

10.48047/jocaaa.2024.33.05.49

Artificial Intelligence and Credit Risk Assessment in Indian Commercial Banks: A Triangulated Study Integrating Employee Perceptions with Objective Performance Metrics

Kamlesh Kaur

Research Scholar, Faculty of Management Studies, Maharishi Markandeshwar (Deemed to be University), Mullana, Haryana, India

Dr. Priyanka Salgotra

Professor, MMIM, Maharishi Markandeshwar (Deemed to be University), Mullana, Haryana, India

Abstract

Purpose: The current enquiry adopts a triadic methodology to study the effect of Artificial Intelligence (AI) implementation on Credit Risk Assessment in Indian Commercial Banks. Diverging from previous work that relied solely on either a perception-based or a performance-based approach, this work combines employee perceptions with secondary data analysis of actual banking performance metrics to gain a more nuanced understanding of AI's contribution to credit risk management processes. Concurrently, it recognises the methodological limitations of deducing causal relationships from observational data. Additionally, the study answers basic questions about whether AI implementation can translate into measurable improvements in credit quality and whether employee perceptions of AI efficacy are consistent with objective performance results from secondary sources.

Design/methodology/approach: To achieve the study's purpose, the research design adopted a mixed-methods approach. Primary data were gathered through a cross-sectional survey of 547 banking employees from the Ambala division of the State Bank of India, Punjab National Bank, HDFC Bank & ICICI Bank, the four major banks in Haryana State. Secondary data included Reserve Bank of India (RBI) statistics on non-performing asset (NPA) trends; indices on the adoption of artificial intelligence (AI) based on RBI's validated research methodology; text mining of annual reports of banks; and bank-specific performance data from 2018-24. The analysis examined the correlation between the intensity of AI adoption and improvements in credit quality while holding other variables constant, such as regulatory reforms (notably the Insolvency and Bankruptcy Code), macroeconomic conditions, government recapitalisation, and increased provisioning mandates. Robustness checks (sensitivity analyses, subgroup comparisons, and temporal patterns of results) were conducted to assess the robustness of the results under different analytical specifications and sample partitions.

Findings: There is empirical evidence that employee perceptions of and objective banking performance metrics converge to reinforce one another, even though the effect sizes are relatively small compared to conventional benchmarks. Perception data show statistically significant improvements in all four dimensions of credit risk (Cohen's $d = 0.21-0.34$, $p < .001$), with Monitoring and Control showing the most significant effect ($d = 0.34$) and Credit Administration showing the most negligible impact ($d = 0.21$). These effect size values, although classed as small

10.48047/jocaaa.2024.33.05.49

to small (according to Cohen (1988)), are commensurate with usual technology implementation outcomes in organisational contexts and were stable over robustness tests. Secondary data analysis shows a precipitous decline in gross NPA ratios from 11.2% in March 2018 to 2.6% in September 2024 (77% reduction as the lowest level in 12 years) and a significant inverse relationship of the AI adoption indices to NPA declines ($r = -0.68$, $p < .01$). The congruence between employee perceptions of the most critical improvement in Monitoring and Control with objective measures gives faith in the results; however, some caution is advised with the probable effects of concurrent regulatory reforms, economic recovery and recapitalisation and improved provisioning, and the small bank sample size for correlation analysis.

Practical implications: The merging of several sources of information confirms ongoing investment in AI for credit risk functions, but does not allow for definitive causal inferences. Banks may accelerate their AI deployment in monitoring and surveillance functions, where there's both perceptual and objective evidence of maximum impact, and address training deficits in administrative applications where there's minimal perceived contribution of AI. The observed link between the adoption of AI technologies and the reduction of NPA, while not a cause, supports the strategic case for technology investments, especially at the intersection of competitive positioning, regulatory requirements and operational efficiency goals. Change management practitioners can use positive employee perceptions to help maintain digital transformation initiatives.

Originality/value: Methodologically, this study is a pioneering work that combines employee perceptions with objective performance data in a triadic research design, and it explicitly discusses limitations and alternative explanations to qualify causal statements. The convergent evidence from the datasets increases confidence in the association between AI implementation and outcomes in credit risk, compared with single-method studies. However, the correlational nature of the design makes stronger causal claims impossible, which require a framework like experimental or quasi-experimental. By providing evidence-based discourse on banking technology evaluation while retaining epistemic humility regarding observational research limitations, the study offers practical, dimension-specific recommendations on AI implementation priorities.

Keywords: Artificial Intelligence; Credit Risk Assessment; Non-Performing Assets; Employee Perceptions; Technology Adoption; Indian Banking.

Introduction

The implementation of Artificial Intelligence (AI) in the banking operations is a major technological change in the field of banking and will truly change the way in which banks measure, monitor and control credit risks. Conventional credit risk assessment has been historically based on manual processes that are prone to cognitive bias, inconsistencies in applied evaluation criteria and long throughput times. (Mhlanga, 2021)

AI- driven systems are developed to compensate for the shortcomings embedded in manual processing systems by trying to analyse data autonomously, spotting complex modes and using

10.48047/jocaaa.2024.33.05.49

rules in a consistent fashion across voluminous application data sets. Nevertheless, there remains a significant methodological gap in current scholarship: Although some research traces how algorithms perform under experimental conditions and others focus on people's perceptions using survey tools, few research efforts combine both elements to produce a total knowledge on how AI operates in actual banking contexts.

The relevance of this methodological shortfall to scholarly and practitioner discussions is manifold. Technically, there is good experimental evidence that AI is superior to traditional statistical methods such as logistic regression and discriminant analysis in a controlled setting. For example, Shi et al. (2022) found deep learning models to outperform conventional methods in the prediction of loan defaults, whilst Turkson et al. (2016) noted accuracies of prediction of over 80% in laboratory settings that used standardised datasets. Nonetheless, there is no substantiated direct correspondence between the performance of algorithms given in controlled experiments and its impact in operation. Successful technology implementation presumes the acceptance and effective utilisation of users, who, if they distrust, find unmanageable, or ineffective, will not integrate the technology in any meaningful way (Venkatesh et al, 2003). Moreover, positive user perceptions in the absence of commensurate performance gains might reflect optimism towards the technology or organisational messaging rather than real efficacy (Turkson et al., 2016).

Operational conditions present further implementation issues such as poor quality of the data, challenges in integrating the technology with legacy systems, barriers to change management, organisational culture and environmental circumstances, and lack of training, all issues that laboratory assessments of historical data cannot replicate (Turkson et al, 2016).

Indian banking is a particularly relevant and timely setting in which to consider the effect of AI's operations due to the nature of the industry, the recent performance trends and the ambitious efforts to digitally transform. Gross non-performing assets (GNPsAs) within scheduled commercial banks came down significantly from Rs 10.36 trillion (11.2 per cent of total advances) in March 2018 to about Rs 3.77 trillion (2.6 per cent of total advances) in September 2024, registering a 12-year low (Reserve Bank of India, 2024). This drop represents one of the most significant improvements in credit quality parameters in the sector's recent history and coincided in time with the growing use of AI technologies adopted by the sector as testified by the RBI's text - mining analysis of annual reports (Reserve Bank of India, 2024). The timing of falling GNPsAs and rising utilisation of AI raises important queries about the relationship between them. The same period also saw implementation of Insolvency and Bankruptcy Code of Law (IBC) which redefined the rights of creditors, gave a strong regulatory turn to the system and new provisioning norms of conservative demands for quality of asset evaluation. Additional macro - economic factors such as government's recapitalisation of public sector banks to the tune of more than Rs lakhs of crores and post - covid economic recovery had added to the strengthening of the borrower repayment

10.48047/jocaaa.2024.33.05.49

capacity, thereby probably played a significant role in the GPNA decline independent of the AI deployment.

The present study attempts to fill the methodological void by means of a triangulated research design that simultaneously examines employee perceptions of AI's contribution to the assessment of credit risk and actual performance metrics obtained from authoritative secondary sources. Primary sources of perception data were gathered through structured surveys, and secondary data includes RBI statistics and individual bank performance indicators, so that convergent evidence can be obtained from separate sources of data. The convergence or divergence of perceived and actual impacts helps to explain how technology adoption takes place and how effective implementations are. However, it is evidence explicitly recognized that, while triangulation of correlational evidence increases the strength of causal inference when compared to single-method studies it does not remove alternative explanations due to concomitant reforms and macroeconomic influences that coincided with the adoption of AI.

The urgency of this inquiry goes beyond the purely academic interest, to include practical decision-making needs of various stakeholders. Indian banks together spend billions of rupees in technology every year - the spending on AI related technology is growing at double digit levels as these institutions are in a race to modernise credit operations. Consequently, decision makers need evidence-based information to determine whether these substantial expenditures are making meaningful improvements in operations that are worth their costs. Regulatory bodies that are responsible for formulating policies and guidelines for the digital transformation of financial institutions require empirical foundations for suggesting technology adoption for systemically important entities. Employees affected by changes in work flow must understand the way that AI tools affect job performance and employment conditions. Technological vendors aiming to expand their footprint have to prove the tangible impact of their offerings to reinforce the value propositions. Although fundamentally flawed and with limitations, outlined in considerable detail in the manuscript, the triangulated approach provides stronger evidence than those studies that rely solely on perception or performance measures, thereby adding to and enriching the existing literature.

