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Artificial Intelligence in Credit Risk Management: A Comparative Study of Traditional vs AI-based Models in Indian Banks

Marisetti Venkata Ramana
Assistant Professor, Department of Management,
Aditya Degree College, Tadepalligudem,
West Godavari District, Andhra Pradesh, India.
mramanamba143@gmail.com
Kanumuri Vinod Varma
Assistant Professor, Faculty of Management,
SRM Institute of Science & Technology, Deemed to be University,
Ramapuram, Chennai, Tamilnadu, India.
vinodvarmak2@gmail.com

ABSTRACT

Effective handling of credit risk is essential to the stability and profitability of the banking environment, particularly in the Indian banking environment context where non-performing assets (NPAs) are increasing, the regulatory environment is adversarial and technology is disruptive. The paper is investigating the comparison of the artificial intelligence (AI)-based credit risk assessment models with the traditional credit risk models within the Indian banks. The work is based on secondary sources and empirical insights by capturing the transformation of rules-based, human expert and statistics-driven methodologies to machine learning and deep learning models, differences in predictive performance, processing speed, interpretability, and serving of underserved borrowers. Findings indicate that AI-based approaches offer superior predictive performance and greater scalability, but they also raise issues of data quality, transparency ("black-box" risk), ethical bias, regulatory oversight and organisational readiness. The paper concludes by suggesting that Indian banks adopt a hybrid model combining human judgement with AI, strengthen data governance and model explainability, and develop regulatory frameworks for responsible AI deployment in credit risk.

Keywords: *credit risk management, artificial intelligence, Indian banking, machine learning, traditional models, predictive accuracy, model interpretability.*

1. INTRODUCTION

Credit risk management constitutes one of the most important functions of banks: the ability to assess the probability that a borrower will default, decide on loan approval, set appropriate pricing and monitoring, and provision for potential losses, directly affects bank profitability, capital adequacy and resilience. In the Indian banking sector, persistent challenges such as high NPAs, heterogeneous borrower profiles (including MSMEs and first-time borrowers), digital transformation pressures and regulatory changes make effective credit risk assessment more complex.

Traditionally, Indian banks have relied on statistical credit scoring models, expert judgement, credit bureau scores, financial statement analysis and collateral assessment. However, with the advent of large data volumes (structured and unstructured), digital transactions, alternative data sources (mobile, behavioural, social media) and advanced computing capabilities, artificial intelligence (AI) and machine learning (ML) models are increasingly being adopted for credit risk assessment in banking. For example, Indian studies note that AI, ML and deep learning are already intensively used in banking risk management, including credit risk assessment.

This paper aims to comparatively analyse traditional versus AI-based models for credit risk management in Indian banks, by exploring: (i) how the two approaches differ in model design, data sources, predictive accuracy and operational speed; (ii) the benefits of AI-based models in the Indian banking context; (iii) the limitations, risks and regulatory challenges; and (iv) recommendations for Indian banks to adopt responsible, hybrid frameworks.

The remainder of the paper is structured as follows: Section 2 gives a literature review; Section 3 describes the research method; Section 4 presents discussion and analysis; Section 5 outlines findings; Section 6 concludes; and Section 7 offers suggestions. (Note: numbering adjusted to match your template.)

2. LITERATURE REVIEW

In recent years, multiple studies have investigated credit risk management in banks globally and in India, the adoption of AI/ML for credit risk, and comparative performance of models.

Brown (2024) emphasizes that AI models, especially those based on ensemble and neural network algorithmologies, are much more accurate in predicting credit risk and more economical in their operation than older statistical algorithms.

Dhanya, Prathibha, and Mohanty (2024) demonstrates that AI-based credit scoring is useful in underwriting thin-file borrowers but has implementation issues including the old system and regulatory conservatism.

Hadji Misheva et al. (2021) underline that owe to explainable AI (XAI) instruments such as SHAP and LIME, there is a balance between model accuracy and interpretability in credit risk management.

Kothari (2025) examines the Indian regulatory situation regarding AI in lending, emphasizing the need to comply with data governance, transparency, and algorithmic fairness.

Lopes, Massano-Cardoso, and Pedrosa (2025), the willingness to use AI based mobile banking systems largely depends on consumer trust, transparency and perceived fairness.

Mortezapour and Afzali (2013) show that neural networks, genetic algorithms, and Bayesian models are better at credit scoring using hybrid computational optimization.

The article Redefining Credit Risk Management for Banks in India (2025) presents workable structures of integrating AI in banking, promoting incremental integration, data-sharing projects, and sound governance.

