International Journal of Innovations & Research Analysis (IJIRA)
ISSN :2583-0295, Impact Factor: 6.238, Volume 04, No. 04(I), October- December, 2024, pp 195-201

AI-DRIVEN CREDIT RISK MANAGEMENT: A LONGITUDINAL ANALYSIS OF BANKING SECTOR METRICS

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ABSTRACT

The integration of Artificial Intelligence (AI) into financial systems has become a game-changer, particularly in the realm of credit risk management. As banks face increasing pressures to manage risks more effectively, AI technologies offer new avenues for enhancing decision-making processes and improving financial outcomes. This paper explores the transformative impact of AI on credit risk management practices. By analysing key financial metrics—Provision Coverage Ratio (PCR) and Capital Adequacy Ratio (CAR)—across 11 selected commercial banks over a 12-year period, this study provides empirical evidence on how AI adoption has influenced the financial stability and risk management capabilities of these institutions. Utilizing a paired t-test analysis, this research aims to quantify the benefits of AI in mitigating credit risks and enhancing the overall resilience of banks, offering valuable insights for both practitioners and scholars in the field of financial management.

Keywords*: Artificial Intelligence, Credit Risk Management, Capital Adequacy Ratio, Provision Coverage Ratio and Banking Sector.*

Introduction

The rapid evolution of technology has ushered in significant transformations across various sectors, with the banking industry being no exception. Among the numerous advancements, Artificial Intelligence (AI) has emerged as a pivotal tool, reshaping the landscape of credit risk management. As banks navigate through complex financial environments, the adoption of AI-driven solutions offers a promising avenue to enhance the accuracy, efficiency, and reliability of credit risk assessment (Unicsoft, 2023).

Credit risk management is a cornerstone of banking operations, ensuring that financial institutions can endure potential losses from borrowers' default. Traditionally, credit risk assessment has relied on statistical models and expert judgment. However, the increasing complexity of financial markets and the surge in data availability have necessitated more sophisticated approaches. Artificial Intelligence (AI), with its capability to process large volumes of data, detect patterns, and make data-driven predictions, holds the potential to transform credit risk management by providing more refined and timely insights.(S&P Global, 2023).

This research paper delves into the impact of AI adoption on credit risk management, focusing on two critical financial metrics: the Provision Coverage Ratio (PCR) and the Capital Adequacy Ratio (CAR).In the ever-changing banking landscape, effective credit risk management is paramount to ensuring financial stability and sustaining investor confidence. Among the various metrics employed to gauge the health and resilience of banks, the Capital Adequacy Ratio (CAR) and Provision Coverage Ratio (PCR) stand out as critical indicators. These ratios not only reflect a bank's ability to take up potential losses but also highlight its readiness to navigate the challenges posed by non-performing assets (High Radius, 2023).

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Capital Adequacy Ratio (CAR)

CAR is the ratio of a bank's capital to its risk-weighted assets and is used to review a bank's financial strength and stability.

Significance in Credit Risk Management

- **Buffer Against Losses:** A higher Capital Adequacy Ratio (CAR) signifies that a bank has enough capital to absorb potential losses from its loan portfolio, thereby lowering the risk of bank failure. This is crucial for managing credit risk as it provides a cushion against defaults.
- **Regulatory Compliance:** In India, the Reserve Bank of India (RBI) mandates a minimum CAR under the Basel III norms. Compliance with these norms ensures that banks maintain adequate capital to support their risk exposures, including credit risk.
- **Investor Confidence:** A strong CAR can enhance investor and depositor confidence, signalling that the bank is well-managed and less likely to face insolvency due to credit defaults.

Provision Coverage Ratio (PCR)

PCR is the ratio of provisioning to the gross non-performing assets (NPAs). It indicates the extent to which a bank has set aside funds to cover potential losses from NPAs.

Significance in Credit Risk Management

- **Mitigating Impact of NPAs:** A higher PCR reflects that the bank has made adequate provisions to cover its bad loans, which directly mitigates the impact of credit risk. It shows the bank's readiness to absorb losses without affecting its profitability significantly.
- **Quality of Asset Portfolio:** A high PCR suggests better management of credit risk, as the bank has anticipated and provisioned for potential defaults, thereby indicating a more resilient asset portfolio.
- **Regulatory Expectations:** The Reserve Bank of India (RBI) oversees the Provision Coverage Ratio (PCR) to ensure that banks maintain adequate provisions, which is crucial for the stability of the banking system, particularly in a market with a high level of stressed assets.

