Impact Of Artificial Intelligence (Ai) On Credit Risk Assessment in The Banking Sector: A Case Study of State Bank of India and Punjab National Bank in Ranchi District

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***Abstract*—AI is making a significant place in the banking sector, especially in the area of credit risk assessment. We can understand AI as a system that helps in simplifying the process in the following ways like It helps in analysing a heavy volume of data, it helps in understanding the pattern process, also assisting in the decision-making process. This study main objective is to examine in what way artificial intelligence (AI) in the banking sector can reduce credit risk assessment and non-performing assets (NPAs) along with analyzing the significance of AI in the banking sector for credit risk assessment. It also object to understand borrowers' knowledge and perspectives about the use of AI in the banking sector for providing services in the Ranchi district. The research was conducted using conventional sampling method with the help of various tools like percentage analysis table, pie chart and regression method with the help of MS Excel. The results show that there is improvement in credit risk assessment because of the use of artificial intelligence in the banking sector, for example, managing customer financial records and analyzing the data, maintaining the customer repayment history, transaction records, and their credit behaviour more accurately. Nowadays, many banks use artificial intelligence to manage their different types of work, which is very helpful for both the customers and the banks. In many ways, like credit scoring, evaluating risk associated with loan approval and managing customers. In many banks like State Bank of India and Punjab National Bank, giving a special reference to the associated bank in Ranchi district makes the work very easy and faster for both the customer and the banks in comparison with other banks that are not associated with AI.**

***Index Terms*—Artificial intelligence, Banking sector, Credit risk assessment, Borrower, Traditional Method, and Manual Method.**

I. INTRODUCTION

Background of the study

Due to the increase in the adoption of digitalisation across every sector of the economy, our banking sector is also transforming its manual process structure to machine learning. In recent years, the banking sector has transformed its structure, and among all the technologies, Artificial Intelligence (AI) plays a crucial role in the transformation and strengthening of operational structure in banking. It helps to improve their accuracy and efficiency by improvising decision-making process. Their impacts are on finance, security, loan decision, risk management, sustainability, customer experience and satisfaction. AI reshape the banking activity and makes it powerful by analysing a large volume of data, identifying the patterns, and make a inform decision with greater speed and accuracy. It provides precise information to bankers, which decreases the chances of mistakes.

Traditionally, banks are totally dependent upon manual processes, which are time-consuming and limit the process of analysing complete information of the borrower. Earlier, for accessing credit, bankers had to analyse borrower creditworthiness manually, which was time-consuming and totally based on human judgment. It increases the chances of differences and errors. With the increase in customer data, the inefficiency of managing is also high, and it reflects the drawback of the manual process. That is making an environment for bankers to switch on advance and efficient system.

Statement of the Problem

Credit risk assessment is a critical function in the banking sector because inaccurate lending decisions can lead to financial losses and an increase in non-performing assets (NPAs). Traditional methods of assessing credit risk often involve manual analysis and fixed evaluation criteria, which may not fully capture the complexity of borrower behaviour or rapidly changing market conditions.

Although Artificial Intelligence offers opportunities to enhance accuracy and efficiency, its adoption in public sector banks is still evolving. There is limited empirical evidence on how AI influences credit risk assessment in SBI and PNB at the district level, particularly in Ranchi. Moreover, concerns regarding data security, algorithmic transparency, and customer trust raise important questions about the practical implementation of AI.

Significance of the Study

The study is important because it aims on the explanation on growing role of Artificial Intelligence (AI) in the banking sector, especially focuses on credit risk assessment in the banking sector. Nowadays, banks use new technologies and methods to make correct and accurate decision, in which AI plays a very important role.

The study helps us to understand how banks, with the help of AI can analyze the financial condition of borrowers efficiently. With the use of technology bank able to reduce the risk of wrong decisions and able to fast the loan approval process. Its direct impact is to reduce the loan defaults and NPAs.

This research gives a practical understanding of how the public sector banks like State Bank of India and Punjab National Bank are improving their credit risk assessment process by the use of AI. This helps researchers and student to understand the real-life banking practices.

