# Impact of Artificial Intelligence on Credit Risk Assessment in Indian Commercial Banks

**Shri. Pruthviraj Narayan Ghatage**
Course Co-Ordinator, Online MBA
Centre for Distance and Online Education,
Shivaji University, Kolhapur.
Mob. 8888973344, E-mail – ghatagepruthviraj2015@gmail.com

**Abstract -**

This paper examines how AI affects credit risk assessment in Indian commercial banks. A mixed-methods approach was used, combining surveys of bank risk officers and analysis of secondary data (e.g. RBI NPA statistics and bank reports). We find that AI-driven credit-scoring models can significantly improve default prediction accuracy and reduce non-performing assets (NPAs) in high-volume segments (retail, MSME). Employees' perceptions of AI's benefits (faster processing, better monitoring) align with these modest performance gains. However, banks also emphasize risks: data bias, model opacity, and dependency on vendors, echoing RBI warnings to use explainable and fair AI. Regulatory frameworks (e.g. RBI's FREE-AI guidelines and model risk norms) now mandate governance and transparency in AI use. In summary, AI holds promise for more efficient and inclusive credit delivery, but must be implemented with robust oversight.

**Introduction -**

Artificial intelligence (AI) is rapidly transforming credit risk management in banking. AI systems can analyze vast amounts of financial and behavioral data at high speed, uncovering complex patterns that traditional methods may miss. In emerging markets like India, this matters especially as digital lending grows: one study estimates India's digital credit market may reach $515 billion by 2030. By leveraging AI for credit scoring and fraud detection, banks can extend loans to "credit invisibles" (borrowers without formal credit histories) and strengthen early-warning systems for default.

However, AI also introduces new risks. RBI officials have highlighted dangers from algorithmic bias, opaque "black-box" models, and cybersecurity vulnerabilities if many lenders use similar AI systems. They urge human-in-the-loop oversight, explainable models, and high-quality data to keep AI-driven decisions fair and transparent. Recent RBI frameworks (e.g. the FREE-AI Committee's "Seven Sutras" for responsible AI) emphasize trust, accountability, and explainability in financial AI.

This study explores AI's impact on credit risk assessment in Indian commercial banks. We integrate primary data from bank officials with secondary data on loan performance, aiming to quantify AI's effects on key risk outcomes (NPAs, default prediction accuracy) and understand banks' experiences and challenges.

**Objectives of the Research -**

The research objectives are to:

- **Assess performance impacts.** Measure how AI adoption affects credit risk metrics (e.g. NPA rates, default prediction accuracy) in Indian banks.
- **Capture stakeholder perceptions.** Survey credit-risk officers and loan managers to gauge their views on AI's benefits, challenges, and changes in workflow.
- **Examine regulatory context.** Review RBI guidelines and industry standards on AI in lending to understand how governance and compliance shape AI use.

- **Identify best practices.** Derive practical recommendations for banks to implement AI responsibly (ensuring fairness, explainability, and alignment with regulations).

**Research Methodology -**

- **Primary data collection:** A structured questionnaire was administered to credit risk managers and officers across major Indian banks. The survey probed changes in decision accuracy, processing speed, staff training, and perceived biases since AI tools were introduced. In-depth interviews complemented the survey, allowing risk officers to elaborate on implementation experiences and specific case studies. (This approach mirrors Kaur *et al.*'s use of employee surveys to study AI in Indian banking.)
- **Secondary data analysis:** We compiled bank performance data and RBI publications. Quantitative metrics included NPA ratios, loan defaults, and credit score distributions before and after AI deployment. Secondary sources also comprised RBI reports and model risk guidelines, such as the Aug 2024 draft circular mandating that credit models be "unbiased, explainable, and verifiable", and RBI's FREE-AI framework outlining ethical AI principles. Annual reports of banks and industry studies were text-mined to track AI adoption levels and organizational changes over 2018–2025.
- **Analytical methods:** Quantitative data were analyzed using statistical tests to compare pre- and post-AI metrics (e.g. difference-in-differences for default rates). Qualitative responses were coded for common themes (efficiency gains, challenges, oversight mechanisms). We controlled for confounding factors (economic cycles, regulatory changes) when attributing changes in risk outcomes to AI. Robustness checks (sensitivity analyses, subgroup splits) ensured findings were not driven by outliers or specific banks.

**Theoretical Framework -**

The study draws on technology adoption and risk management theories. We adopt the Technology Acceptance Model (TAM) to interpret how bank employees adopt AI tools. TAM posits that *perceived usefulness* (does AI improve decision quality?) and *perceived ease of use* (is the AI tool user-friendly?) drive acceptance. In our interviews, these constructs help explain attitudes: for instance, staff were more favorable toward AI when they saw clear gains in screening accuracy (high usefulness), and when interfaces were intuitive.

Beyond TAM, we recognize sociotechnical systems theory, which emphasizes that AI effectiveness depends on the interaction of technology with human expertise and processes. For example, even the best algorithm requires skilled analysts to interpret borderline cases, and processes must be re-engineered to leverage real-time scoring. We also consider the resource-based view, which suggests AI can yield competitive advantage if it provides valuable, rare capabilities (like proprietary risk models). Finally, institutional theory reminds us that adoption is influenced by norms and regulations – banks may implement AI not only for efficiency, but because RBI and peers expect it.

**Major Findings –**

- **Improved prediction accuracy and lower NPAs.** Consistent with recent studies, we find that algorithmic credit models **significantly boost default prediction accuracy** and **reduce NPA ratios**, especially in retail and MSME loan portfolios. For example, lenders that adopted ML-based scoring saw more accurate probability-of-default estimates, and aggregate NPA levels fell relative to peers who lagged in AI. This aligns with Singh & Mohanty's panel analysis, which showed "significant improvement in prediction accuracy and reduced NPA ratios" post-AI adoption.

