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Research Paper

Human – AI Collaboration in Credit Risk Management Enhancing Decision – Making and Risk Governance in Indian Banking Sector

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Abstract:
Artificial intelligence (AI) is increasingly influencing credit-risk management by enabling banks to analyse extensive borrower information, recognise risk patterns and support more informed lending decisions. Kalyani and Gupta (2023), through a systematic review of 734 studies, demonstrate the expanding role of AI and machine learning across banking activities, including credit scoring and risk management. (Springer) However, stronger predictive capability does not necessarily eliminate the need for professional judgement. Shi et al. (2022) found that machine-learning approaches can improve credit-risk prediction, while also identifying concerns relating to data imbalance, model transparency and consistency. (Springer) These concerns have increased interest in approaches that combine technological capability with human expertise. Sachan et al. (2024) show that human–AI collaboration can support augmented financial underwriting by reducing decision inconsistency and improving the quality and explainability of lending decisions. (ScienceDirect) Against this background, the present study examines human–AI collaboration in credit risk management, with particular emphasis on decision-making and risk governance in Indian banking. The study adopts a quantitative research approach and proposes primary data collection from 400 banking professionals engaged in credit assessment, lending, risk management and related functions. The conceptual framework incorporates AI predictive capability, explainability, data quality, risk-detection capability, human–AI collaboration, trust, human oversight and governance maturity as important dimensions influencing credit decision quality and risk-management effectiveness. The study argues that AI should function as an intelligent decision-support mechanism rather than an autonomous replacement for banking professionals. Effective collaboration between AI systems and human decision-makers can potentially improve analytical efficiency while preserving contextual judgement, accountability and responsible oversight.

Keywords: Scoring, Augmented, Lending, Underwriting, Replacement, Preserving..Etc,

1.0 Introduction:

1 Emergence of Artificial Intelligence in Banking:

Artificial intelligence (AI) is becoming an increasingly important part of modern banking. Banks now handle large amounts of information relating to customers, transactions, financial behaviour and credit histories. Analysing such information through conventional methods can be time-consuming and may not always reveal relationships that are important for assessing credit risk. AI and machine-learning techniques provide banks with the ability to examine large datasets, identify patterns and support more informed assessments of borrowers. The Reserve Bank of India (RBI) has recognised credit scoring as one of the significant applications of AI and machine learning in financial services, while also drawing attention to responsible use, including privacy, transparency, explainability and accountability (Reserve Bank of India).

2 Changing Role of Human Judgement in Credit Decisions:

Although AI can process information rapidly, credit decisions cannot always be reduced to numerical predictions. Financial information may be incomplete, unusual or affected by circumstances that are difficult for an automated system to interpret. Experienced credit professionals can consider the broader context of a borrower, question unexpected results and apply professional judgement when an AI recommendation does not appear appropriate.

This makes the relationship between human expertise and AI particularly important. Research in financial underwriting indicates that combining human judgement with AI-based decision support can reduce inconsistencies in lending decisions and improve the overall decision process rather than completely replacing human underwriters (Sachan et al., 2024). (ScienceDirect)

3 Human–AI Collaboration in Credit Risk Management:

The movement from complete automation towards human–AI collaboration represents an important development in credit risk management. In a collaborative arrangement, AI generates analytical insights or recommendations, while the final assessment can involve human review, interpretation and, where necessary, intervention. Such an approach recognises that humans and machines may possess different but complementary strengths.

AI can examine large quantities of information within a relatively short period and identify relationships that may be difficult for an individual to detect. Human decision-makers, on the other hand, can consider circumstances surrounding the borrower and challenge recommendations that appear questionable. Evidence from financial decision-making research suggests that human involvement in AI-supported processes can provide an additional layer of judgement rather than necessarily weakening decision quality (Management Science).

4 Indian Banking Context and Regulatory Relevance:

The Indian banking sector provides an important setting for studying human–AI collaboration because banks are increasingly adopting digital technologies while operating within a developing regulatory framework for AI-based financial services. The growing use of automated and AI-supported systems creates a need to balance technological innovation with prudent risk management.

The emerging regulatory direction places greater emphasis on appropriate AI and machine-learning governance, model validation, monitoring and human oversight of automated decision-making. Recent RBI proposals concerning model-risk management have also highlighted the importance of managing risks associated with AI and machine-learning models throughout their lifecycle (Reuters).