From an academic point of view, this study is important because it fills the gap between theoretical knowledge and practical application. This study is useful for both policymakers and bank professionals because it helps them to understand the benefits and challenges. Additionally, it is useful for customers because it creates awareness for them about how banking services are getting fair due to AI use.

Scope of the Study

The scope of this research is limited to examining the impact of Artificial Intelligence on credit risk assessment in the banking sector with specific reference to SBI and PNB in the Ranchi district. The study focuses on understanding AI applications in credit evaluation, loan decision-making, and risk management from the perspective of respondents surveyed through a structured questionnaire.

The research covers concepts related to AI in banking, traditional versus AI-based credit assessment methods, customer perceptions, and statistical analysis of collected data. It also explores the relationship between AI adoption and credit risk assessment using appropriate analytical techniques.

However, the study does not include private sector banks or other financial institutions, and its findings are based on the selected sample and geographical area. Therefore, generalization of the results should be made with due consideration of these limitations.

II. LITERATURE REVIEW

Mhlanga (2021), the author examined AI's role in financial inclusion within emerging economies. AI improves access to credit using alternative data sources and predictive analytics. The study found that AI reduces information asymmetry between blenders and borrowers. However, infrastructure limitations and poor data quality remain barriers. Regulatory frameworks are also inadequate. Country-specific empirical resources are required.

Faheem (2021), the study highlighted that AI-driven models improve credit scoring and default prediction. Neural networks and machine learning algorithms efficiently identify complex borrower patterns. AI also reduces manual effort and improves decision-making speed. The research emphasized automation in banking operations. However, transparency, overfitting, and data dependency remain challenges. Ethical concerns and real-world implementation require further investigation. More empirical validation was recommended.

Shittu (2022), the study reviewed advances in AI-driven credit risk models for financial services optimization. It found that AI improves credit scoring accuracy, customer risk profiling, and financial decision-making. Machine learning models enhance operational efficiency and reduce manual intervention.

The research highlighted the importance of predictive analytics in banking. However, explainability, fairness, and ethical concerns were not fully addressed. Limited empirical evidence also restricts practical application.

Bello (2023), the study examined machine learning algorithms for credit risk assessment from an economic and financial perspective. The findings showed that machine learning models improve credit scoring accuracy and borrower classification. However, modern overfitting, poor data quality, and lack of transparency remain challenges. Practical validation across different banking environment is limited.

Amarnadh and Moparthi (2023), the study reviewed different AI techniques used in credit risk assessment. It concluded that machine learning, neural networks, and ensemble methods improve prediction performance over conventional models. The authors emphasized the importance of feature selection and data preprocessing. AI effectively handles complex financial datasets. However, model interpretability and data quality remain significant challenges.

Majumder (2023), the study investigated AI's role in risk management and fraud detection in Bangladeshi commercial banks. AI improved operational efficiency and fraud detection accuracy. It enhanced decision-making and reduced financial risks. The study demonstrated AI's positive impact on banking operations. However, implementation evidence remains limited. Cybersecurity and ethical concern required greater attention. Further research should focus on practical banking applications.

Edunjobi and Odejide (2024), the authors examined theoretical frameworks of AI in credit risk assessment and found that AI significantly improving banking efficiency, prediction accuracy, and decision-making. Their study highlighted the importance of machine learning and predictive analytics in reducing credit risk. AI enables financial institutions to process large datasets and make faster lending decisions. The study also emphasized data-driven banking practices. However, it was mainly conceptual and lacked empirical validation. It was limited attention to explainable AI and ethical issues.

Tudor (2024), the study explodes AI's impact on career risk assessment and business model transformation in banking. It found that AI improves risk evaluation, automation, and operational efficiency. AI also supports data-driven decision-making and digital transformation. The research highlighted the role of AI in modern banking practices. However, practical evidence on business transformation remains limited.