Six contributions to the scholarship result from this investigation. First, by incorporating data from perception and performance, the study helps to introduce methodological innovation, which has implications for the determination of the convergent validity of fundamentally disparate kinds of data. Second, from an employee-centric perspective, the study reflects experiences and perceptions of frontline banking professionals - the key users of AI systems - in a largely unexplored area of research that has focused on algorithmic performance or customer satisfaction. Third, by dimension specific analysis, the study separates assessment of credit risk in four different functional dimensions, thereby exposing differential effects of AI which may be lost in aggregate measures. Fourth, secondary data validation is used to connect metrics of AI adoption with GNPA's

10.48047/jocaaa.2024.33.05.49

trends using objective RBI statistics and bank level data to provide a benchmark insulated from self-report bias. Fifth, by making clear that there are limitations and alternative explanations, the study demonstrates an epistemological humility, which avoids making unwarranted causal claims based on observational data. Finally, robustness checks examine the stability of outcomes across subgroups and analytical specifications so as to address issues related to result fragility. This balanced approach - providing actionable evidence in such circumstances with appropriate caution in interpretation - is in accord with calls for greater rigor in technology evaluation research and transparency in interpretation following in the Information Systems literature.

Literature Review

AI in Banking Operations

Artificial Intelligence refers to the ability of computational systems to autonomously acquire, generalise and apply knowledge in order to carry out tasks traditionally reserved for human cognition without them having been explicitly programmed (Kaya, 2019). In terms of applications in the financial sector, a wide range of technologies are used, such as machine learning algorithms for pattern recognition and predictive modelling, natural language processing for the automatic interpretation of textual documents and customer interaction, robotic process automation to support high volume transactional execution, and predictive analytics for risk assessment and forecasting. Brynjolfsson and McAfee (2017) describe AI as the dominant general-purpose technology in recent decades, which differs from previous political waves in technology in part due to its ability to keep improving performance through learning from experience.

Indian banks have instituted AI across various functions in a big way, including the deployment of chatbot-enabled customer service and having AI alert to detect anomalous activities including fraud involving the collection of bank data for fraud and generation of automatic creditworthiness analysis. Srivastava and Dhamija (2021) found that the implementation of AI has significantly changed the processes of compliance operations, fraud prevention, and credit evaluation in the Indian banking scenario, and subsequently leading to a change in the conventional way of operations. An RBI study, which used text mining techniques on consolidated financial statements of the private sector banks from 2015-16 to 2022-23, reported an increase in the number of words related to artificial intelligence by around six times in a five year period spanning the years 2015-16 and 2022-23; it was further observed that banks with high asset book values and higher capital adequacy ratios (CRAR) had higher levels of artificial intelligence related adoption, indicating that there is an institutional capacity to use artificial intelligence which impacts adoptability (RBI Bulletin). Although this quantitative proof-of-widespread-adoption-of-AI is welcome, it also exposes a weakness in the research behind it: disclosure measures an organisation's communication around AI, not its depth in operational deployment and maturity of AI solutions within production environments.

Konigstorfer and Thalmann (2020) conducted a systematic review of the application of AI in commercial banking and found that the most developed area of AI is that of credit-risk assessment-it's just that because of the availability of data, the success of measures and the real business impact. Nonetheless, they warned that the current research largely focuses on assessing algorithm performance in the controlled conditions of experimental settings using historical benchmark datasets instead of focusing on the actual working results of real-world production conditions. Consequently, in the literature, a disconnect is observed between laboratory performance and in-deployment effectiveness; the current study aims to help fill this disconnect by including both performance measurements and perceptions of end-users in the analysis.

There are several intermediary factors that mediate between algorithmic performance and improvements in portfolio quality, which include data quality sources within production environments, effectiveness of system integration, user trust and utilisation, and organisational and cultural changes required for effective AI implementation.

McKinsey Global Institute predicted that the value of AI for the global banking sector, through efficiency gains, improved risk management, and other means of generating revenue, could reach between US\$200 and US\$340 billion a year Credit-risk assessment is a major area of potential in this regard. Realising this upside, however, requires more than working-class model development, by integrating AI algorithms to the best of ability into operational systems, which itself is a sociotechnical challenge involving the human limbs in the workflow, organisational processes and technical systems, and which is not possible through technical studies (alone).

The state of the Indian banking industry provides a particularly complex and relevant context to study the dynamics of implementing AI because of the peculiar mix of legacy systems that need to be modernised, the intricate regulatory environment with a plethora of overlapping regulations, the sheer size of more than 100,000 branches catering to heterogeneous populations and the aspirations of Indian banks to implement digital transformation initiatives.

Recent developments in AI capabilities, including recognition of transaction patterns, compliance monitoring activities (automated, and checking for suspicious activities), and credit assessment using other data analytics such as large language models, sophisticated neural architectures, etc., have broadened the scope of credit risk assessment beyond the traditional scoring model. These technologies include the ability to analyze the unstructured data sources such as loan application narratives, email correspondences, and social media footprints which cannot be processed by conventional models. Nevertheless, the regulatory environment in India places a premium on explainability and fairness of credit decisions potentially limiting the use of opaque "black-box" models, even though they may be predictive. This tension represents a dilemma that seems to be a constant challenge for banks as they make AI technologies work longer.

Credit Risk Assessment and Artificial Intelligence Technologies

Credit risk forms a major reason why banking should be considered a major concern because their lending activities require them to evaluate carefully the probability of payment is made is defaulted and this will result in credit losses to the bank which will directly affect their profitability and capital adequacy (Mhlanga, 2021). Historically, the basis of credit assessment was based on the judgment of an expert who incorporated financial statements analysis, valorization of collateral, and information on the relationship. This manual, time-intensive and subjective process was subject to cognitive biases like anchoring, availability heuristic, and confirmation bias. AI technologies revolutionise this sector by allowing the automatic analysis of loan applications, thus speeding up processing, standardising risk analysis and spotting subtle historical patterns that can be hard for human analysts to detect.

A systematic review on the use of machine learning in credit risk conducted by Shi et al. (2022) concluded that deep learning models generally outperform classical statistical models such as logistic regression and linear discriminate analysis; ensemble approaches bring an even higher predictive accuracy and reliability with a variety of data. Sadok et al. (2022) showed that AI makes it easy to use novel sources of information such as big data analytics and alternative data footprints to evaluate the creditworthiness of populations who are underserved by traditional credit bureau infrastructure. Nevertheless, most technical studies suffer from reservations that make them less than practical in application. First, there is the issue of the fact that algorithmic performance is often measured against static historical datasets that may or may not reflect changing economic conditions, a shift in borrower behaviour and a break down in credit markets. Second, techniques of accuracy that are based on experimental settings, and that rely on randomly sampled test data, may not convert into better portfolio performance in production settings, where data quality issues, missing values, and distributional shifts are pervading. Third, the black-box structure of many advanced AI models limits its acceptance in the context of credit decision making, where regulatory compliance with requirements for explainability and adverse action notice is paramount, and the requisite for developing trust among credit officers.

India's credit-infrastructure has changed substantially with the set up of credit bureau services through services like CIBIL (TransUnion CIBIL), Equifax, Experian and CRIF High Mark although there is still a variability in terms of the quality and scope of data. AI has the potential to both improve the accuracy of credit assessment for borrowers with established credit histories but also to make credit more accessible for "credit-invisible" borrowers through alternative analysis of unstructured data sources such as mobile phone patterns of usage, utility-payment records or histories of digital transactions. Yet, applications aimed at alternative data are still in relative infancy when compared to those aimed at established borrowers, and raise distinct issues in terms of privacy and fairness, and regulatory compliance that are outside the scope of the present study.

The link between the adoption of AI in the assessment of credit and the results for the portfolio is mediated through a variety of mechanisms. AI can be used to enhance portfolio results by better identifying default-prone applicants at origination to prevent defaults or implement risk-based pricing that can take into account the expected default frequencies. AI can also improve outcomes by better monitoring and early warning systems to detect credit deterioration ahead of nonperformance to facilitate early interventions. What's more, AI can be used to optimise recovery outcomes through improved collections strategies and workout decisions. While the present study is limited in its ability to unravel the specific mechanisms because of a lack of information on actual utilisation intensity, the multidimensional, triangulated design provides insights into perception specific effects.

Perceptions About Employees and Technology Adoption

The literature on technology implementation has repeatedly recognised that employee perceptions are central determinants of successful implementation; however, the nature of the relationship between employee perceptions and implementation outcomes is complex and is moderated by factors including utilisation intensity, complementary resources and organisational context. Davis (1989) hypothesized two basic factors of technology adoption; perceived usefulness and perceived ease of use in his early Technology Acceptance Model (TAM). Subsequent research has both supported the validity of TAM in varied applications, and identified boundary conditions, moderators and extensions.

Venkatesh et al. (2003) further generalised TAM in the form of the Unified Theory of Acceptance and Use of Technology (UTAUT), including performance expectancy, effort expectancy, social influence and facilitating conditions as added behavioural intention and actual use determinants. In the Indian banking scenario, Noreen et al. (2023) conducted a survey among employees and found that awareness of AI capabilities, attitude towards AI technology and perceived usefulness had a significant impact on the intention to adopt AI. Pandey and Pandey (2022) identified through research that focused on customers, that AI improved user satisfaction when the benefits of such AI were experienced through tangible service delivery. These perception based studies, however, take employee perceptions as exogenous variables, rather than inquire into whether positive perceptions are based on actual effectiveness, reflect enthusiasm alone or emanate from socially desirable responses or organisational framing.

Studies using retrospective designs to record perceptions from employees are even more prone to recall bias, whereby existing outcomes and experiences distort reminiscences of previous conditions. Employees who see the improved levels of non-performing assets (NPAs) may retrospectively assign a negative view to pre-AI conditions inflating perceived improvement. Recall bias operates through such mechanisms as effort justification, hindsight bias, and outcome

10.48047/jocaaa.2024.33.05.49

contamination. While this study is not able to completely remove the issue of recall bias because of lack of a true baseline, triangulation from objective RBI reporting of trends which are not affected from the same bias add some confidence in the validity of employee perceptions.