1.2 Need of the Study:

The growing use of artificial intelligence in banking is changing the way credit decisions are assessed, monitored and managed. AI can process extensive borrower information and identify risk patterns quickly, but its increasing use also raises concerns about data quality, bias, transparency, model reliability and excessive dependence on automated recommendations. The Reserve Bank of India has highlighted both the potential of AI/ML to improve credit assessment and the need for responsible adoption, including appropriate governance and oversight. (Reserve Bank of India)

The study is therefore needed to understand whether combining AI-based analytical capabilities with human judgement can produce more reliable credit decisions than relying on either approach independently. It also examines how human oversight, explainability, accountability and governance can reduce potential AI-related risks. This is particularly relevant for Indian banks seeking to adopt advanced technologies while maintaining financial stability, responsible lending and regulatory compliance. (Reserve Bank of India)

1.3 Objectives of the Study:

1. To examine the role of AI in credit risk management in Indian banking.
2. To assess the impact of human–AI collaboration on credit decision-making.
3. To evaluate the role of AI governance in strengthening credit risk management.

4. To identify the challenges associated with human–AI collaboration in banking.

1.4 Scope of the Study:

The study focuses on the growing role of human–AI collaboration in credit risk management within the Indian banking sector. It examines how AI-supported systems assist banking professionals in evaluating borrowers, identifying potential credit risks and improving lending decisions. The study covers key dimensions including AI capability, human judgement, explainability, trust, decision quality and risk governance. Its scope includes banking professionals involved in credit appraisal, risk management, lending operations, analytics and related functions. Particular attention is given to the interaction between AI-generated recommendations and human oversight. The study also considers governance concerns such as accountability, transparency, bias, model reliability and responsible use of AI in credit-related decisions within the Indian regulatory environment.

1.5 Review of Literature:

1 Mirabile, Corazza and Alonso-Moral (2026): Examined trust in human–AI collaboration in finance through a bibliometric and systematic literature review. Their study shows that AI is increasingly embedded in credit scoring, risk management and other financial activities. The authors emphasise that trust influences collaboration, accountability and the acceptance of AI-supported decisions. Their findings suggest that effective financial AI requires technical capability together with explainability, governance and appropriate human involvement. (Springer)

2 Kou et al. (2026): Proposed a human–AI hybrid finance perspective that moves beyond viewing AI as an isolated predictive tool. Their framework considers financial decision-making as a joint process involving information gathering, interpretation, recommendations, approval, human override, monitoring and feedback. The study highlights delegation, explainability, meaningful oversight and calibrated reliance as important elements of hybrid financial decision systems. This perspective is particularly relevant to developing responsible human–AI credit-risk decision processes in banking. (Springer)

3.Goyal, Garg and Malik (2025): Investigated the adoption of AI for credit-risk assessment and fraud detection in banking using a hybrid SEM–ANN approach. Their study examined factors influencing continued AI utilisation and identified technological knowledge and attitudes towards technology as important considerations. The findings indicate that AI adoption can support more sophisticated credit-risk and fraud-management practices, while issues such as privacy, ethics and regulatory compliance remain important considerations for financial institutions. (Springer)

4 Vuković, Dekpo-Adza and Motivic (2025): Conducted a systematic scient metric review of AI integration in financial services. Their analysis examined developments in areas including credit scoring, fraud detection, financial inclusion and other financial applications. The study demonstrates the rapid expansion of AI across financial activities while identifying regulatory and governance challenges accompanying this transformation. Its findings reinforce the need to balance technological efficiency with responsible implementation, particularly where AI influences high-stakes financial decisions. (Nature)

5 Sachan, Almaghrabi, Yang and Xu (2024): Examined human–AI collaboration in financial underwriting and argued that completely eliminating human underwriters is not necessarily an effective strategy. Their study developed an augmented decision-support approach to examine inconsistencies in human lending judgements and improve decision quality. The research demonstrates the value of combining AI analysis with human expertise, particularly through explainable lending decisions and systematic evaluation of previous underwriting decisions. (ScienceDirect)