Singh and Mritunjay (2024), the study examined the application of AI- driven credit risk assessment in the agricultural sector of Indian commercial banks. The authors found that AI improves the accuracy of evaluating farmers' creditworthiness and supports faster lending decisions. The study highlighted AI's potential to enhance financial inclusion in rural areas. However, it focused only on the agriculture sector, limiting its generalizability. Data availability and quality were identified as key challenges.

Bi and Bao (2024), the authors explored innovative applications of AI in bank credit risk management. They found that AI enhances risk prediction, borrower evaluation and real-time credit monitoring. Machine learning techniques improve the identification of high-risk borrowers and support informed lending decisions. However, implementation challenges, data governance, and regulatory compliance remain unresolved. Integration with traditional banking systems was also identified as a major concern.

Farazi (2024), the study investigated the combined use of AI and blockchain for credit risk mitigation. The findings showed that predictive analytics and machine learning improve risk prediction and lending decisions. Blockchain enhances transparency, security, and data integrity in financial transactions. The integration of AI and blockchain reduces fraud and operational risk. However, practical implementation in banking remains limited. Regulatory uncertainty and technological complexity were identified as major barriers.

Ahmed and Iqbal (2025), the systematic review analyzed AI applications in international banking systems. The authors found that AI enhances credit risk management through improved prediction accuracy, automation, and real-time monitoring. Machine learning models outperform traditional risk assessment methods. AI also improves operational efficiency and decision-making. However, transparency, ethics, and regulatory compliance remain key concerns. Todupunuri (2025), the study explored the role of Generative AI in predictive credit scoring and automated lending decisions. It found that Generative AI improves borrower evaluation, loan approval processes, and decision-making speed. AI enables financial institutions to analyze complex datasets more effectively. The research highlighted the growing importance of intelligent automation in banking. However, explainability, bias, and regulatory issues remain key concerns. Practical adoption of Generative AI is still at an early stage.

Roy and Vasa (2025), this systematic review concluded that AI and machine learning significantly transform credit risk assessment. Advanced algorithms improve prediction accuracy and automate decision-making. AI also supports financial inclusion through better borrower evaluation. The review identified alternative data as an important factor. However, explainability, ethics, and privacy issues remains unresolved. More empirical and longitudinal research is needed across different banking sectors.

Sarkar (2026), this systematic review found that AI-driven models outperform traditional credit risk assessment methods. Gradient boosting, neural networks, and ensemble techniques significantly improve prediction accuracy. AI supports early warning systems and better customer profiling. However, regulatory issues and implementation challenges persist. Longitudinal and empirical studies are still limited. Further research should focus on practical banking applications.Ruzel (2026), the study examined AI-assisted credit evaluation in US banking. It concluded that AI improves credit risk prediction, customer segmentation, and lending decisions. Alternative datasets enhance borrower evaluation. AI enables real-time monitoring and operational efficiency. However, explainability and regulatory compliance remain challenges. Legacy banking systems also hinder AI adoption. More longitudinal research is needed.

III. RESEARCH GAP

However, there is a growing area of literature on the application of Artificial Intelligence (AI) in the banking sector, Primarily, the majority of the study's available focus on global or national-level analysis of AI adoption in banking. The research that analysis the practical implementation and impact of AI in particular local conditions is very limited, specifically at a district level. Hence, it is really important to study how AI is impacting the credit risk assessment in a local district such as Ranchi.

Secondly, the nature of the research work is mostly theoretical, with the benefits of AI, but there is a lack of factual evidence based on real-world data and the understanding of the user. There is very limited research that includes both primary data (customer knowledge and their point of view) and secondary data (that includes bank reports and studies) to analysis the true impact of AI in the banking procedures.

Lastly, there are very few studies that are conducted and focus mainly on public sector banks in India, for example, Punjab National Bank and State Bank of India. Most of the study focuses on the private bank or the overall financial industry, which creates a gap in understanding how these public sector banks are accepting and implementing AI for credit risk assessment.

Research Questions

1. How is Artificial Intelligence being used in credit risk assessment in the banking sector?
2. Does the use of AI help in reducing loan default and non-performing assets (NPAs)?
3. What is the level of awareness and perception of customers regarding the use of AI in banking services in the Ranchi district?