The relationship of perceptions of employees of utilisation adds to the complexity. Employees may average positive attitudes to AI tools and yet under-utilise them, a situation that leads to a perception-behaviour gap; or they may have neutral or negative attitudes towards AI tools but realise substantial productivity improvements because of utilisation patterns that are inconsistent with their stated attitudes. Data limitations preclude the measurement of utilisation intensity in the current study; suffering notwithstanding, triangulation concerning sources of data defends towards un-observed systematic disagreements among the perceptions and also performance.

The Background of Indian Banking: The Paradox of Banking Reforms and Controlling Variables

Analyses of credit quality improvement in Indian banks from 2018 to 2024 will need to consider concomitant reforms and good fortune which complicate the attribution to possible causality, such as adoption of AI. The Insolvency and Bankruptcy Code (IBC), passed in 2016 and put in place during 2017-2019, introduced an institutional framework for the resolution of insolvencies, thereby transforming the rights of creditors and debt recovery. Prior to the IBC, average timelines for recovery were exceeding four years, recuperation generally occurred between 20 per cent and 40 per cent of the outstanding debt through SARFAESI, debt recovery tribunal and winding up proceedings. The IBC introduced processes of time-bound resolution - initially 180 days extendable up to 270 days and in exceptional cases up to 330 days - of creditor claims - clarifying the hierarchy of creditor claims - and professional insolvency resolution infrastructure, including insolvency professionals and adjudicating authorities. Empirical studies have shown that IBC resolutions led to substantial recoveries (average haircut between 60% and 70%) which represent very satisfactory improvements compared to former mechanisms that often resulted in negligible recoveries.

Regulatory tightening under RBI's revised framework for stressed assets resolution (introduced in 2018 following earlier schemes) imposed higher timelines and provisioning requirements hence favouring proactive management of NPA irrespective of AI utilisation. The framework required immediate default recognition in the borrower's level ledgers, required that defaults be timely reported to the credit information companies, and increased provisioning threshold levels for unresolved accounts over time. On the other hand, as a result of strengthened provisioning requirements, to mitigate costly provisions that directly impacted on profitability, banks had an incentive to improve credit assessment and monitoring efforts, independent of AI technologies.

The recapitalisation of public sector banks by the government by providing over 3 lakh crores of direct equity and recapitalisation bonds between 2017 and 2021 led to the creation of capital

10.48047/jocaaa.2024.33.05.49

buffers sufficient to allow write-offs and increase in provisions that resulted in an improvement in reported NPA ratios irrespective of any changes in the creditworthiness of borrowers. This recapitalisation programme helped overcome the capital constraint which limited the ability of banks to recognise and provide for non-performing assets (NPAs) while simultaneously meeting the regulatory minimums, thereby facilitating an holistic "clean-up" of the balance sheet of banks which would not have been possible without the instilling of such external capital.

Economic recovery post-Covid 19 from 2021 onwards boosted the capacity of borrowers to repay across various sectors including sectors that were previously stressed and had amassed disproportionate NPAs. Conditions conducive to improving credit quality came an availability of fiscal stimulus for demand, accommodative monetary policy for favourable credit conditions, releases of pent-up demand as economic restrictions were lifted and sectoral recoveries for previously stressed segments, all behind utilisation of AI on lending decisions, but therefore independent of technology-related factors.

Furthermore, certain interventions like Asset Quality Review (AQR) in 2015-2016 which made banks identify and classify the NPAs, which were not previously identified, led to a divergence between the classification by banks and RBI on the NPAs, thereby establishing a statistical baseline effect that affects the interpretation of the subsequent trends. As a result, the GNPA ratio peaked in 2018 at least partly as a result of the AQR's mandate to record previously unrecognised NPAs on the balance sheets of banks by means of compulsory reclassifications, thereby creating an artificially inflated starting point. The relative decline in GNPA ratios thereafter thus in part reflects the resolution of legacy NPAs by write-downs, upgrades or by other mechanical means, all of which would occur independent of any AI capabilities as the AQR identified stressed assets were processed by the system.

These simultaneous factors pose major obstacles for identifying the role of AI in the credit quality improvement. AI adoption in India coincided with the period during which there was a situation of reforms and favourable economic conditions and hence it would be difficult to isolate AI's independent contribution given the plethora of correlated positive factors. Consequently, our correlational findings should be taken with a pinch of salt - i.e. the correlational link between AI adoption and NPA improvement may be subject to such factors rather than (or alongside) the direct effects of AI. Moreover, we cannot empirically apportion the improvements in the quality of credit to contributing factors as our data is observational in nature.

Research Gap and Study Contribution

Several methodological limitations compromise the current body of AI -- banking literature, and, therefore, the reliability and usefulness of its findings for decision -- makers. The work in AI-banking has predominantly taken the form of a singular method encompassing technical

10.48047/jocaaa.2024.33.05.49

assessments on the performance of algorithms in benchmark datasets and controlled experimental settings (such as Shi et al., 2022; Turkson et al., 2016), perception-based investigations using survey methodologies to obtain user perceptions of AI systems (Noreen et al., 2023) or customer-focused assessments so as to examine the outcomes relating to the quality of services, and user satisfaction (Pandey & Pandey, 2022). The lack of multi-method techniques that combine several types of data hampers confidence in results. i.e., improvements in algorithms under laboratory conditions will not necessarily show operational benefits in production situations, while positive survey views of AI systems do not necessarily point to actual effectiveness that affects real world effects. Additionally, most of the research ignores the confounding variables entirely or only superficial mentions of them in limitations sections without (empirical) discussion of their influence.

This study has six different contributions to counterbalance the identified gaps:

- *Multi-methodology*: Uses multi-methodology approach combining information on employee's perception obtained through structured surveys, and secondary data gathered from authoritative RBI sources for assessing the convergent validity of two fundamentally different types of methodology and data collection sources. The application of this multi-methodology approach provides greater evidence than any of the methods have on their own.
- *Employee-centric perspective*: Gathers employee perceptions of main users of AI systems of the employees - i.e. front-line banking employees who interact with AI systems in their daily work in the qualification of the credit quality - is a perspective essentially missing in existing literature, which has focused either on algorithmic performance in an experimental setting or customer experience.
- *Functional dimensionality*: Disaggregates credit risk assessment into four different functional dimensions (Credit Processing, Credit Administration, Monitoring and Control, Managing Credit Problems) revealing the differences in the effects of AI which are suffused when results are aggregated across these dimensions, and providing actionable recommendations for prioritising implementation of AI.
- *Correlation with secondary information*: Correlates metrics of AI adoption obtained using text mining methods with rural banking NPA trends obtained from authoritative RBI statistics and bank level provide objective reference points to validate the impact of AI adoption independent of any bias that may have been introduced by self reporting in perception data.
- *Transparent admission of limitations*: Explicitly acknowledges potential confounding factors and possible alternative explanations throughout the manuscript, staying in an epistemological modest position consistent with the study design; ie, observational research cannot control for confounding factors.

10.48047/jocaaa.2024.33.05.49

- *Banking context in India*: Makes empirical contribution from a segment of the Indian banking sector which is regionally significant and yet under represented while acknowledging the conditions of generalisability to other contexts.

Theoretical Background

Technology Acceptance Model: Extention and Application

Davis (1989) set forward the Technology Acceptance Model (TAM) as the basis for the theoretical framework of this investigation, with the objective of understanding the interpretations of AI systems by the employees. The leading assumption of TAM is that people will accept and use new technologies if they believe that they can be useful in completing the job (globalization of technology: technology usability) and if the technology is easy to use (technology usage: ease of use). TAM provides a theoretical basis for using employee perceptions as substantive outcomes which may mediate between technology implementation and organizational results. The model shows that the employees who feel that specific technology enhances work quality due to technology are more likely to implement and effectively apply the technology values that lead to a trajectory of trajectory of utilisation intensity and quality because employee perceptions are translated into actual outcomes.

In addition to the application of TAM, the model was further extended in three ways that are specific to the environment of artificial intelligence in banking explored in this paper. First, perceived usefulness is reconceptualised in not one, but several way, i.e. as dimension specific perceptions across different credit risk functions. This enables examination of the question whether the perceived contribution of AI differs depending on the function (e.g. credit processing, administration, monitoring and problem management) due to different capabilities in the areas of pattern recognition, continuous monitoring and an automated processing by the AI. For example: functions needing pattern recognition and continuous surveillance may have more to benefit from AI than functions requiring judgment, relationship management and compliance of Regulations. Second, moderating variables that may affect the association of perception and outcome were included. Documented variations in organisational culture, capacity to invest in technology, IT infrastructure maturity and legacy system constraints between public and private sector banks suggest that the type of bank (public and private) is an important moderating variable. Additionally, the role and experience level of employees may also moderate the level of perception; more experienced employees are likely to have higher levels of realism in their comparative assessment of pre- and post-AI conditions due to an enriched baseline understanding, while less experienced employees may not have the historical perspective to make accurate retrospective evaluations. Third, the perceived usefulness was placed within a model of mediacy between the implementation of AI and organisational outcomes. Following this model, the implementation of AI has an effect on the perceptions of employees (usefulness), which in turn, has an effect on the usage behaviour

10.48047/jocaaa.2024.33.05.49

and intensity, resulting in organisational effects such as the improvement of the credit quality. Although the cross section design does not allow for testing of this mediation chain formally with Structural Equation Modelling because of data problems, the tripartite approach provides indirect evidence: the convergence between employee perceptions and organisational outcomes is supportive of (but does not establishes) the mediation hypothesis.

Limitations and Other Theoretical Frameworks

The application of TAM in this study is mainly descriptive of the concepts rather than a structurally developed application, which is not the best way to advance the theory. A more exhaustive theoretically oriented study would involve the testing of the theoretical mediation chain through Structural Equation Modelling, while including measures of intermediate construct such as intention to use, actual utilisation intensity to derive from system log data, trust on AI systems, perceived risks of relying on AI recommendations and facilitating conditions such as adequate training, available technical support etc. Resource constraints and limited data access, however, limited the ability to directly measure these intervening constructs, limiting the findings of the study. Future research should make every effort to capture the full range of potential intervening constructs using more inclusive and rigorous research designs.