In an analysis of the role of artificial intelligence in transforming credit risk evaluation (2025), the authors provide a meta-analysis of research that reveals a consistent performance improvement in AI/ML models in retail credit scoring but warns about data leaks and bias.

“Artificial Intelligence in the Indian Banking System: A Systematic Analysis” (2025) maps AI applications across the banking ecosystem and notes uneven adoption levels among public, private, and NBFC sectors.

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"Credit Risk Prediction Using Machine Learning and Deep Learning" (2023) empirically compares ML and DL models, concluding that ensemble methods outperform traditional approaches though deep learning requires extensive data and sacrifices interpretability.

2.1 Traditional credit risk models

Historically, credit risk assessment has relied on logistic regression, discriminant analysis, scorecard models, expert-based judgment, and rules-based systems. In the Indian banking context, NPAs remain a key risk metric: for example a study found substantial linkage between NPAs and bank profitability, liquidity and operations in India. Models typically use borrower credit bureau scores, income, past behaviour, collateral, macro-economic indicators (such as bank-specific, regulatory and institutional factors influencing credit risk). Traditional models also face limitations: inability to incorporate large unstructured/alternative data, slower processing, limited scalability, and potentially weaker predictive power in complex, dynamic environments.

2.2 AI / Machine Learning in Credit Risk Assessment

AI and ML techniques (such as neural networks, decision trees, ensemble models like XGBoost, LightGBM) have been increasingly applied for credit risk prediction. For example, a study using credit-card default data found XGBoost achieved 99.4 % accuracy outperforming other models. Another Indian-context study on AI adoption in credit risk found that although AI adoption improves credit risk assessment, its direct impact on reducing processing time is weak in some cases. A recent empirical IR study found AI-based models demonstrate superior performance in identifying risky borrowers and capturing complex risk patterns compared to traditional methods. Moreover, Indian banks are increasingly using AI/ML in credit risk, fraud detection, cost management, etc.

2.3 Comparative advantages and challenges

The literature indicates several advantages of AI based models:

- Enhanced predictive accuracy due to the ability to use large volumes of structured + unstructured data, detect non-linear patterns and interactions.
- Real-time processing and decision-making, which speeds up loan approvals and improves customer experience.
- Improved inclusion of thin-file borrowers (those with no formal credit history) via alternative data and behavioural analytics.
- Scalability and automation benefiting operational efficiency.

Nonetheless, the challenges also are pointed out in the literature:

• Model interpretability (black-box AI) and the requirement of explainable AI (XAI) methods (e.g. SHAP, LIME) to make the model transparent and accountable under regulations.

Data quality, prejudice, morality and equity problems (e.g. whether previous data is prejudiced).

• India has regulatory, governance and oversight systems that are still developing; e.g., the Reserve Bank of India (RBI) warns NBFCs not to be too dependent on algorithmic credit models.

• Integration and change-management challenges: banks should establish organisational capability, infrastructure and risk governance in the adoption of AI.

2.4 Research Gap

Although literature on the utilisation of AI in the Indian banking industry is increasing and the performance of the models, there is still a need to critically compare and contrast traditional and AI-based credit risk models as applied in Indian bank contexts with respect to empirical data, model performance (accuracy, speed, coverage), and regulatory/organisational aspect. The paper will fill that gap by summarizing the available information and providing comparative impressions.

3. RESEARCH METHOD

The proposed research will utilize a mixed-methodological approach based on a review of secondary data and a comparative model analysis framework. With the limitation in accessing primary data (the proprietary models of banks are secretive), the process is majorly desk based but designed in a way that attracts comparative inferences.

3.1 Data Sources

The secondary data was gathered through academic journal articles, industry reports and regulatory publications on credit risk assessment in Indian banks and AI models in banking. The papers mentioned in Section 2 are considered key sources.

3.2 Comparative Framework

The paper compares classic credit risk models and AI-based models in terms of the following areas:

• Precision of input Data traditional (financial statements, bureau scores, collateral) vs AI-models (alternative data, transaction logs, unstructured behavioural data)
• Model method: logistic regression / scorecards against ML/ensemble/DL models.
• Predictive accuracy: according to literature (e.g., accuracy, F1, ROC-AUC)
• Speed and scalability: automation potential, processing time.
• Interpretability: understandable output of human vs black-box and XAI requirement.
• Potential to include: possibility to evaluate thin-file borrowers.
• Risk and governance transparency, bias, compliance with regulations, capacity requirements.

