that the value of AI in credit risk lies not simply in adopting advanced technology, but in integrating AI into a well-governed credit-risk framework. More rigorous longitudinal and bank-level empirical research is required before making strong causal claims about AI adoption and asset quality.

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