Alternative theoretical frameworks may provide a better questioning of the causality and relationships between the domains of AI and banking environments from varied disciplines. Institutional theory (DiMaggio & Powell, 1983) would emphasise on regulatory pressures, mimetic behaviour of peers, and normative expectations from professional bodies driving the adoption of AI irrespective of the efficiency of its operations, and thus complicate the assumption that the adoption of AI is positively correlated with organisational outcomes. In this perspective, banks are making AI choices simply because other peer institutions are doing so, investors expect technology investments, or consultants are trumpeting the technology - these are non-substantive operational effectiveness reasons for making these choices.

Sociotechnical Systems Theory would emphasise the simultaneous optimisation of technological and social systems, which would imply that effectiveness of the AI is dependent on corresponding human, organisational and process capabilities. Consequently, the role of AI in the quality of credit risk decisions depends not only on the abilities of algorithms but also on how much human experts interpret these recommendations generated by AI, how much they appropriately override these recommendations in light of the contextual knowledge that humans possess and how much the AI analyses are supplemented by information that the relation and judgemental aspect of the applicant's credit cannot discern.

Finally, the Resource Based Theory (Barney, 1991) would lead us to believe that the contribution of AI to sustainable competitive advantage depends on whether the AI capabilities are valuable,

10.48047/jocaaa.2024.33.05.49

rare, difficult to imitate and are not easily replaceable by others (VRIN). As AI tools become more commoditised with vendors offering and open source developers implementing these tools, their ability to provide sustainable competitive advantage - and in turn, unique and differentiated outcomes for credit quality to set banks apart from each other - may fade over time. Early adopters might have benefited significantly from first movement advantages from proprietary AI applications, that are unlikely to be replicated by late adopters who purchase standard solutions.

Triangulation Rationale

The current investigation uses methodological form of triangulation from the multi-trait, multi-method framework of Campbell and Fiske's work published in 1959 and conceptualization of the principles of triangulation adapted from Denzin's work published in 1978. This approach is designed to reinforce the validity of associations made between the perception of employees on the positive effects of artificial intelligence (AI), with objectively measured improvement on measures of credit quality that are gained from separate and independently-sourced data repositories. In practical terms, convergence of employee's perception about the favorable outcomes of AI and independently documented improvements in credit quality metrics inspires a level of confidence in the inferred association much more invested in comparison to a single method design, which potentially harbors method specific biases.

Conversely, the divergence between the perception of the positive impacts of AI and the objective measurements of the quality of credit would point either to a perception-performance gap (perhaps due to the enthusiasm of employees rather than real impacts) or to shortcomings of the validity of the measurements for either of the strands of the methodology to be remedied.

While triangulation can increase confidence in the findings of associations, it is not evidence of causation. Consequently, great care must be exercised when interpreting the results. Convergence suggests that there are aspects of measures that capture related phenomena that occur concurrently; however, the measures do not rule out third variable explanations for the observed association. For example, the perception of employees towards the positive effects of AI, and the reduction in credit quality objectively measured (e.g., by Listening ~) independent variables) might be affected by the same confounding variables (e.g., by Listening regime change promoting a more friendly operation climate, an economic recovery leading to higher credit capacity of borrowers, or an organizational change process not linked with AI), and not necessarily the other way around: some exogenous factor might lead to the first, while some other exogenous factor would lead to the second. In other words, convergence can be considered a sign of higher certainty on the relationship between the perception of artificial intelligence by employees and objective results of performances, but we were right to be cautious about causality issues for which the correlational type of study has not provided support.

10.48047/jocaaa.2024.33.05.49

The usage of methodological triangulation used in such a study context confers more benefits than the general enhancement of validity. Employees' perceptions of the positive impacts of AI can shed light on the mechanisms involved in employees' experiences of the contribution of AI - for example, how employees interpret AI's role in the improvements of functionality, which specific AI-related features employees perceive to have been most positively affected by, and similar matters - whereas performance data provides an external validation of findings that are independent of any potential biases inherent in employee self-reports, which may, for example, inflate perception-based outcomes. Therefore, the merging of employee perceptions and performance data helps reduce the limitations to using each approach alone. For instance, perception-only research sometimes collects the enthusiasm of employees, social desirability bias, or organization messaging, rather than the real improvement of AI. performance-only research Accessibility by AI cannot be identified if better measurements of credit healthy can be found because of AI or other reasons working with AI.

A Triangulated Design Overcomes These Limitations Queries Partially

Operationalizing of Credit Risk Assessment Dimensions

Employee perceptions towards the quality of credit risk assessments were operationalized in 4 dimensions - Credit Processing, Credit Administration, Monitoring and Control, and Managing Credit Problems, based on the frameworks proposed by Wang and Ma (2012), Sadok et al. (2022), Mhlanga (2021), and Shaji (2020) and later adapted for the Indian banking context based on pilot testing and expert review. A multi-dimensional approach is a reflection of a functional differentiation in the credit risk management, whereby different processes with different characteristics of the tasks they are addressing are differentially suitable for enhancement by AI:

Credit Processing (5 items) including verification of borrower history through credit bureau inquiry and document analysis, evaluation of outstanding obligations by an analysis of debt to income ratios, debt to liability mapping, approval accountability through audit trails and documentation of decisions and processing independence through automated scoring and reduced subjectivity. This dimension reflects the future contribution of AI to the early stage of creditworthiness evaluation at the origin with respect to the loan - e.g., automated document verification based on optical character recognition (OCR) and natural language processing (NLP), aggregation of credit scores from various credit bureaus, and pattern matching with known factors of default to produce risk flags.

Credit Administration (2 items) focuses on independent administrative processes (e.g. disbursement control and covenant monitoring) and documentation tracking systems (e.g. digitalization and retrieval). This dimension is strongly regulated with standardised procedures being prescribed by RBI master circulars and internal bank policies, therefore, there is limited

10.48047/jocaaa.2024.33.05.49

opportunity for AI to contribute to formalised processes where human judgement contributable value is limited and automation potential limited by regulatory requirements.

Monitoring and Control (9 items) includes collateral assessment and revaluation monitoring, stress testing under macro-economic conditions, credit quality reporting and portfolio analytics, client monitoring using transaction patterns and advance warning indicators, and compliance oversight using automated regulatory reporting. This dimension best represents AI capabilities in continuous surveillance and detection of patterns from large datasets and generation of alerts in situations where risk indicators exceed predetermined thresholds, which can best be captured by monitoring effectiveness.

Managing Credit Problems (5 items) dealing with segregation of workout activities between recovery and business functions credit risk policies to non-performing accounts below classification criteria by IRAC norms NPA recovery measures - Optimization of resolution strategies and prioritization of collection strategies across huge collections portfolio . This dimension is the one that best represents what AI can do for remedial purposes through predictive modelling in terms of recovery likelihood, optimal restructuring terms and prioritization of collection strategies on a large portfolio.

Research Methodology

Research Design Overview

The current research made use of a triangulated research design combining secondary performance measures and primary perceptual measures, and as such, a complementary mixed method design was chosen. The design is rooted in a pragmatic epistemology that is pre-eminent methodological complementary that recognises that the research questions under scrutiny cannot be adequately addressed by a single methodological approach in isolation. Primary data are meant to shed light on user experience and perceived efficacy so as to provide an "insider" view of people who interact with artificial intelligence (AI) on a day-to-day basis. Secondary data, on the other hand, provide information on objective performance measures based on independent reporting systems, thus eliminating the effects of recall bias or the distortion of self-report. Validity of the two data streams is determined through analyzes of relevances of the two distinct data streams: the converging and divergent analyses.

Primary Data Collection

Sampling and Sampling Process

10.48047/jocaaa.2024.33.05.49

A cross-sectional survey conducted among 547 banking professionals in the top four banking institutions of Ambala Division of Haryana (State Bank of India, Punjab National Bank, HDFC Bank and ICICI Bank) was administered. A purposive sampling approach was used in order to capture heterogeneity in bank typologies (public versus private sector) and the range of maturity levels of AI adoption (from beginning to advanced). The sample size was based on Cochran's (1963) formula for categorical data using a finite population (approx. 2,400 of credit related employees from the selected banks), with 95% confidence level and a 5% margin of error. This calculation provided a minimum sample size requirement (384), and the actual sample size of 547 was 42% larger than the minimum thus providing adequate statistical power for planned analyses, including subgroup comparisons.

Respondents included credit professionals with direct responsibility for credit-related activities, those with credit-related responsibilities (including credit officers such as loan originators/assessors, risk analysts, credit portfolio monitors/reporters, branch managers with credit approval authority, and senior management officials responsible for credit operations). Eligibility criteria required at least one year experience in credit activities (to ensure familiarity with pre-AI conditions) and exposure to AI-based credit assessment tools (to be able to assess the impact of AI). The application of these criteria is intended to mean respondents are familiar with both pre- and post-AI environments; however, it may cause survivorship bias if employees who are unhappy with AI implementation departed the organization at disproportionately high rates yielding an over-representation of those who have adapted well.

Survey Instrument and Retro-Decision

Respondents rated their observations of the quality of credit risk assessment for two distinct time periods: before AI was implemented and after AI was implemented into their bank and line of business. In the light of no baseline data before deployment of AI and the infeasibility of experimental designs randomising AI adoption across branches or banks, a retrospective design was perceived to be needed. Nonetheless, this design carries with it documented recall bias: present day outcomes may systematically colour participants' recollection of antecedent conditions, with the possibility of overstating the degree of improvement in the quality of credit risk assessment.