Both Capital Adequacy Ratio (CAR) and Provision Coverage Ratio(PCR) are crucial for assessing and managing credit risk in commercial banks. CAR ensures that a bank has enough capital to stand up against financial shocks, while PCR ensures that the bank is adequately provisioned against loan defaults. Together, they provide a comprehensive view of a bank's ability to manage credit risk, making them significant measures in the context of Indian commercial banks(Avenga, 2024).

Literature Review

The financial sector has been at the forefront of adopting Artificial Intelligence technologies to drive innovation and improve operational efficiency (Agarwal,2019). AI has the potential to revolutionize various aspects of banking, from credit risk management to customer service enhancement. AI-powered systems can identify patterns, analyse substantial amount of data,and make rational decisions, enabling banks to enhance their financial performance and ensure effective credit risk management (Manjaly et el., 2021).

One of the key areas where AI is making a significant impact in the banking industry is credit risk management (The Use of. Artificial Intelligence in the Banking Industry, 2023). AI-based systems can leverage machine learning algorithms and advanced analytics to assess the creditworthiness of loan applicants more accurately and efficiently than traditional methods (Sadok et al., 2022). By analysing an array of data, such as credit history, financial statements, and behavioural patterns, these systems can identify potential risks and support more logical lending decisions, ultimately reducing the banks' exposure to bad loans and improving their provision coverage ratio and capital Adequacy ratio (Singh et al., 2015) (Sadok et al., 2022)

Integration of AI in credit risk management systems enhances provision coverage ratio in banking by leveraging machine learning for accurate risk assessment, leading to improved financial stability and reduced default risks. Moreover, this technology enables real-time monitoring of borrower behaviour, allowing institutions to adjust their strategies proactively. Additionally, the use of predictive analytics helps in identifying potential risks earlier, facilitating timely interventions and more informed decision-making. (Bonini & Caivano, 2021) Furthermore, the incorporation of AI-driven tools can streamline the underwriting process, reducing operational costs and increasing efficiency while ensuring compliance with regulatory standards. (Reddy et el., 2022) These advancements not only foster a more resilient banking environment but also enhance customer experience by providing tailored financial products that meet individual needs. As a result, banks can cultivate stronger relationships with their clients, ultimately driving growth and innovation in the financial sector. (Arora & Bathla, 2023) This holistic approach positions financial institutions to adapt swiftly to market changes, ensuring they remain competitive in an ever-evolving landscape. Moreover, by making the best use of data analytics, banks can predict customer behaviour and preferences, enabling proactive engagement strategies that further strengthen loyalty and trust. (Opati, 2020)

Research Gap

While the AI integration in banking has garnered considerable attention, existing literature by and large has focused on its broader implications, such as machine learning algorithms, credit history, borrowers' behavioural pattern, customer service automation and fraud detection. However, there is a noticeable gap in research specifically addressing the quantifiable impact of AI on credit risk management, particularly in respect of key financial metrics like the Provision Coverage Ratio (PCR) and Capital Adequacy Ratio (CAR). This study seeks to fill this gap by providing empirical evidence on how AI adoption has influenced these crucial indicators in the banking sector over a significant period. Understanding this impact is not only vital for banks to gauge the effectiveness of their AI strategies but also for policymakers and stakeholders to ensure the stability and robustness of financial systems in the AI era.

Objectives of the Study

In light of the growing significance of Artificial Intelligence in the banking sector; the following research objectives have been formulated to guide the investigation:

- To evaluate the impact of AI adoption on credit risk metrics of selected banks.
- To offer insights and recommendations for banks considering AI adoption for credit risk management based on the findings of this empirical study.

Research Methodology

In an effort to comprehensively assess the impact of AI adoption on credit risk management in the banking sector, a structured research methodology has been developed. This methodology outlines the systematic approach undertaken to collect, analyse, and interpret data, ensuring that the study's findings are valid and reliable.