3.3 Comparative Analysis

Qualitative analysis of each dimension is done, using the literature. In the situation, when quantitative measurements can be found (e.g., accuracy of ML studies), these are cited. As an illustration, the credit risk prediction model that attained an accuracy of 99.4 with the help of XGBoost. The discussion highlights the situation in Indian banking, citing Indian-based literature (e.g., Redefining Credit Risk Management for Banks in India).

3.4 Limitations

Although the study has been thoroughly reviewed and comparatively analyzed, the research is not without limitations which should be admitted:

1. Relying on Secondary Data Sources: The research mostly uses secondary data in the form of journals, reports and documents that are publicly accessible. No direct access to proprietary datasets of the Indian banks restricts the empirical depth of the analysis.
2. Limited Availability of Banks Internal Bank Models: The majority of banks consider their credit scoring and AI models designs to be secrets. In turn, that meant that the comparative study was not able to incorporate direct quantitative analysis of model accuracy, validation processes, or internal performance estimations.

3. Absence of Primary Empirical Data: The conclusions of the study are not based on information collected by stakeholder interviews or surveys but on a synthesis of literature, because of the unavailability of the firsthand data about credit officers, data scientists, or regulators.
4. Heterogeneity Indian Banks: There is heterogeneity in the size, technology adoption, regulatory exposure, and maturity of Indian banks data. The generalised analysis of this study is not conclusive enough to reflect the subtle distinction among the public, and the non-banking financial institutions (NBFCs).
5. Fast Technological Change: AI and machine learning models grow fast, and new algorithms or regulatory frameworks could be developed after a study period. Thus, the findings might have to be updated periodically to keep them relevant to the existing practices.
6. Weak Quantitative validation: The research is a synthesis of reported accuracy scores (ROC-AUC, F1 scores) of previous studies, rather than producing them directly. Therefore, the outcomes are relative trends, and not original statistical testing.
7. Potential Publication Bias in Literature: The literature with positive results of AI models will have increased chances of publication as compared to those with non-positive results. This can create a bias of publicizing the benefits of AI over conventional models.

4. DISCUSSION AND ANALYSIS

Historically, the traditional credit risk management techniques in Indian banks, including logistic regression, discriminant analysis, and credit scoring system, have been based on the structured financial data and decision frameworks that are rule-based. These models have transparency and interpretability that is essential in regulatory compliance and internal audit. They usually, however, have constraints on capturing nonlinear relationships, behavioural patterns and unstructured data sources like social media activity or transaction stories. This means that conventional models may have issues of prediction accuracy, especially in dynamic lending systems whereby customer creditworthiness varies too quickly as a result of market changes, digital transactions, and socio-economic determinants. In addition, manual data processing and minimal automation also participate in the inefficiencies of operations, slowing down the cycle of loan approvals and exposing it to the risk of misclassification.

Contrarily, AI-powered credit risk management algorithms, which are motivated by machine learning (ML) and deep learning (DL) algorithms, increase predictive accuracy because they can combine both structured and unstructured data to detect more intricate patterns. Research on the implementation of AI systems in Indian banks (with random forests, gradient boosting, and neural networks) has reported greater accuracy and early detecting default than traditional models. AI facilitates real time credit scoring, portfolio analysis as well as adaptive learning which allow institutions to react promptly to borrower behaviour change. Nevertheless, explainability and transparency issues remain a problem because AI models are frequently black boxes, which attracts regulatory and ethical issues. Moreover, privacy of data, algorithm favoring as well as the proficient data scientist are also major impediments to massive application. Therefore, AI-based systems can be efficient and accurate, but their responsible introduction into the system of human control and governance is the key to long-term implementation in the Indian banking ecosystem.

4.1 Data Input and Model Technique.

The model that is commonly used in traditional models of Indian banks is based on credit bureau ratings, the financial statements of the borrowers, use of collateral and previous disbursement behaviour. These models are clear and easily known by risk-managers, but they can only work in segments whose credit history is thin and cannot work with large, high-dimensional data.

Conversely, AI-based models use wider sources of data such as transaction logs, mobile usage, payment/utility records, social behaviour, and geolocation, among other alternative data. As an example, AI application in credit underwriting assists in thin-filing borrowers with the help of hundreds of alternative data variables. Machine-learning algorithms (decision trees, random forests, gradient boosting, neural networks) are able to pick up non-linear patterns and interactions which are not captured by traditional linear models. An example of this is the credit-card default prediction study that employed the use of XGBoost and was found to be accurate.

Therefore, in terms of techniques and data, AI models provide a significant improvement: more complex pattern recognition, richer data, and flexibility.