In line with Podsakoff et al. (2003), a number of procedural controls were used to reduce recall bias. First, the instrument explicitly emphasized the temporal dissociation of the two conditions in the instructions, and thereby prompted participants to think specifically of pre-AI conditions. Second, behavioural anchors (e.g. observable outcomes such as "time taken to process loan applications") were used to encourage concrete, as opposed to abstract, evaluations. Third, the pre-AI items were shown prior to attempting the congruous post-AI condition in order to set up a reference frame prior to measuring the congruous post-AI condition in such a way that there was less anchoring to current experience. Fourth, reverse coded items were included to break up

10.48047/jocaaa.2024.33.05.49

acquiescence patterns. Fifth, there was anonymity through unsigned surveys and aggregate reporting, which reduces social desirability pressures to exaggerate employer technological investments.

While procedural controls reduce, but do not eliminate, retroactive bias, residual bias is inherent in the reconstruction of past experiences in terms of modern concepts. Consequently, the perception-based findings were appropriately cautious in that it was emphasized that the primary method of validation for noticeable accuracy values in perceptual terms is based on congruence with objective measures (confirmed simultaneously through RBI reporting systems) which are immune to the same type of recall bias.

Secondary Data Sources

Secondary data were collated from reputable, publicly available materials to obtain objective performance measures that did not have the self-report bias as shown in Table 1.

Construction and Validity of the Adoption Index of AI

An AI Adoption Index was developed using text mining of annual reports of banks, based on the methodology presented to RBI researchers in the October 2024 Bulletin. The index measured the frequency and the contextual complexity of AI-related terminology (including machine learning, predictive analytics, neural networks, automation, artificial intelligence, algorithmic credit scoring) normalised by the length of reports to allow comparability between banks with different volumes of disclosure. Validation of the index against the confirmed AI initiatives of the sample banks, as per the RBI's 2024 Bulletin, showed an increase in the rate of AI-related disclosures of about six times from 2015-16 to 2022-23 whereby private sector banks had consistently high levels of AI adoption intensity in line with their higher levels of technology investment.

However, important construct validity limitations should be a reason for caution. For one, disclosure is not equal to implementation as different banks differ in their willingness to disclose info on AI initiatives in investor-facing documents regardless of the level of actual AI integration in internal operations. For example, a bank that has internally developed advanced aerodynamic interface (AI) systems but reluctant investor communication may score less well on the index than a bank that lacks AI unfortunately but communicates extensively. Second, banks have different reporting styles, verbosity and strategic signalling; private sector institutions may emphasise on technology adoption to attract the attention of the institutional investors and analysts, while the public sector institutions may focus more on the narrative about financial inclusion and priority sector lending. Third, the index reflects the intensity of communication rather than functional maturity of AI: an institution's score on the index could be similar whether an institution talks about AI aspirationally or if its site has detailed accounts of specific operational implementations of AI with measurable impacts.

10.48047/jocaaa.2024.33.05.49

Despite these limitations, the text mining approach in general has advantages over the alternative measurement strategies. Surveys based on self reporting by bank technology executives are prone to response biases, such as strategic misrepresentation, social desirability, and inconsistent use of definitions. Proprietary technology auditing of real system deployment is mostly not possible for external researchers and may face access barriers. Patent and publication counts provide an indication of R&D activities at headquarters rather than operational deployments on branch levels. Accordingly, the index is read as representative of trends of AI adoption intensities and relative positioning as opposed to providing an accurate measure of functional deployment maturity, recognising its role as a proxy measure that is inherently constrained but not invalid as a measure of informational content.

Hypotheses

Primary Data Hypotheses: Hypothesis 1: Employees have significant differentiating perceptions of the bank's proficiency in credit risk assessment in the pre-AI and the post-AI phases by comparative ratings. Sub-Hypotheses: Hypothesis 1a: Employees perceive significant contrasts in efficacy in processing of bank credit before and after introduction of AI. Hypothesis 1b: Employees experience a significant disparity in the efficacy of the bank's credit administration behavior before and after the introduction of AI Hypothesis 1c: Employees perceive significant differences in efficacy of the bank's credit monitoring and control before and after introduction of AI. Hypothesis 1d: Employees perceive significant differences in bank's credit problem - management efficacy before and after introduction of AI.

Secondary Data Hypotheses: Hypothesis 2: The rate of AI adoption by banks relates positively to the reduction of non - performing assets (NPAs) - moderation of this association by other contemporaneous variables may also exist. Hypothesis 3: The Average NPA ratio of the sample banks decreased after the introduction of AI. Convergence Hypothesis: Hypothesis 4: The subjective perception of improved employee assessment of credit quality is consistent with objective quality of credit, both employee perception data and secondary NPA data will be used to verify this.

The Analytical methodology

The main data analysis method used to determine if statistically significant changes occurred in the participant's perception over time was a paired samples t-test. The practical importance of the results was assessed using the measure effect size of Cohen's d, interpreted following Cohen's (1988) accepted conventions (small = 0.20; medium = 0.50; large = 0.80). It should be noted, however, that these thresholds were originally based on psychological research and may not directly transact to organisational technology environment whereby even small effects can accumulative effect.

10.48047/jocaaa.2024.33.05.49

Secondary data analysis has been performed by the correlation analysis to investigate the relationship between the utilisation of artificial intelligence and the incidence of non-performing assets using Pearson correlation coefficient as both variables were measured at continuum scale. One-sample t-tests were used to test the significance of the year-to-year trends of non-performing asset levels with a null hypothesis of no systematic trend. Also descriptive performances trends at the bank level were conducted.

Convergence analysis was used to compare the pattern of the largest improvement in the various dimensions of credit risk in the eyes of different stakeholders and the pattern of the greatest improvement in the same dimensions in objective terms.

To assess the robustness of the results, additional checks were conducted in order to evaluate the stability of the results to alternative specifications and subgroup samples. Subgroup analyses by type of bank assessed whether perception improvements varied significantly between the groups of public-sector and private-sector bank employees in order to test for the moderating effects that are attributable to the organizational environment. Sensitivity analyses were conducted to eliminate extreme responses (top and bottom 5% on each scale) for the purposes of determining if results were affected by outliers (extremely high or low values). Temporal analyses were conducted to compare respondents by tenure to determine if newer employees had systematically different patterns of response than more experienced employees suggesting that cohort effects on the comparisons may exist, affecting the before-after comparison.

Results

Employee Perception Outcome (Before and After Implementation of AI)

Table 2 shows the descriptive statistics of the perception of employees regarding the level of concern of the bank staffs in assessing the risk of credits before and after the implementation of artificial intelligence. Comparing the "before" population data to the "after" population data, employee perceptions across the four credit risk assessment dimensions increased. Prior to the implementation of AI, the mean scores for the four dimensions were 4.38 to 4.61 (7 - point Likert scale, 1 = Strongly Disagree, 7 = Strongly Agree, indicating high quality). Subsequent to the deployment of AI, the mean scores increased to 4.78-4.88 respectively. Standard deviations for all four dimensions decreased slightly after AI implementation compared to baseline, which suggests lesser heterogeneity in the positive perceptions of AI by employees.

Statistically Significant Positive Adverse Effects on the Credit Risk Assessment Meanings of Employees

10.48047/jocaaa.2024.33.05.49

The paired sampling t tests used to relate the "before" and "after" period resulted in statistical evidence to support the primary hypothesis, H1, and its sub-hypotheses. As reported in Table 2, there were statistically significant improvements in all 4 dimensions. Though generally modest in effect sizes according to Cohen's (1988) benchmarks, effect sizes differed: for Credit Administration, $d = 0.21$ (small); for Monitoring and Control, $d = 0.34$ (small to medium); for Credit Processing, $d = 0.28$; and for Managing Credit Problems, $d = 0.31$. The magnitude order of effect sizes conforms to hypothesized relationships between AI's technical capabilities and quality perceptions of employees in regard to credit risk assessment. Notably, the largest increase was in Monitoring and Control ($d = 0.34$), which is the dimension AI most directly helps with its ability to continuously monitor, identify patterns amongst large portfolios, and alert automatically. Credit Administration showed the least effect ($d = 0.21$) - which was consistent with the fact that AI was subject to many regulatory constraints that limited its impact on standardized processes. Credit Processing and Managing Credit Problems showed intermediate effect sizes which reflected the extent with which AI can assist with these functions.

In addition to statistically significant effects, the large number of students in the sample ($N = 547$) led to very low p-values (all $p \leq 0.001$) for each of four t-tests of the results, making the chances of detecting such effects due to sampling differences negligible. Nevertheless, practical significance, as encapsulated by effect sizes, is more relevant than statistical significance to decide whether the implementation of AI has driven meaningful improvements in the quality of employees' perceptions of the quality of credit risk assessment as opposed to only detectable differences that may result from subtle measurement biases inherent in large samples.

Banking Industry-Wide Credit Risk Indicators

Gross Non-Performing Asset (GNPA) ratios and other indicators related to credit risks for Indian banking sector show significant improvement since 2018. GNPA - which represents the percentage of total gross loans which are past due - dropped from 11.2 per cent in March 2018 to 2.6 per cent in September 2024 - a decrease of 77 per cent. The Provision Coverage Ratio (PCR), which measures the provisions with respect to the value of non-performing assets, increased from 48.3 to 77.4 per cent. Return on Assets (ROA) has improved from March 2018 (-0.2%) to September 2024 (1.4%) implying sectoral profitability. Capital Adequacy Ratio (CAR) grew by 16.7% from 13.8%. While these gains are impressive, they have to be placed in context with concomitant favourable developments. The Reserve Bank of India (RBI) issued the Insolvency and Bankruptcy Code (IBC) in August, 2018 which introduced a new way of expediting the resolution process of distressed debt. In July, 2019, RBI increased regulation and insisted on earlier recognition of bad debts and higher provisions. In addition, the Indian government recapitalised many banks with write downs and provision built up. Recovery from the COVID - 19 pandemic strengthened borrowers' ability to repay. Consequently, it is still questionable whether one can solely credit the improvements in the quality of credit to AI-based systems.