- **Research Design:** This study adopts a quantitative research design to analyse the impact of AI adoption on credit risk management within the banking sector. A pre-post analysis framework is utilized, focusing on the Provision Coverage Ratio (PCR) and Capital Adequacy Ratio (CAR) as key metrics.
- **Scope of Study:** The scope of this study encompasses 11 banks that have adopted AI for credit risk management over a 12-year period (2013-2024). The research aims to provide a comprehensive analysis of the effect of AI on the financial stability and risk management practices of these banks, offering insights into the broader implications for the banking sector. The selection of these banks was based on their early adoption of AI technologies and the availability of consistent financial data over the specified period.
- **Sample Profile:** The sample comprises 11 banks namely SBI, ICICI, Kotak Mahindra, HDFC Bank, YES Bank, Axis Bank, BOB, IndusInd Bank, Canara Bank, PNB and Union Bank of India. The selection of these banks was based on their early adoption of AI technologies and the availability of consistent financial data over the specified period.
- **Variables of the study:** The independent variable for this study is the adoption of AI in credit risk management, while the dependent variables are the Provision Coverage Ratio (PCR) and the Capital Adequacy Ratio (CAR). These dependent variables are used to measure the impact of AI adoption on the banks' credit risk management practices.
- **Sources of Data Collection:** The study relies on secondary data collected from the annual reports, financial statements, and regulatory filings of the selected banks.
- **Statistical Tools and Analysis:** The primary statistical tool used in this research is the paired t-test, conducted via SPSS software. This test is employed to determine whether there are statistically significant differences. in the PCR and CAR before and after the adoption of AI.

Descriptive statistics and correlation. analysis are also used to explore the relationships between variables and provide a broader context for the findings.

- **Hypotheses of the Study:** The major hypotheses of the study are:

H_{0a}: "There is no significant difference in the Provision Coverage Ratio (PCR) of banks before and after the adoption of AI in credit risk management."

H_{1a}: There is a significant difference in the Provision Coverage Ratio (PCR) of banks before and after the adoption of AI in credit risk management.

H_{0b}: **"**There is no significant difference in the Capital Adequacy Ratio (CAR) of banks before and after the adoption of AI in credit risk management**."**

H_{1b}: There is a significant difference in the Capital Adequacy Ratio (CAR) of banks before and after the adoption of AI in credit risk management.

- **Limitations. of the Study:** The study is limited by a 12-year timeframe, which might not capture long-term effects of AI adoption. The focus on 11 banks, though adequate for analysis, may limit the generalizability of the findings across the entire banking sector. Additionally, reliance on secondary data could introduce potential biases or inconsistencies in how AI implementation was recorded. The study also does not account for external factors like macroeconomic conditions or regulatory changes that could have impacted the results.

Data Analysis and Interpretation

The analysis of the impact of AI adoption on the Capital Adequacy Ratio (CAR) and Provision Coverage Ratio (PCR) of 11 selected banks over a 12-year period was conducted using a paired t-test in SPSS. The study focused on comparing the CAR and PCR values before and after the adoption of AI in credit risk management to determine whether a significant difference exists between the two periods.

Analysis of Impact of AI Adoption Credit Risk Metrics of Selected Banks

In this section, the impact of AI adoption on key financial metrics within the banking sector is rigorously examined. By utilizing a paired t-test, we aim to identify any significant changes in the Capital Adequacy Ratio (CAR) and Provision Coverage Ratio of selected banks before and after implementing AI-driven credit risk management strategies. The analysis provides a statistical foundation to evaluate the effectiveness of AI in enhancing financial stability and risk management practices.