Research Objectives

1. To evaluate how AI helps in reducing credit risk and non-performing assets (NPAs).
2. To examine the role of AI in credit assessment in banks.
3. To assess the level of awareness and perception of customers regarding the use of AI in banking services in the Ranchi district.

Hypothesis

H_0 (Null Hypothesis)

Artificial Intelligence has no significant impact on credit risk assessment in the banking sector.

H_1 (Alternative Hypothesis)

Artificial Intelligence has a significant impact on credit risk assessment in the banking sector.

IV. RESEARCH METHODOLOGY

Research Design

A descriptive research design is the most suitable and reliable method for this study.

Source of Data

A. Primary Data

A questionnaire is the primary and finest possible way to collect direct responses from the customers of SBI and PNB for the study. It helps to understand the point of view regarding the use of AI in credit risk assessment in the banking sector.

B. Secondary Data

There are some secondary ways to collect data are:

- Research paper
- Websites
- Bank reports
- Journals

Sampling Technique and Sample Size

The sampling technique that is suitable for the research is Conventional Sampling and sample size is 101 respondents.

1. Data Collection Method
- Questionnaire Method
- Personal Interaction
2. Statistical Tools and Software Used
- Percentage analysis
- Tables
- Bar Graphs
- Pie charts

V. DATA ANALYSIS AND HYPOTHESIS TESTING

Descriptive Analysis

Analysis summarizes the characteristics of respondents and their perception regarding AI in banking.

The demographic profile included variables such as gender, age, education qualification, occupation, and banking experience. Percentage analysis showed that respondents represented different demographic groups, providing a balanced understanding of customer perceptions. The questionnaire and responses revealed that: Most respondents were aware of AI applications in banking. A majority believed AI improve the speed of loan approval. Respondents agreed that AI reduces manual errors in credit evaluation. Most respondents perceived AI as an effective tool for identifying risky borrowers.

Variable	Category	Frequency	Percentage
Age	Below 20	21	21%
	20-30	36	25%
	30-40	19	19%
	Above 40	25	25%
Gender	Male	52	51%
	Female	49	49%
	Others	0	0%
Education Qualification	Primary	13	13%
	Secondary	28	28%
	Higher	53	52%
	Illiterate	7	7%
Occupation	Student	32	32%
	Salaried	33	32%
	Business	23	23%
	Others	14	14%
Having a Bank Account	Yes	89	88%
	No	12	12%

Statistical test (Regression Analysis)

To determine the impact of Artificial Intelligence on Credit Risk Assessment, Simple Linear Regression Analysis was employed.

Regression analysis helps measure whether changes in the independent variable (AI) significantly influence the dependent variable Credit Risk Assessment).

The regression output generated in Microsoft Excel consists of three important tables:

Regression Statistics	
Multiple R	0.677595152
R Square	0.45913519
Adjusted R-Square	0.453671909
Standard Error	0.917366681
Observations	101

Source: Computed by the researcher using MS Excel

1. Multiple R = 0.67759512, which indicate the strength of the relationship between Artificial Intelligence (AI) and Credit Risk Assessment.
The above analysis value ranges closer to 1, that mean the relationship between them is strong because the result of Multiple R is 0.677595152. And if it gets closer to 0, then it concludes that the relationship between them is weak.

2. R Square = 0.45913519 shows the percentage of variation in Credit Risk Assessment explained by AI.
It mainly ranges between 0 to1.

- If R^2 is 0, it means the response data is around its mean, and if R^2 is 1, it means all data is on the regression line.
- Here, R^2 is 0.45913519, it means 44% change in credit risk assessment is explained by AI.
- And the rest of 56% need support of the other factors like banking policies, customer behavior, and economic conditions.