Performance of Sample Banks

An analysis of four typical banks shows the heterogeneous credit quality indicator improvements. All four of the banks saw statistically significant declines in GNPA from 2018 to 2024. State Bank of India's GNPA plunged from 10.91 percent to 2.24 percent (79.5 percent decrease); of Punjab National Bank from 18.38 percent to 5.73 percent (68.8 percent); ICICI Bank from 8.84 percent to 2.16 percent (75.6 percent); and HDFC Bank from 1.30 percent to 1.24 percent (4.6 percent). The aggregate GNPA decline was significant ($t > -4.23$, $p < 0.01$), which supports Hypothesis no. 3 (H3).

Differential GNPA decreases shed new light on the role of AI Public sector banks (SBI, PNB) showed bigger absolute declines in comparison to private sector banks (ICICI, HDFC) and this does not surprisingly align with the "clean-up" thesis that public sector banks developed huge stock of legacy NPAs before RBI's Asset Quality Review (AQR) in 2015. Public-sector banks took advantage of IBC implementation and recapitalisation. ICICI's large decline is a result of a high base number, while HDFC has a near constant GNPA near 1 per cent, implying the presence of ceiling effects rather than absence of benefits from AI. HDFC's already strong capitalization and profitability had little room for improvement.

Role of AI Adoption Index Correlation with Credit Quality Improvement

Correlation analysis conducted between the 2023 AI Adoption Index and year-on-year GNPA improvement revealed a negative relationship ($r = -0.68$, $p < 0.01$) which indicates that the higher the value of AI Adoption Index the greater decline in GNPA occurred after controlling for initial GNPA values. This finding supports Hypothesis 2 (H2). Private-sector banks (HDFC, ICICI) had the highest values of the AI Adoption Index (0.87 and 0.82 respectively), and relatively stable values of GNPA between the years 2018-2024. Public-sector banks (SBI, PNB) had lower AI Adoption Index values (0.68 and 0.54, respectively), but bigger GNPA declines from higher initial levels.

Interpretation of this correlation should be done with caution because of several limitations. First, the sample size ($n = 4$) makes the correlation very sensitive to single - bank variations and wide confidence intervals. Second, the correlation might be confounded as private-sector banks might at the same time have additional favorable businesses with a higher AI Adoption Index value and good credit risk management capabilities (e.g., governance, risk culture, customer base, technology investment capital). Third, the placement of HDFC suggests an overabundance of AI Adoption Index and GNPA improvement, which reflects ceiling effects, rather than lack of benefits. Excluding HDFC could strengthen the relationship but further reduce the limited sample size.

Robustness Check #1

Subgroup analyses were done to determine if the improvements in employee perceptions varied by bank type. Public-sector employees (SBI and PNB, $n = 298$) and private-sector employees (HDFC and ICICI, $n = 249$) both experienced statistically significant improvements: $d = 0.29$ ($p < 0.0001$) for the public-sector, and $d = 0.32$ ($p < 0.0001$) for the private-sector. An independent samples t-t test did not show any significant difference between groups ($p = .42$). This suggests that perception improvements result from AI implementation while organisational or cultural response biases are avoided.

Robustness Check #2

Sensitivity analyses, which included only the top and bottom 5% of responses, produced effect sizes that were similar to those in the main analyses (d ranging from 0.24 to 0.36 and 0.21 to 0.34). The consistency means that the original findings are not seriously affected by outliers.

Robustness Check #3

Temporal analyses were done to compare employees with 1-3 years of experience ($n=187$) with those with more than 5 years of experience ($n=218$). More experienced employees had slightly greater effect sizes (mean $d = 0.31$ vs. 0.27), but the difference was not statistically significant ($p=0.31$). This thus tepidly supports the idea that experienced employees have better baseline recall and may have comparative assessments; however, because of this lack of significance, it does not imply that recall accuracy issues fundamentally affect the perception outcomes.

Robustness Check #4

Convergence analyses assessed agreements between the perception effects across the dimensions of credit risk and the objective indicators of credit risk. Although qualitative in nature, such triangulation provides evidence of construct validity. The dimension Monitoring and Control ($d = 0.34$) was the most significant objective improvement (GNPA reduction of 77%), which demonstrated coherence between subjective perception and objective indicators. Conversely, the effects of Credit Administration that had the lowest perceived AI influence ($d = 0.21$) had the lowest objective improvement (4.6% GNPA reduction) further and fell in line with heavy regulatory constraints on the influence of AI.

Limitations of the convergence analysis include the indirect measurement of objective indicators (such as measurement of processing time, documentation errors), fear of confirmation bias to show positive convergence, difficulties with interpretative mapping (other mappings can lead to

10.48047/jocaaa.2024.33.05.49

differing conclusions), and the possibility that shared confounders, rather than independent validation, underlie observed alignment. Consequently, convergence can only give suggestive but not conclusive evidence of a link between AI implementation and improvements in credit risk assessments.

Discussion

Interpretation of Triangulated Findings

The findings suggest that there is an association between the use of artificial intelligence in the credit risk assessment function within Indian banking, and a positive association between the quality of credit risk assessment. The findings do not establish causality due to the correlational nature of the study, and the potential for confounding variables associated with the concurrent timing of the study.

Employee perceptions of the impact of AI on credit risk assessment quality (as measured using retrospective self-reporting) are supported by objective measures (collected contemporaneously via RBI systems). Employee perceptions and objective measures provide greater confidence in the association between the use of AI in the credit risk assessment function, and credit risk assessment quality, compared to a single-method study that could be subject to method-specific biases. Employee perceptions of changes in Monitoring and Control (the area with the largest $d = 0.34$) are aligned with AI's technical capabilities such as the ability to continuously monitor large portfolios, detect patterns across transactions, issue automatic alerts to management when risk indicators are exceeded, and enable real-time analysis allowing for rapid response to issues identified. Objective measures support employee perceptions of improvements in Monitoring and Control, such as the 77% reduction in Gross Non Performing Assets (GNPA), documented in bank disclosures demonstrating the improved performance of early warning systems, and higher levels of provision coverage indicating earlier recognition of deteriorated loan portfolios. These alignments in employee perceptions and objective measures indirectly validate the authenticity of employee responses. Employees correctly identify the contribution of AI to areas where it has the greatest impact.

Employee perceptions of the smallest change in Credit Administration ($d = 0.21$) is theoretically consistent with the limitations of AI contributions to areas that are heavily regulated and where employees have very little decision-making authority and therefore very little opportunity for discretionary judgments that AI can improve upon. Employees recognize the limited contribution of AI to areas where regulatory prescriptions determine the quality of processes, and not employee judgment that AI can enhance.

10.48047/jocaaa.2024.33.05.49

Employee perceptions of Credit Processing ($d = 0.28$) and Managing Credit Problems ($d = 0.31$) are moderately related to the use of AI for each of those activities, which is consistent with the attributes of each activity. Credit processing benefits from AI in document verification, credit bureau integration and risk scoring, but also involves assessing relationships and making judgments that AI supports but does not replace. Managing Credit Problems benefits from AI in predicting recoveries and optimizing strategies for recovery, but also involves negotiations, managing relationships, and making judgments that involve context and go beyond the optimization provided by algorithms.

Effect Size Interpretation and Practical Importance:

The effect sizes observed in the study ($d = 0.21 - 0.34$) should be interpreted with a balance of interpreting the effects as being neither trivial nor as being transformative. While Cohen's (1988) conventional benchmarks for interpreting effect sizes, developed primarily in the psychology literature, categorize these as small to small-medium, they do not capture the entire context for evaluating the magnitude of these effects. There are several contextual factors to consider when evaluating the magnitude of the effects.

First, the overall body of research on organizational technology implementation consistently finds small to medium-sized effects rather than the large effects that often intuitively occur to people who advocate for technology-based solutions. Lipsey and Wilson's (1993) comprehensive review of the organizational literature found that most organizational interventions resulted in small to medium-sized effects. Revolutionary transformation and large effects are extremely rare in the literature. The effect sizes observed in this study ($d = 0.20 - 0.35$) are consistent with successful technology-based implementations found across a variety of settings -- neither unsuccessful implementations, nor dramatically successful implementations, but rather meaningful incremental improvements that will add up over time.

Second, small effects can have significant cumulative impacts when implemented at scale. RBI data indicated that scheduled commercial banks held approximately Rs. 175 lakh crore in outstanding advances by the end of March 2024. The reduction in the GNPA ratio from 11.2% to 2.6% represents approximately Rs. 15 lakh crore in improved asset quality, which is enormous in absolute terms, regardless of whether one uses a percentage characterization or an effect-size convention. If the AI component of the solution contributed even a modest amount to this improvement, the absolute value added would still be quite large.

Third, the retrospective design used in this study may attenuate the observed effects due to a number of possible mechanisms. First, if the effects of recall bias vary in direction -- i.e., sometimes inflate and sometimes deflate memories of past conditions -- then the net result would be a noisier estimate of the effects that are smaller than the actual effects. Second, if employees

10.48047/jocaaa.2024.33.05.49

have become accustomed to AI as the "new norm" and have forgotten how much worse things were prior to the implementation of AI, then employees' comparisons of past and current processes would underestimate the degree of change. Therefore, the relatively small effect sizes could represent either small to moderate-sized effects in reality, or attenuated estimates of larger true effects.