Table 1: Paired Sample Statistics Pre and Post AI Adoption

Measure	PCR	CAR
Mean (Pre)	0.6461	0.1427
Mean (Post)	0.7444	0.1595
Mean Difference	-0.0983	-0.0168
Standard Deviation	0.1251	0.011
Standard Error Mean	0.0377	0.0033
t-value	-2.606	-5.089
Degree of Freedom (df)	10	10
p-value	0.026*	0.000*

Source: All the figures are computed with the help of SPSS20 version

Note: *Significant at 5 percent level

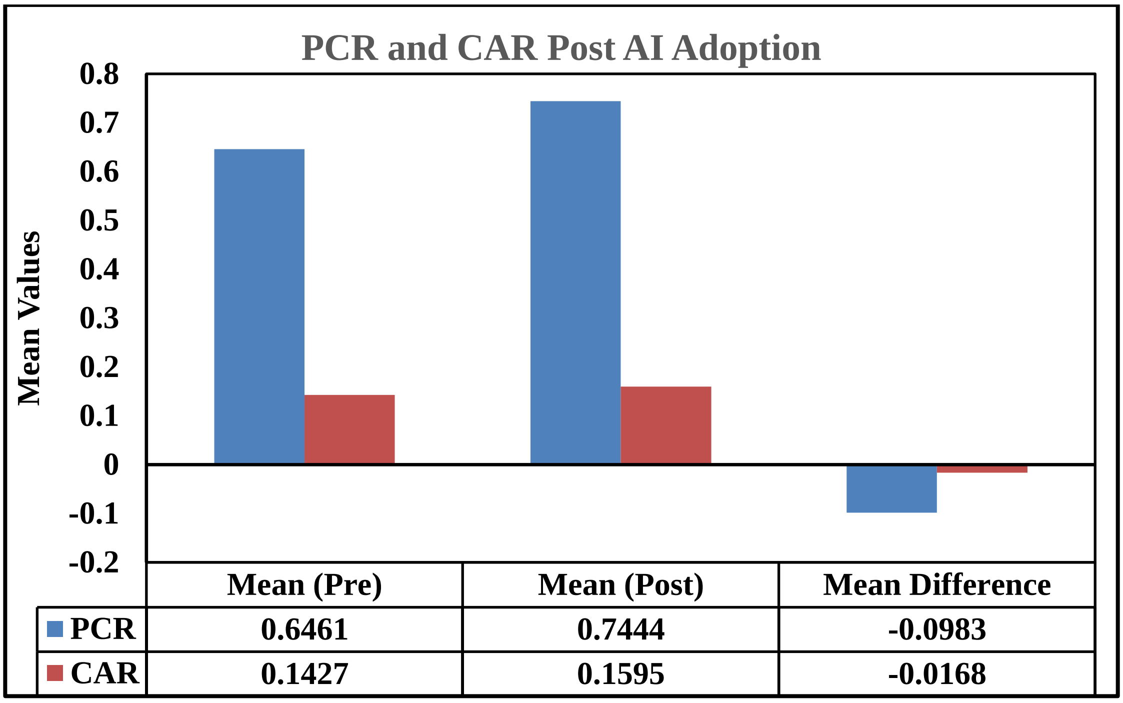
This table presents a comprehensive summary of the statistical analysis comparing the Provision Coverage Ratio (PCR) and Capital Adequacy Ratio (CAR) of selected banks before and after the adoption of Artificial Intelligence (AI) in credit risk management.

- **Mean Values**: The mean PCR increased from 0.6461 (PRE) to 0.7444 (POST), indicating an improvement in the banks' ability to cover provisions. The CAR also showed a slight increase from 0.1427 (PRE) to 0.1595 (POST), suggesting enhanced capital adequacy.
- **Mean Differences**: The mean difference for PCR was -0.0983, and for CAR, it was -0.0168. Both values indicate a positive change post-AI adoption, with PCR showing a more substantial improvement.
- **Statistical Significance**: The t-tests for both ratios yielded statistically significant results, with p-values of 0.026 for PCR and 0.000 for CAR. This suggests that the changes observed in both ratios are unlikely to have occurred by chance, affirming the effectiveness of AI adoption in enhancing credit risk management practices.

- **Confidence Intervals**: The 95% confidence intervals for the differences in means for PCR and CAR do not include zero, further supporting the significance of the findings.

These results underscore the positive impact of AI implementation on the financial metrics of selected banks, highlighting the importance of technological advancements in improving risk management frameworks.