- **Modest effect sizes and uneven gains.** Despite statistical significance, effect sizes are generally small to moderate. Kaur *et al.* report Cohen's d of 0.21–0.34 for credit-risk improvements after AI introduction. We observe that **monitoring and control functions benefit most** (e.g. real-time portfolio surveillance), while **administrative tasks see smaller changes**. In other words, AI automates early warning and screening, but core lending decisions still rely on human judgment.
- **Employee perceptions confirm outcomes.** Surveyed officers overwhelmingly noted faster processing and better risk flagging since AI tools were deployed. Importantly, these perceptions **converge with our performance data**: banks where staff reported improved decision quality did in fact show relative gains in metrics. This mirrors Kaur *et al.*'s finding that employee perceptions and objective credit outcomes "reinforce one another". Positive staff feedback suggests that AI is being integrated in ways that enhance (rather than replace) expert input.
- **Challenges: bias, explainability, and data quality.** Officers frequently cited concerns about biased inputs and opaque models. Without interpretability tools, some managers are uneasy about algorithmic "black-box" suggestions. This echoes RBI Deputy Governor Rao's warnings of algorithmic bias and the need for explainable AI in credit decisions. Our qualitative data reveal that banks are instituting human-in-the-loop reviews for outlier cases, and investing in data-cleaning to mitigate skewed training data (e.g. correcting historical bias against certain regions).
- **Regulatory influence fosters governance.** Following RBI guidance, banks have developed formal AI governance frameworks. Notably, the draft circular requires each bank to have a board-approved model risk policy addressing model lifecycle management. Several banks have set up committees to monitor AI model performance and to ensure models remain explainable. These moves align with RBI's FREE-AI principles (trust, fairness, accountability) and suggestions for continuous model validation. In practice, we find that **compliance pressures are pushing banks to adopt hybrid solutions** (combining human and machine scoring) and to regularly audit models for bias.

**Research Summary –**

In summary, this research used a triadic methodology (survey, interview, and data analysis) to paint a nuanced picture of AI's impact on credit risk in Indian banks. We found **clear signs of efficiency and accuracy gains**, but also confirm that these gains are incremental. The study reinforces the view that AI supplements human expertise: banks that leveraged both data-driven insights and experienced judgment achieved the best credit outcomes. Our mixed approach highlights the value of triangulating subjective and objective data – an approach pioneered by Kaur *et al.* – providing confidence that findings are not artifacts of a single method.

Practically, the research suggests that Indian banks can and should continue deploying AI for credit decisions, but with care. Benefits are maximized when AI is accompanied by employee training, robust data governance, and transparent processes. The convergence of perceptions and performance in our results suggests that when staff trust the tools, the institution reaps rewards. Finally, by aligning our analysis with current RBI guidelines and industry best practices, we ensure our recommendations (e.g. continuous validation, explainability provisions) are actionable and compliant.

**Keywords –**

- Artificial Intelligence (AI)
- Credit Risk Assessment
- Commercial Banking (India)

- Non-Performing Assets (NPA)
- Model Risk Management
- Regulatory Compliance

**Conclusion -**

This study demonstrates that AI can positively transform credit risk assessment in Indian commercial banks, though the impact is measured and conditioned by governance. Algorithmic credit-scoring tools improve risk prediction and lower NPAs, confirming that data-driven methods add value to lending. These gains are, however, modest in magnitude and uneven across portfolio segments. Crucially, we find that **human oversight remains essential**: banks address model limitations by incorporating expert review and prioritizing interpretability.

Importantly, the Indian regulatory environment is evolving to support responsible AI. RBI's recent frameworks explicitly require that AI models used for credit are explainable and free of bias. Banks that heed these principles – by instituting board-approved AI policies, regular audits, and customer transparency – are better positioned to harness AI effectively.

In conclusion, AI is a powerful tool for credit risk management in India, but not a panacea. Our findings suggest the best outcomes occur when advanced analytics are blended with strong institutional controls and human judgment. Policymakers and practitioners should continue to refine AI governance (per RBI's "Seven Sutras" of trust and fairness) as AI becomes more pervasive. Future research should track longer-term impacts (e.g. post-2026 data) and explore emerging technologies (like explainable ML) to further strengthen India's credit ecosystem.

**References -**


- Kaur, K., & Salgotra, P. (2024). *Artificial Intelligence and Credit Risk Assessment in Indian Commercial Banks: A Triangulated Study Integrating Employee Perceptions with Objective Performance Metrics.* Journal of Computational Analysis and Applications, 33(5), 3226–3260.
- Singh, H., & Mohanty, A. (2025). *Algorithmic Risk or Risk Mitigated? A Comparative Study of Credit-Risk Assessment Accuracy Pre- and Post-Automation in Indian Commercial Lending.* Journal of Contemporary Business Research. DOI: 10.1177/3049513X251405596.
- Goyal, K., Garg, M., & Malik, S. (2025). *Adoption of artificial intelligence-based credit risk assessment and fraud detection in banking services: A hybrid approach (SEM-ANN).* Future Business Journal, 11, Article 44.
- Chambers and Partners (2025). *RBI Committee Report on Responsible AI in the Financial Sector (FREE-AI Framework).* [Online article summarizing RBI guidelines].
- MediaNama (2025). *"Trust is the Currency of Banking—And AI Could Undermine It Without Guardrails, Says RBI."* (Sept 23, 2025). [Report on RBI Deputy Governor Rao's speech].
- Fox Mandal & Associates (2024). *"RBI Releases Draft Circular on Model Risk Management in Credit for Lenders."* Lexology (India) (Sept 10, 2024). [Discussion of RBI's model risk guidelines]


❑❑❑