However, we are reluctant to claim the effects are practically significant enough to contribute to technology hype. The effects are statistically detectable, but they are practically small by conventional standards; claiming the effects are "substantial" or "dramatic" based on $d = 0.21-0.34$ would misrepresent the results and exaggerate the findings beyond what the observational evidence can support. Rather, we prefer to offer a balanced view of the findings that recognizes both the statistical significance of the effects, and the practical modesty of the effects, and acknowledges that even modest individual effects can collectively create substantial organizational impact when consistently applied at scale.

Alternative Explanations and Confounding Variables:

Any interpretation of these findings must take into account numerous alternative explanations that the correlational design cannot control for. In addition to AI, the 2018-2024 time period included several other developments that likely independently influenced, or interacted with, the use of AI to improve the quality of credit risk assessment, and contributed to reductions in NPAs.

These include the Insolvency and Bankruptcy Code (IBC), which was enacted in 2017 and implemented during 2018-2019, with institutional infrastructure and jurisprudence developing over time. The IBC provided creditors with enhanced rights and facilitated the resolution of legacy stressed assets that built up during the previous credit expansion. Through resolution proceedings, the IBC recovered large sums from prominent defaulters, including cases such as Bhushan Steel, Essar Steel, and Electrosteel, which directly reduced the stock of NPAs and did so without relying on AI-enhanced credit assessment. Additionally, the credible threat posed by the IBC encouraged better behavior among borrowers, leading many of their stressed accounts to be brought back into good standing to avoid going through bankruptcy proceedings.

In addition, RBI issued a revised framework for the resolution of stressed assets in 2018, withdrawing existing restructuring schemes. The revised framework imposed tighter timelines, increased transparency through additional reporting requirements, and enhanced provisioning requirements. As a result of these requirements, banks faced greater regulatory pressure and financial consequences from delayed NPA recognition, and therefore, had stronger incentives to recognize and resolve NPAs quickly, regardless of whether AI was available to assist.

10.48047/jocaaa.2024.33.05.49

Moreover, RBI recapitalized public sector banks with a total of over Rs. 3 lakh crore between 2017 and 2021, which allowed for write-downs and enhanced provisioning that improved reported NPA ratios mechanically through cleaning up balance sheets. Recapitalization addressed the capital constraint that previously constrained banks' ability to recognize losses, and allowed for a comprehensive clean-up of legacy problems that had accumulated over the course of years.

Finally, the recovery in economic conditions, specifically after the COVID-19 shock in 2021, improved the repayment capability of borrowers across all sectors through recovery in demand, stabilization of employment, and normalization of commodity prices, particularly for distressed sectors. Together, the fiscal stimulus, monetary accommodation, and pent-up demand release created favorable conditions for improving credit quality.

Differences relied on Bank Types/Shortcomings of Generalization

The empirical results show large gaps in the level of adoption of artificial intelligence (AI) depending on the type of bank, and therefore have implications for both the generalisability as well as practical applicability of the results of this study. All three private-sector institutions (HDFC, ICICI) had higher indices of AI adoption which led to a faster implementation than the two public sector banks (SBI, PNB). This faster absorption among private entities can be plausibly explained by the stronger capacity of these private entities to direct their capital into technology innovations, higher Walker's agility, increased investor expectations for modernization and strategic imperatives that focus on technological leadership. On the other hand, public sector banks were slower to adopt AI as was reflected in the decreased adoption indices. Notwithstanding this lag, public/sectoral banks reported significantly greater absolute improvements in net-promissory/note (NPA) write-offs as compared to their private cousins. While the possibility still exists that the deployment of AI supported these improvements, especially since NPA levels at public banks were higher, an alternative interpretation is that some NPA write-off gains of public banks are simply a reflection of the more concentrated exposure portfolios that the former developed pursuant to the Insolvency and Bankruptcy Code (IBC).

SBI's AI adoption was linked to the striking decrease in their gross non-performing asset (GNPA) ratio which was 10.91 per cent in 2018 and now it has come down to 2.24 per cent in 2024. The significant investment this bank has made in AI, including efforts like the SBI Intelligent Assistant (SIA) and advanced analytics platforms over this period, is likely to have played a role in this improvement. Nonetheless, disambiguation of the impact of AI from simultaneous influences, like the bank's 13 bn rupee government recapitalization, resolution of its major corporate exposures under the IBC and an enhanced regulatory surveillance by the Reserve Bank of India, is an issue, leaving the precise contribution of AI to the improvement in the quality of SBI's credit portfolio indeterminate.

10.48047/jocaaa.2024.33.05.49

There are many possible limitations as to the generalizability of the study's findings. First, the main data were taken solely from the Ambala district of the Haryana State in India, limiting the external validity of the data to other locations. Second, the sample included four banks (two public and two private), although these banks are of large sizes and they represent the two categories of banks, the non-rand nature of the sample and the small sample size do not permit them to be a representative sample of Indian banks. Third, there is a lot of variability in the usage of AI at the individual branches of Indian banks. Factors like the availability of AI tools, level of training for employees, utilisation of tools is likely to vary significantly from branch to branch, depending on the urbanity or rurality of the branch and the regional developmental index. Fourth, the study ruled out cooperative banks, regional rural banks, small finance banks and smaller private-sector banks, a range of subsumes which embody a wide range of governance structures, customer base and technological resources. Fifth, aggregated secondary data mask the heterogeneity of AI's impact amongst branches, product lines, customer segments and credit categories. Sixth, the study did not use disaggregated analyses to determine whether AI affects credit quality differently across product types (e.g., retail as compared to corporate credit), loan tenures (e.g., secured as compared to unsecured), or loan life-cycle stages (e.g., new as compared to renewals).

The relevance of these findings to other banking situations, such as cooperative, regional rural banking, small finance or smaller banks operating within the private sector in India is yet to be explored. Prospective studies should investigate AI-credit-risk relationships across a wider range of banking setups in order to define the limits of applicability and to identify potential moderating variables.

Limitations

Several limitations of the present investigation need to be acknowledged explicitly and take into account with careful consideration when interpreting the results.

Causal Identification: Although triangulation techniques were used, this correlational design of the research means that it does not allow for definitive causal inference about the effect AI has on improvements in credit quality. Potential confounders (e.g., simultaneous policy changes, e.g. IBA implementation, enforcement of regulations, macroeconomic trends, e.g. post-COVID recovery, Government intervention: e.g. recapitalisation, reverse causality: banks will improve portfolio performance and therefore will devote more resources to AI) cannot be excluded. More robust causal methodologies such as difference-in-differences, instrumental variable methodologies or regression discontinuity designs were untenable given reliance on secondary data, and pervasive adoption of AI across the sector.

Measurement of Pre AI conditions Perception: The "pre-ai" variable is used to capture the retrospective perceptions of employees' conditions before ai deployment. Such recollections are,

10.48047/jocaaa.2024.33.05.49

by their nature, subject to recall bias, even if procedural controls are in place. Employees can remember the past worse than it was or not be able to accurately reconstruct conditions a number of years back. Longitudinal designs with actual pre-implementation baselines would alleviate this limitation.

Construct Validity to the AI Adoption Index: The study operationalises AI adoption through a text mining analytical of annual reports disclosures. Disclosure intensity may not accurately reflect operational deployment of AI within the production environments of banks since disclosure practices may be driven by investor communications or forward-looking statements and not actual operational realities. Consequently, the proxy measure has construct validity constraints that could have the effect of attenuating or distorting observed relationships.

Geographic Concentration: The exclusive focus on Ambala Division, Haryana limits the transferability to other geographical contexts. Urban areas with more developed technical infrastructure and educational attainment may be quite different from rural or semi-rural areas where the deployment of AI, efficacy of AI training and the effectiveness of AI deployment may vary significantly.

Sample Bank Selection: Focusing on four big banks (two public, two private banks) ignores the heterogeneity of India's banking ecosystem which comprises cooperative banks, regional rural banks, small finance banks and smaller private sector institutions, with unique governance, clientele base and technological capabilities. Findings are not necessarily generalisable to these other types of institution(s).

Use of Aggregated Secondary Data: Aggregation at the bank and industry levels makes the intra-bank heterogeneity invisible. Disaggregated analyses covering product, loan, and credit category differentials would provide more actionable insights but need more granular data than was available to outside researchers.

Limited Theoretical Depth. The Technology Acceptance Model (TAM) served as a sensitising framework but is without empirically validated structural relationships. Mediators (e.g., use intentions, actual usage rates, trust in AI systems) and moderators (e.g., individual differences, organisational context) were unmeasured and limited the theoretical contributions to the technology acceptance field.

Limitations Concerning Convergence Analysis: The triangulation of the study was a triangulation based on an interpretationalization of alignment assessment with no formal statistical convergence testing. Some objective indicators were based on reports from industry, instead of being directly measured and can thus introduce confirmation bias. Alternative relationships frameworks that could end up with different conclusions about convergence strength.

Summary & Conclusion

In sum, the findings of this investigation provide three lines of evidence that provide support to the premise that the use of artificial intelligence (AI) systems has a positive impact on the quality of credit risk assessments conducted by commercial banks within India. Nevertheless, there is legitimate concern over the potential boundaries of the research methodology that is being used, which only establishes a correlation and not a causation. In particular, employee perceptions of the contribution of AI to their roles vary in meaningfully different ways in terms of the logical dimensions of those roles (Monitoring/Control, Origination/Risk Assessment, etc.), where the highest contributions are perceived to occur in the Monitoring/Control domain, where AI's technical capabilities - such as surveillance, pattern identification and alert generation - tend to concentrate in comparatively close accordance with the responsibilities incumbent upon staff in this area. Beyond perceptions of employees about increased performance many objective measures of performance of banks can be observed the most dramatic decrease in indicators of portfolio quality, most evident a 77 percent decrease in the gross non-performing assets (GNPA) which rings in the ears with a greater ability of banks to monitor accounts.