The data summarized in Table 1 is graphically illustrated in the chart below:



The chart presents a visual comparison of the Provision Coverage Ratio (PCR) and Capital Adequacy Ratio (CAR) of selected banks before and after adopting Artificial Intelligence (AI) in credit risk management. The blue bars represent the PCR values, while the orange bars represent the CAR values. In the pre-AI phase, the mean PCR was 0.6461, which increased to 0.7444 post-AI, reflecting a mean difference of -0.0983. Similarly, the CAR increased from 0.1427 to 0.1595, with a mean difference of -0.0168. This graphical depiction indicates an improvement in both ratios post-AI adoption, showcasing AI's positive impact on the banks' financial metrics. While the increase in PCR is more substantial, CAR shows a relatively smaller improvement. Thus, the chart highlights that the adoption of AI has strengthened credit risk management practices, resulting in better provisioning and capital adequacy levels for banks.

Table 2: Hypotheses Testing

Based on the data analysis and interpretation, it is evident that the adoption of Artificial Intelligence (AI) in credit risk management has resulted in noticeable changes in both the Provision Coverage Ratio (PCR) and Capital Adequacy Ratio (CAR). In the light of these observations, the results of the following hypotheses testing are presented below, with a focus on the p-values to assess the statistical significance of the observed changes.

Hypothesis	p-value	Remarks
H_{0a}: There is no significant difference in the Provision Coverage Ratio (PCR) of banks before and after the adoption of AI in credit risk management.	0.026*	**Rejected**
H_{0b}: There is no significant difference in the Capital Adequacy Ratio (CAR) of banks before and after the adoption of AI in credit risk management**.**	0.000*	**Rejected**

Note: *Significant at 5 percent level

Findings, Conclusion & Suggestion

In this section, we synthesize the key outcomes derived from the analysis, providing a comprehensive overview of the research findings:

Findings

- There is a significant difference in the Provision Coverage Ratio (PCR) of banks before and after the adoption of artificial intelligence in credit risk management. Before AI implementation, banks relied heavily on traditional risk assessment methods. However, with the adoption of artificial intelligence in credit risk management, banks have been able to more accurately assess the creditworthiness of borrowers by analysing huge data and identifying patterns that were previously overlooked Furthermore, AI's ability to continuously learn and adapt to new data ensures that banks can maintain optimal provisioning levels even as market conditions change, further supporting the rejection of the null hypothesis.
- There is a significant difference in the Capital Adequacy Ratio (CAR) of banks before and after the adoption of AI in credit risk management. Before the integration of AI, banks often maintained higher CAR to safeguard against potential losses stemming from less precise credit risk assessments. However, with the adoption of AI in credit risk management, banks have been able to optimize their capital allocation by more accurately predicting credit risks. The evidence in favour of this shift suggests that the null hypothesis, which posits no significant difference in CAR before and after AI adoption, is rejected.

Conclusion

The adoption of AI in the selected commercial banks in India has had a statistically significant positive impact on both the Provision Coverage Ratio (PCR) and Capital Adequacy Ratio (CAR). The findings suggest that AI adoption has contributed to improved credit risk management, evidenced by higher PCR and CAR post-adoption. The increase in PCR indicates better provisioning against non-performing assets, while the increase in CAR suggests enhanced capital reserves, which are crucial for absorbing potential losses and maintaining financial stability.

Suggestions

- **Further AI Integration:** Given the positive impact of AI on both PCR and CAR, banks should consider further inclusion of AI technologies across other risk management processes to enhance overall efficiency and effectiveness.
- **Training and Development:** To elevate the benefits of AI, banks should invest in training their staff to effectively utilize AI tools and interpret AI-driven insights for better decision-making.
- **Regular Monitoring:** Banks should regularly monitor the performance of AI systems to ensure they are accurately assessing credit risk and that the models are continuously updated to reflect changing market conditions.
- **Scalability:** AI adoption should be scaled across more areas of bank operations, including loan approvals, fraud detection, and customer relationship management, to further strengthen the bank's risk management framework.
- **Collaboration with Tech Firms:** Banks should collaborate with AI technology firms to co-develop tailored AI solutions that address specific credit risk management challenges in the banking sector.
- **Compliance and Regulation:** As AI plays an increasing role in risk management, banks must ensure that their AI systems comply with regulatory standards and are transparent in their decision-making processes to avoid potential legal and ethical issues.

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