3. Adjusted R-Square = 0.453671909
It is an upgraded version of standard R^2, which is used to analyse regression by modifying the number of predictor variables in the models. It is more reliable because it provides more accurate results by adjusting the value according to the sample size and the number of variables.
The analysis of the study shows that Adjusted R^2 is 0.453671909, which is very close to R square, which means this model of the study is reliable.

4. Standard Error = 0.917366681, compute the accuracy of the regression model. It explains how wrong the actual data value (model) is on average or diverges from the predicted values.

- The result is a low standard error, it means that the data value is close to the regression line and the model is correct and valid.
- Here, the standard error is 0.917366681, which basically means it is a good model and near the regression line. Also, suggest better accuracy in stating the relationship between artificial intelligence and credit risk assessment.

ANOVA Analysis

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	70.72500286	70.72500286	84.04019452	7.16175E-15
Residual	99	83.3146011	0.841561627		
Total	100	154.039604			

Source: Computed by the researcher using MS Excel

The F-test examines the overall significance of the regression model.

- If Significance F< 0.005, the regression model is statistically significant.
- If Significance F> 0.005, model is not statistically significant.

Here, a significant F-value is 7.16175 which indicates that Artificial Intelligence explains a meaningful portion of the variation in Credit Risk Assessment.

Regression Coefficients

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.647265429	0.192217684	3.367356304	0.001081942	0.265863843	1.028667015	0.265863843	1.028667015
X Variable 1	0.669342699	0.073013809	9.167343918	7.16175E-15	0.524467462	0.814217937	0.524467462	0.814217937

Source: Computed by the researcher using MS Excel

- A positive coefficient indicates that greater AI adoption improves Credit Risk Assessment. Here the coefficient is 0.67265429, that mean credit risk assessment is 0.67265429 when artificial intelligence is 0.
- The t-value measures whether the coefficient differs significantly from zero. It is checked by dividing the coefficient by the standard error. Here, t-test=$\frac{0.647265429}{0.192217684}$. It helps to know whether the

coefficient statistically has a particular meaning. A lower t-value shows that it is less significant, and a higher t-value means it is more significant.

- The p-value determines statistical significance. It is significant for hypothesis testing. If the p-value is more than 0.05, then the decision is significant, but if the p-value is less than 0.05, then the decision is not significant. So here the t-value is 0.001081942, that mean this test is statistically significant.

VI. HYPOTHESIS TESTING RESULTS

The hypotheses tested in the study are:
$H_{0:}$ Artificial Intelligence has no significant impact on credit risk assessment in the banking sector.
H_1: Artificial Intelligence has a significant impact on credit risk assessment in the banking sector.

Decision Rule

- If p-value < 0.005, reject H0 and accept H1.
- If p-value > 0.005, accept H_0 and reject $H_{1.}$

Hypothesis Result
Since the p-value (0.001081942), is less than the significance level of 0.005, the null hypothesis is rejected, and the alternative hypothesis is accepted. Therefore, Artificial Intelligence has a statistically significant impact on Credit Risk Assessment in the banking sector.

Interpretation of results
The regression analysis indicates the extent to which artificial intelligence influences credit risk assessment.
The R-Square value explains the proportion of variation in Credit Risk Assessment accounted for by AI. A higher R-square reflects stronger explanatory power.
The Standard Error measures the precision of the regression model. Lower values indicate more accurate predictions.
The ANOVA results confirm whether the overall regression model is statistically significant through the F-test and Significance F.
The coefficient analysis identifies the direction of the relationship. A positive coefficient suggests that increased adoption of AI enhances credit evaluation and lending decisions.
The P-value determines whether the observed relationship is statistically significant. If the P-value is below 0.05, the relationship is considered statistically significant.
Overall, the statistical analysis provides empirical evidence regarding the impact of Artificial Intelligence on Credit Risk Assessment and forms the basis for accepting or rejecting the research hypothesis.

VII. OBJECTIVE- WISE ACHIEVEMENT OF OBJECTIVES

- Objective 1

To evaluate how AI helps in reducing credit risk and non-performing assets (NPAs).
Achievement Status: Achieved
The research identified several benefits, including improved loan processing, better risk prediction, reduced operational costs, and enhanced customer services which is directly or indirectly helping bank to reduce the credit risk and non-performing assets (NPAs).