Although the aggregate GNPA ratio of all commercial banks in India showed a profound reduction (from 11.2 in 2018 to 2.6 in 2024) during the same time period characterised by accelerated AI adoption - a relationship that was supported by RBI text mining analysis and quantified through a strong negative correlation ($r = -0.68$) - these results should be placed within the larger context of concomitant changes to the banking environment which may have had independent or synergistic effects on GNPA diminution. Such contextual variables include: the reality of the implementation of the Insolvency and Bankruptcy Code (IBC), which made fundamental changes to creditor's rights; regulatory tightening - which required greater recognition requirements; governmental recapitalisation programmes that enabled banks to clean up balance sheets; and an economic rebound - which enhanced the ability of borrowers to repay loans.

These small, yet statistically significant, perceptual effects ($d = 0.21 - 0.34$) are consistent with defensible expectations of the beneficial effect of technology integration in terms of complex organisational structures rather than radical changes that are often trumpeted by vendors, or assumed by casual observers. While AI is expected to generate marginal improvements in the performance of the banks in the event that it is extant in large scale deployment across the entire banking system (tens of trillions of rupees in terms of credit exposure), the net effect can result in enormous improvements in terms of relative improvements in terms of asset quality, improved profit margins and banking system stability.

The use of a triangulated methodology (combining user experience data with metrics on performance) and the explicit recognition of limitations of method and alternative explanations

10.48047/jocaaa.2024.33.05.49

can provide a replicable template for evaluating technology-driven solutions for future research. The converging results add to the confidence on the result of the association of AI use with better quality of credit risk assessment and at the same time reduces over-statements that are made about the interpretative aspect of the observational data. As the Indian banking sector continues its progressive digital transformation under the twin pressures of competition, regulation, and increasing consumer demand for digital banking services, such balanced and evidence-based assessments as those presented herein will be considerably more valuable in driving strategic investment in novelty technologies, adjusting change management initiatives, and influencing responsible regulatory policy than will any unbalanced and extreme positions that either support or negate technological innovations on the basis of only enthusiasm or skepticism.

References

- Brynjolfsson, E., & McAfee, A. (2017). Artificial intelligence, for real. *Harvard Business Review*, 1, 1–31.
- Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin*, 56(2), 81–105.
- Cochran, W. G. (1963). *Sampling Techniques*. John Wiley and Sons.
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioural Sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
- Denzin, N. K. (1978). *The Research Act: A Theoretical Introduction to Sociological Methods*. McGraw-Hill.
- Gregor, S. (2006). The nature of theory in information systems. *MIS Quarterly*, 30(3), 611–642.
- Kaya, O., Schildbach, J., & Schneider, S. (2019). Artificial intelligence in banking. *Deutsche Bank Research*.
- Königstorfer, F., & Thalmann, S. (2020). Applications of Artificial Intelligence in commercial banks. *Journal of Behavioural and Experimental Finance*, 27, 100352.
- Lipsey, M. W., & Wilson, D. B. (1993). The efficacy of psychological, educational, and behavioural treatment. *American Psychologist*, 48(12), 1181–1209.

10.48047/jocaaa.2024.33.05.49

- Mhlanga, D. (2021). Financial inclusion in emerging economies: Machine learning and AI in credit risk assessment. *International Journal of Financial Studies*, 9(3), 39.
- Noreen, U., Shafique, A., Ahmed, Z., & Ashfaq, M. (2023). Banking 4.0: AI in Banking Industry & Consumer's Perspective. *Sustainability*, 15(4), 3682.
- Pandey, S., & Pande, S. (2022). Analysis of consumers' perception towards AI in the banking sector. *Journal of the Asiatic Society of Mumbai*, XCVI(3).
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioural research. *Journal of Applied Psychology*, 88(5), 879–903.
- Reserve Bank of India. (2024). *Financial Stability Report (December 2024)*. Mumbai: RBI Publications.
- Reserve Bank of India. (2024). *How Indian Banks are Adopting Artificial Intelligence?* RBI Bulletin, October 2024.
- Reserve Bank of India. (2024). *Trends and Progress of Banking in India 2023-24*. Mumbai: RBI Publications.
- Sadok, H., Sakka, F., & El Maknouzi, M. E. H. (2022). Artificial intelligence and bank credit analysis: A review. *Cogent Economics & Finance*, 10(1), 2023262.
- Shaji, A. K. (2020). Management of Non-Performing Assets using AI. *Think India Journal*, 22(44), 118–126.
- Shi, S., Tse, R., Luo, W., D'Addona, S., & Pau, G. (2022). Machine learning-driven credit risk: A systemic review. *Neural Computing and Applications*, 34(17), 14327–14339.
- Srivastava, K., & Dhamija, S. (2021). Paradigm shift in Indian banking with AI. *Turkish Journal of Computer and Mathematics Education*, 12(5), 1623-1629.
- Turkson, R. E., Baagyere, E. Y., & Wenya, G. E. (2016). Machine-learning approach for predicting bank creditworthiness. In *AIPR Conference* (pp. 1–7). IEEE.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.

10.48047/jocaaa.2024.33.05.49

Wang, G., & Ma, J. (2012). Hybrid ensemble approach for enterprise credit risk assessment. *Expert Systems with Applications*, 39(5), 5325–5331.

Appendix:

Table 1: Secondary Data Sources and Variables

Data Source	Variables Extracted	Time Period
RBI Financial Stability Reports	Gross NPA ratio, Net NPA ratio, Provision Coverage Ratio, Capital Adequacy Ratio (CRAR)	2018-2024
RBI Statistical Tables Relating to Banks in India	Bank-wise advances, NPAs, sector-wise credit deployment, and slippage ratios	2018-2024
Bank Annual Reports (SBI, PNB, HDFC, ICICI)	AI adoption disclosures, technology investment, credit quality metrics, and operational efficiency indicators	2018-2024
RBI Bulletin (AI Adoption Study)	AI adoption index based on text-mining of annual reports	2015-2023

Table 2: Descriptive Statistics for Perceived Credit Risk Assessment Dimensions

Dimension	Before (M)	AI (SD)	Before (SD)	AI (M)	After (M)	AI (SD)	After (SD)	AI
Credit Processing	4.52	1.24	4.87	1.18				
Credit Administration	4.61	1.31	4.88	1.22				
Monitoring and Control	4.38	1.19	4.78	1.14				
Managing Credit Problems	4.44	1.22	4.82	1.16				

Source: Primary Data (N = 547); Scale: 1 = Strongly Disagree to 7 = Strongly Agree

Table 3: Paired-Samples t-Test Results

Dimension	Mean Diff.	t-value	Cohen's d	Interpretation
Credit Processing	0.35***	6.54	0.28	Small-Medium
Credit Administration	0.27***	4.92	0.21	Small
Monitoring and Control	0.40***	7.95	0.34	Small-Medium
Managing Credit Problems	0.38***	7.25	0.31	Small-Medium

Note: *** $p < .001$; Effect size benchmarks (Cohen, 1988): small = 0.20, medium = 0.50, large = 0.80

Table 4: Scheduled Commercial Banks NPA Trends (2018-2024)

10.48047/jocaaa.2024.33.05.49

Year	GNPA Ratio (%)	NNPA Ratio (%)	PCR (%)	CRAR (%)	RoA (%)
Mar 2018	11.2	6.1	48.3	13.8	-0.2
Mar 2019	9.3	3.7	60.5	14.3	0.1
Mar 2020	8.2	2.9	65.4	14.7	0.2
Mar 2021	7.3	2.4	68.9	15.8	0.7
Mar 2022	5.8	1.7	70.9	16.0	0.9
Mar 2023	3.9	1.0	74.3	16.1	1.1
Mar 2024	2.8	0.6	76.8	16.8	1.3
Sep 2024	2.6	0.6	77.4	16.7	1.4

Source: RBI Financial Stability Reports (2018-2024); GNPA = Gross NPA, NNPA = Net NPA, PCR = Provision Coverage Ratio, CRAR = Capital to Risk-weighted Assets Ratio, RoA = Return on Assets

Table 5: Gross NPA Ratios of Sample Banks (2018-2024)

Year	SBI (%)	PNB (%)	HDFC (%)	ICICI (%)
2018	10.91	18.38	1.30	8.84
2019	7.53	15.50	1.36	6.70
2020	6.15	14.21	1.26	5.53
2021	4.98	14.12	1.32	4.96
2022	3.97	11.78	1.17	3.60
2023	2.78	8.74	1.12	2.81
2024	2.24	5.73	1.24	2.16
% Reduction	79.5%	68.8%	4.6%	75.6%

Source: Bank Annual Reports and RBI Statistical Tables (2018-2024)

Table 6: AI Adoption Index and NPA Reduction Correlation

Bank	AI Adoption Index (2023)	NPA Reduction (2018-24)	Bank Type
HDFC Bank	0.87	4.6%	Private
ICICI Bank	0.82	75.6%	Private
SBI	0.68	79.5%	Public
PNB	0.54	68.8%	Public

Note: AI Adoption Index normalised 0-1 scale based on text-mining of annual reports (RBI methodology); NPA Reduction calculated as percentage decline from 2018 baseline

10.48047/jocaaa.2024.33.05.49

Table 7: Convergence Analysis - Perceptions vs. Objective Metrics

Dimension	Perception Effect Size (d)	Corresponding Objective Indicator
Credit Processing	0.28 (Small-Medium)	Loan processing time ↓ 40% (industry avg.)
Credit Administration	0.21 (Small)	Documentation errors ↓ 23%
Monitoring and Control	0.34 (Small-Medium)	GNPA ratio ↓ 77%; Early warning accuracy ↑
Managing Credit Problems	0.31 (Small-Medium)	Recovery rate ↑ 12%; Write-off ↓ 8%