6 Kalyani and Gupta (2023): Conducted a systematic literature review and meta-analysis covering 734 studies on AI and machine learning in banking. Their review identified substantial applications across banking functions, including credit scoring and risk management. The authors noted that AI can strengthen credit-risk modelling and improve predictive capabilities, while challenges associated with security, trust and implementation remain. The study provides evidence that AI has become an important component of contemporary banking transformation. (Springer)

7 Shi et al. (2022): Systematically reviewed 76 studies examining machine-learning approaches to credit-risk assessment. Their analysis found that deep-learning and ensemble techniques frequently outperform conventional statistical approaches in prediction accuracy. At the same time, the authors identified data imbalance, dataset inconsistency and model transparency as continuing challenges. The study demonstrates that technological accuracy alone is insufficient for effective credit-risk management and highlights the importance of developing reliable and interpretable AI-based credit models. (Springer)

8 Bussmann et al. (2021): Developed an explainable machine-learning approach for credit-risk management. Their research demonstrates how AI models can be applied to credit-risk assessment while improving the interpretability of model outputs. The study is particularly relevant to banking because complex AI models can create difficulties when decision-makers need to understand the reasons behind predictions. The authors therefore contribute to the argument that explainability should accompany predictive performance in responsible credit-risk applications. (Springer)

9 Bhatore, Mohan and Reddy (2020): Reviewed machine-learning techniques used for credit-risk evaluation. They emphasised the importance of credit scoring, continuous monitoring of borrower behaviour and the identification of patterns associated with default and fraud. Their review indicates that machine-learning methods can support more effective risk assessment than purely conventional approaches. The study also demonstrates the growing importance of data-driven techniques in reducing potential non-performing assets and improving lending decisions. (ResearchGate)

10 Gambacorta, Huang, Qiu and Wang (2019): Compared machine-learning-based credit-scoring models with traditional credit-risk models using transaction-level fintech data. Their research examined how machine learning and non-traditional information affect the prediction of credit losses and defaults. The findings indicate that machine-learning approaches can improve predictive performance, particularly when richer information is available. The study provides an important foundation for understanding how AI-supported credit assessment can complement conventional banking risk models. (Bank for International Settlements)

1.6 Research Gaps:

1.Limited Evidence on Human–AI Collaboration: Existing studies largely examine AI-based credit scoring and prediction accuracy, while limited empirical evidence explains how human judgement, AI recommendations and professional intervention jointly influence credit-risk decisions in Indian banks.

2.Insufficient Integration of Governance and Decision Quality: Previous research frequently evaluates technological performance separately from governance. Limited attention has been given to how explainability, accountability, human oversight and model governance collectively influence credit decision quality.

3. Lack of Indian Banking-Specific Empirical Evidence: Much existing evidence originates from international financial institutions and fintech environments. There remains insufficient empirical research examining human–AI collaboration within India's distinctive banking, regulatory and institutional environment.

4. Underexplored Human Factors in AI-Assisted Lending: Existing literature emphasises predictive accuracy but gives comparatively less attention to human trust, professional experience, willingness to challenge AI recommendations and human override behaviour during actual credit-risk assessment processes.

1.7 Research Methodology:

1 Research Design:

The study adopts a quantitative, cross-sectional research design to examine human–AI collaboration in credit risk management within the Indian banking sector. A structured questionnaire is used to collect primary data from banking professionals who have knowledge of credit assessment, risk management, lending operations, analytics or AI-supported banking systems. The design enables the study to examine relationships among AI capabilities, human–AI collaboration, credit decision quality and risk governance.

2 Population and Sampling:

The target population comprises employees working in Indian banking institutions, particularly those associated with credit appraisal, credit risk, loan processing, risk analytics, compliance and related functions. A sample of 400 respondents is proposed for the study. Purposive sampling is adopted because respondents need relevant professional exposure to credit-related decision-making. Wherever feasible, respondents are drawn from public-sector and private-sector banks to provide broader representation of the Indian banking environment.

3. Data Collection Instrument:

Primary data are collected through a structured questionnaire developed from the study objectives and relevant literature. The questionnaire covers AI capability, AI explainability, human–AI collaboration, trust in AI, human oversight, credit decision quality and AI governance. Responses are measured using a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree. A small pilot study may be undertaken before final administration to identify unclear or ambiguous statements.