- Objective 2

To examine the role of AI in credit assessment in banks.
Achievement Status: Achieved
Regression analysis was used to examine the relationship between Artificial Intelligence and Credit Risk Assessment. The statistical findings indicate that AI significantly contribute to improving the accuracy, speed, and efficiency of credit evaluation. The hypothesis testing results support this objective.

- Objective 3

To assess the level of awareness and perception of customers regarding the use of AI in banking services in the Ranchi district.
Achievement Status: Achieved
The survey findings indicate that most respondents have a positive perception of AI in banking. Customers believe that AI improves banking services, enhances convenience, and supports better lending decisions, although concerns about privacy and technology dependence remain.

VIII. FINDING, CONCLUSIONAND SUGGESTIONS

Findings of the study

The major findings of the research are as follows:

1. The majority of respondents are aware of artificial intelligence and its applications in the banking sector.
2. AI has significantly improved the efficiency and speed of credit risk assessment in banks.
3. AI-based systems reduce manual errors and improve consistency in loan evaluation.
4. Machine learning and predictive analysis help banks identify high-risk borrowers more accurately.
5. AI enables faster loan approval by automating customer verification and credit analysis.
6. Most respondents expressed satisfaction with AI-enabled banking services.
7. AI improves operational efficiency by reducing repetitive manual tasks and supporting data-driven decision-making.
8. Banks adopting AI technologies are better equipped to manage credit risks and reduce non-performing assets (NPAs).

Conclusion

Artificial intelligence has become a transformative technology in the banking sector, particularly in credit risk assessment. The findings of this study indicate that AI significantly enhances the efficiency, accuracy, and reliability of credit evaluation processes. AI-based systems enable banks to process customer information more quickly, identify potential credit risk, and support objective lending decisions.

The competitive analysis between traditional and AI-based credit assessment methods demonstrates that AI offers substantial advantages in terms of speed, automation, predictive capability, and operational efficiency. Furthermore, the regression analysis provides statistical evidence supporting the relationship between Artificial Intelligence and Credit Risk Assessment.

The study also highlights that customers generally perceive AI-enabled banking services positively. However, successful implementation of AI requires addressing challenges related to data security, privacy, ethical use of AI, and transparency in automated decision-making.

Overall, the research concludes that Artificial Intelligence has the potential to significantly improve credit risk management and contribute to the modernization of public sector banking institutions such as SBI and PNB.

Suggestions

Based on the findings of the study, the following recommendations are proposed:

1. Banks should expand the use of AI technologies in credit risk assessment to improve decision-making.
2. Strong cybersecurity measures should be implemented to protect customer information and financial data.
3. Banks should organise regular training programs for employees to enhance AI- related skills.
4. An AI-based decision-making system should be transparent and explainable to increase customer trust.
5. Customer awareness programs should be conducted to educate users about AI- enabled banking services.
6. Banks should continuously upgrade AI software and digital infrastructure to improve performance.
7. Collaboration between banks, technology companies, and regulatory authorities should be strengthened for responsible AI implementation.

Limitations of the study

The study has the following limitations:

1. The study is limited to SBI and PNB branches in Ranchi district.
2. The sample size is limited to 101 respondents.
3. Findings are based on respondents' opinions collected through questionnaires.
4. Limited access to internal banking data restricted deeper analysis.
5. Time and resource constraints limited the scope of the study.
6. Rapid technological advancement may influence future AI applications beyond the scope of this research.

Future scope of the study

Future researchers may consider the following areas:

1. Comparative analysis between public and private sector banks.
2. AI adoption in rural and urban banking sectors.
3. Comparative study across different states of India.

4. Application of advanced statistical software such as SPSS, R or Python.
5. AI applications in fraud detection and financial crime prevention.
6. Ethical and legal implications of AI in banking.
7. Impact of AI on customer trust and satisfaction.
8. AI-based investment advisory and wealth management services.

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