4.2 Predictive Rightness, Speed and Scalability.

Increased accuracy has been cited to be one of the major benefits of the technology. It is observed that ML/AI models are more efficient in risky borrower identification compared to the traditional models. To illustrate the point, one of the studies titled Influence of Artificial Intelligence on Credit Risk Assessment discovered that AI-based models are more effective than conventional ones. Similarly, AI has been seen to change risk management and underwriting in the Indian context.

Speed and scalability: AI models can be used to make real-time or near-real-time decisions, which is one of their advantages considering the development of digital lending in India. The time of loan approval can be shortened using alternative data and automated scoring. With AI and ML, blogs record real-time credit decisions. Traditional models often involve manual review, fixed scorecards, slower decision times, and are less scalable when volumes rise.

Therefore, in the Indian bank context where digitisation and quick turnaround matter (especially for retail, MSME, and fintech-partnered lending), AI models present operational advantages.

4.3 Interpretability and Inclusion of Underserved Borrowers

Interpretability: Traditional models are well understood; scorecards and credit officers can trace decision logic. AI models, especially deep neural networks, often act as “black boxes” unless explainable AI (XAI) techniques are used. Studies emphasise the need for SHAP, LIME to provide trust and transparency. For Indian banks, regulatory oversight and lending fairness demand transparency in credit decisions. Hence the advantage of AI can be limited without sufficient interpretability and governance.

Inclusion of underserved borrowers: One of the strong arguments in favour of AI models in India is that they can assess creditworthiness of borrowers lacking formal credit history (thin-file). As an example, alternative data inclusion will assist lenders in assessing new segments. These segments are not provided in traditional models because of absence of data. Thus, AI models have potential based on financial-inclusion perspective.

4.4 Risk, Governance and Regulatory Challenges.

The AI models introduce extra risks and governance needs. Indian regulators have warned non-bank finance companies (NBFCs) not to over rely on algorithmic credit models, however, rule based models can cause errors, particularly in changing market situations. Although this is a specific reference to NBFCs, the same applies to banks. They include: data bias, model drift, non-auditable, algorithmic discrimination, no interpretability, regulatory transparency. Literature highlights that banks should invest in model governance, data quality, ethical AI structures.

Moreover, organisations have to be prepared: the banks are required to establish infrastructure, data management capacity, AI/ML skills, and to introduce AI into the already existing risk-management systems. An isolated AI model that lacks extended governance might not have the anticipated outcomes.

4.5 Synthesis: Indian Bank in Traditional vs AI-Based Models.

Going by the above, it is possible to summarise the comparative strengths and weaknesses:

Dimension	**Traditional Models**	**AI/ML-based Models**
Data inputs	Structured, conventional (bureau, finance)	Structured + unstructured + alternative data
Model technique	Scorecards, regression, expert judgement	ML/ensemble/deep learning, pattern discovery
Predictive accuracy	Good for known segments, limited complexity	Higher accuracy, better at non-linear patterns
Speed & scalability	Manual elements, slower	Automated, real-time decisioning
Interpretability	High transparency	Often black-box — needs XAI
Inclusion of thin-file	Weak inclusion	Stronger potential to include underserved
Governance & regulatory risk	Established frameworks	Higher oversight demands, risk of bias, auditability
Organisational readiness	Mature in many banks	Requires investment in tech/infrastructure/talent

The AI-based models have a high potential in the Indian banking sector, where the credit environment is complicated (diverse borrowers, inclusion agenda, regulatory attention, increased digital lending). Nonetheless, they are not able to merely substitute traditional models without considering governance, transparency as well as integration to bank processes.

As an example, an Indian study on AI-driven credit risk management across banks revealed that key measures (provision coverage ratio, capital adequacy ratio) are more effective with the introduction of AI. That indicates material stability advantages. In the meantime, policy/regulatory discourses focus on establishing structures to use AI in lending transactions.

In this way, the fact that Indian banks should take a hybrid strategy can be justified: in large, digital, and high-volume segments (retail, thin-file), apply AI models, but in more complicated and large-corporate lending, or limited data, maintain human expertise and traditional scorecards.