1.8 Data Analysis:

The collected data are analysed using SPSS and SmartPLS. Descriptive statistics are used to summarise respondent characteristics and construct responses. Reliability is assessed through Cronbach's alpha and composite reliability, while validity is examined using factor loadings, Average Variance Extracted (AVE) and discriminant validity. PLS-SEM is used to test the proposed relationships, including direct, mediation and moderation effects. Hypotheses are evaluated using path coefficients, bootstrapping, t-values, p-values and explanatory power (R^2).

Recent Credit-Risk Indicators of Indian Banks:

Table 1: Selected Credit-Risk Indicators of Scheduled Commercial Banks:

Indicator	Recent RBI observation	Interpretation
Gross NPA Ratio	3.2%	Indicates substantial improvement in asset quality
Net NPA Ratio	0.8%	Shows relatively lower residual stressed assets
Capital to Risk-Weighted Assets Ratio (CRAR)	16.8%	Indicates strong capital resilience
AI/ML use in credit assessment	Increasing	Supports data-driven credit-risk evaluation
Model-risk governance	Strengthening	Reflects increasing regulatory attention

Source: Reserve Bank of India, *Financial Stability Report* and Annual Report.

Interpretation: The indicators suggest that Indian banks have strengthened their overall financial resilience while continuing to face the need for effective credit-risk identification. The increasing use of AI and machine learning provides opportunities for improved assessment and monitoring. However, stronger model governance remains necessary to ensure reliable, transparent and accountable credit decisions.

2. Recent Banking Credit Indicators

Table 2: Credit Growth and Asset-Quality Indicators:

Indicator	Recent RBI figure	Period
Gross bank credit	₹164.32 lakh crore	2024
Personal-loan credit	₹53.31 lakh crore	2024
Gross NPA ratio	2.8%	2024
Net NPA ratio	0.6%	2024
CRAR (Tier 1)	14.8%	2024

Source: Reserve Bank of India, banking-sector statistical indicators.

Interpretation: The figures indicate substantial expansion in bank credit alongside improvement in asset quality. The relatively low gross and net NPA ratios suggest stronger credit-risk conditions, while the high Tier-1 capital ratio indicates resilience. Nevertheless, continued credit expansion increases the importance of accurate borrower assessment and effective technology-supported risk monitoring**.**

1.9 Discussion:

The findings and recent evidence indicate that artificial intelligence is becoming increasingly relevant to credit risk management in Indian banking. AI-supported systems can process large volumes of financial information, recognise patterns and assist institutions in identifying potential credit risks more efficiently than conventional approaches alone. However, technological capability does not automatically ensure better lending decisions. The effectiveness of AI depends considerably on how its recommendations are interpreted and incorporated into professional judgement. The literature reviewed in this study supports the importance of combining AI capabilities with human expertise. Human–AI collaboration can allow banking professionals to examine AI-generated recommendations, identify unusual cases and exercise judgement when automated outcomes appear inconsistent with borrower circumstances. This collaborative approach may therefore provide greater flexibility than either completely manual or completely automated decision-making.

1.10 Conclusion: Human–AI collaboration is emerging as an important approach to strengthening credit risk management in Indian banking. AI can improve the speed, consistency and analytical depth of credit assessment, while human professionals contribute contextual understanding, experience and accountability. The study highlights that effective collaboration requires more than technological adoption; it depends on explainability, reliable data, appropriate human oversight and strong governance mechanisms. AI should therefore be viewed as a decision-support capability rather than a complete substitute for professional judgement. Indian banks can achieve more responsible and effective credit decisions by combining technological intelligence with human expertise while maintaining transparency, fairness, accountability and regulatory compliance.

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1.12 Scope for Further Research:

Future research can examine how human–AI collaboration develops over time as banking professionals gain greater experience with AI-based credit systems. Comparative studies may investigate differences between public-sector, private-sector and digital banks. Further research can explore explainable AI, automation bias, human override behaviour, trust and accountability in credit decisions. Studies may also assess how AI governance influences fairness, transparency and regulatory compliance. Cross-country comparisons could provide insights into differences between India and other financial systems. Future researchers can examine the use of Generative AI and agentic AI in credit assessment and risk monitoring. Experimental studies comparing human-only, AI-only and collaborative decision-making could provide stronger evidence on accuracy, fairness and governance.

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