5. FINDINGS

Based on the comparative analysis, the following are the major findings:

1. The AI-powered models will provide superior predictive performance and speed: According to the literature, ML/AI models will be superior to the traditional statistical models in both terms of risky borrower identification and minimizing prediction error. Indicatively, XGBoost research was found to be very precise. Indian banks that embrace AI declare better credit risk management capacity.
2. More inclusion of underserved borrowers through AI: AI models have a stronger position to evaluate thin-file borrowers with alternative data therefore facilitating increased financial inclusion, which is among the major policy objectives in India.
3. Interpretability is also a major limitation: As much as AI provides us with performance, many models are not transparent, which prevents trust in the stakeholder, auditability and compliance with regulations. Therefore, it is necessary to adopt explainable AI (XAI) methods.
4. The role of governance, data and organisational requirements are important: Banks need to establish data infrastructure, AI/ML talent, model governance structures, and implement AI in the current risk management procedures. Otherwise, the advantage of AI models will not be as tangible.
5. Caution on the part of the regulator and necessity of regulation: The regulators in India have cautioned against excessive dependence on the use of algorithmic models and have made an assertion that AI models should not be a blind replacement of human judgement. According to literature, regulation in this area is taking a new dimension and banks are supposed to be in control, transparency and to be ethical in their actions.
6. Hybrid model is best: The results indicate that neither traditional nor AI models can be considered adequate to serve the needs of the banks; a combination of the advantages of these two approaches provides the flexibility to the banks, their strength, and coverage of the inclusiveness. As an example, banks may use AI to do retail digital lending and traditional models to use large corporate exposures.

6. CONCLUSION

The management of credit risk is also one of the pillars of banks operations. The use of artificial intelligence (AI)-based credit risk models in the Indian banking sector is a major opportunity since the banking sector is digitally transformed, with the need to include all, regulated by law, and under increasing volumes. The comparison analysis reveals that AI models are better than traditional models in predictive accuracy, speed and the inclusion of thin-file borrowers, as well as assist banks to scale their operations and adopt new data sources.

Nevertheless, AI benefits do not come automatically. The most important issues, including model interpretability, data governance, bias, compliance with regulations, and preparedness in organisations, should be touched upon. Banks run the risk of applying AI models in a less optimal way or even creating new risks without investing in these supporting governance and infrastructure capabilities.

The best next step that the Indian banks can take is a hybrid strategy that will see AI/ML-driven scoring of digital and high-volume segments and traditional expert/scorecard-driven models on complex or high-exposure deals. This will maintain interpretability, control and human decision making where appropriate, and use AI as an asset to speed, accuracy and inclusion.

To recap it all, incorporating AI to change the credit risk management is not only a technical change but also an organisational, governance and regulation change. Banks that align their strategy, infrastructure, talent and risk culture to AI adoption would be in a better position to deal with credit risk in the ever-changing Indian banking environment.

7. SUGGESTIONS

Based on the analysis and findings, the following suggestions are made for Indian banks, regulators and policymakers:

For Banks

- Invest in building robust data infrastructure, including integration of alternative data, real-time transaction data and unstructured data sources.
- Adopt explainable AI (XAI) techniques (e.g., SHAP, LIME) to ensure model transparency, auditability and stakeholder trust. (arXiv)
- Develop a hybrid credit risk assessment framework: apply AI/ML models for digital/retail lending and maintain traditional models with human oversight for large/complex exposures.
- Institute strong model governance, regular validation, bias detection, model-drift monitoring and ethical AI frameworks.
- Engage in change management: train risk staff, data scientists, credit officers; monitor organisational readiness.
- Monitor inclusion metrics, ensuring that AI models do not unintentionally discriminate or exclude segments.
- Collaborate with fintechs/alternative-data providers to enhance data sources for thin-file borrowers and improve inclusion.

For Regulators & Policymakers

- Provide clear regulatory guidelines for AI/ML model deployment in credit risk, including auditability, transparency, bias mitigation and accountability. For example, the RBI's caution to NBFCs is relevant.
- Encourage banks to adopt frameworks for responsible AI use in finance, such as infrastructure, capacity, policy, governance, protection and assurance compartments.
- Support research and standardisation of explainable AI, model validation techniques, industry-wide benchmarks and data-sharing (while safeguarding privacy).
- Promote financial inclusion by facilitating alternative data access (with safeguards) for thin-file borrowers and lending to underserved segments.
- Ensure oversight mechanisms for algorithmic lending, including audit-trails, model documentation, stress-testing and scenario analysis.

For Researchers

- Conduct primary empirical studies using Indian-bank proprietary data (if accessible) to compare model performance over time, by borrower segment, product and region.
- Explore behavioural and psychological factors in credit risk when using AI models (e.g., borrower behaviour changes in digital lending).

- Investigate the interaction of AI models with organisational factors (data culture, talent, governance) and regulatory frameworks in India.

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