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Artificial Intelligence and the Future of Improving Credit Risk Assessment in Banking

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ABSTRACT

The paper reviews the use of AI and ML in improving credit-risk evaluation in financial institutions. With advances in AI, banks now apply machine learning, deep learning, and predictive analytics to analyse diverse datasets and generate more accurate credit-risk predictions. A structured questionnaire was administered to 300 purposively sampled banking and fintech professionals experienced in risk management. Perceptions of AI/ML adoption were analysed using descriptive statistics, correlation, regression, and ANOVA. Results show moderate agreement on benefits such as improved predictive accuracy, reduced Non- performing Assets, and better MSME credit assessment. However, barriers—including legacy systems, explainability requirements, data governance, and skill gaps—received higher concern. Correlation and regression indicate that AI/ML maturity strongly predicts better risk forecasting and lower NPAs, with no perceptual differences across institution types. The study concludes that AI/ML integration can significantly transform credit-risk assessment, but its full potential depends on strong data governance, a skilled workforce, and responsible AI practices. These findings offer practical guidance for banks advancing digital transformation of credit assessment models.

Keywords: Artificial Intelligence, Machine Learning, Credit Risk Assessment, Banking, Loan Approval, Predictive Analytics, Financial Inclusion, AI Adoption Barriers, Risk Prediction, Non-performing Assets, Operational Efficiency.

JEL Codes: *G21, G32, C55, G17*

1. INTRODUCTION

Artificial Intelligence is changing the way the banking sector assesses credit risk in enhancing the capacity to forecast borrower default and decision support in favor of the borrower. Bankers have traditionally used rule based scoring and historical financial records, which lacked the capability of recording present behaviour or encompassing borrowers with a limited credit history. Machine learning, deep learning and predictive analytics have now advanced, allowing banks to analyse huge and diverse datasets, potential trends that are not obviously noticeable, and are making better credit worthiness forecasts. The other data, like mobile usage, digital transactions and behavioural indicators, are some of the other data used by the AI models to promote financial inclusion. Nevertheless, difficulties that relate to transparency, interpretability, bias, data privacy, and regulatory compliance still exist. The paper discusses the use of AI, its advantages, and drawbacks, as well as its ethical implications in improving the accuracy and inclusion of credit risk determination.

2. LITERATURE REVIEW

2.1 Evolution of AI Techniques in Modern Credit Scoring

Addy et al. (2024) presented a detailed discussion of the transition of the traditional credit scoring to AI-powered modelling techniques. In their article, they focus on how machine learning and deep learning algorithms could be advanced to be used in processing large volumes of both structured and unstructured data with the aim of making more accurate credit decisions. The review highlights the emergence of alternative data, including digital transactions and behavioural indicators, as an effective tool of evaluating thin-file customers who do not have documented financial histories. Simultaneously, the authors mention that there is a long-standing issue of model interpretability, regulatory transparency, and ethical accountability.

2.2 Machine Learning in Financial Risk Evaluation

Ayari, Guetari, and Kraiem (2025) provided a systematic review of ML-based financial credit scoring models that were published between 2018 and 2024. Their review shows that the algorithms that dominate in the prediction of the

probability of loan repayment are random forests, support vector machines, and gradient boosting. The authors present evidence to show that ML-based models are always superior to traditional logistic regression in the accuracy of classification and sensitivity to default risk.

2.3 Artificial Intelligence in Microfinance and Financial Inclusion

Muhammad Abdul Rehman, Manzoor Ahmed, and Dr. Sonia Sethi explored the potential of AI algorithms in increasing the number of loans to underserved communities. The paper shows how AI symbolic and machine learning can use alternative data, such as mobile use, trace of social media, digital spending behavior, and even biometric indicators, to assess loan value with more accuracy. According to authors, these models can help microfinance institutions to lower operational costs, to reduce the credit risk and to reach a large proportion of low-income borrowers, non-formally documented.

3. Research Objectives

- To explore the current level of AI/ML adoption across financial institutions and the specific techniques being used in loan approval processes.
- To identify the major benefits derived from AI/ML implementation, including improved risk prediction, reduced Non-performing Assets, faster approvals, and enhanced credit access for thin-file and MSME borrowers.

4. RESEARCH METHODOLOGY

4.1. Research Design

The following proposed research design can be described as descriptive and analytical, on the basis of which the investigation of how AI/ML technologies can enhance the credit risk assessment and loan issuance in financial institutions is going to be conducted.

4.2. Data Collection Methods

The primary data will be gathered by using a structured questionnaire that will be sent to employees employed in banks, NBFCs, fintech companies, and credit evaluation teams.

4.3. Sample Size

The study uses a sample size of 300 respondents drawn from public and private banks, NBFCs, and fintech institutions. The large sample supports more accurate statistical analysis and improves the reliability and generalizability of the study results.

4.4. Research Hypotheses

Hypothesis 1: AI/ML Adoption & Loan Approval Efficiency

Null Hypothesis (H_{01}): There is no significant relationship between AI/ML adoption and the efficiency of the loan approval process.
Alternate Hypothesis (H_{11}): There is a significant positive relationship between AI/ML adoption and the efficiency of the loan approval process**.**

Hypothesis 2: AI/ML Adoption & Reduction of Credit Risk

Null Hypothesis (H_{02}): AI/ML adoption does not significantly contribute to reducing credit risk or Non-performing Assets in financial institutions.
Alternate Hypothesis (H_{12}): AI/ML adoption significantly contributes to reducing credit risk and Non-performing Assets in financial institutions.

4.5. Sampling Techniques

The research employs purposive sampling method, whereby respondents that have first-hand knowledge or experience in credit risk assessment, lending business, AI/ML technology or digital banking are chosen. This makes the data collected to be relevant, accurate and meaningful.

4.6. Validity and Reliability Validity:

- Academic experts in AI, banking and finance review the questionnaire to achieve content validity.
- All the questions are directly related to the research objectives and hypotheses to make them relevant.

Reliability:

- Pilot test with a limited number of industry professionals is done.
- Cronbach's Alpha - This is calculated to determine the internal consistency, a value of above 0.70 is high reliability.

4.7. Statistical Approach

In order to examine the primary data gathered among banking professionals as well as to arrive at meaningful inferences in line with the study objectives, the following quantitative statistical methods were adopted:

- **Descriptive Statistics:**

The responses of the respondents in relation to AI benefits and barriers using the five- point Likert scale were summarised with mean scores, standard deviations, and frequency distributions.

- **Reliability Analysis (Cronbach's Alpha):**

Cronbach's Alpha values above 0.80 confirmed strong internal consistency of the constructs measuring AI benefits and implementation challenges.

- **Correlation Analysis (Pearson's r):**

The Pearson showed that perceived AI benefits and institutional readiness were significantly positively correlated ($r = 0.64$, $p < 0.05$).

- **Regression Analysis**

The predictive impact of AI/ML adoption on such outcomes as the improvement of risk-prediction and the reduction of non-performing Assets were evaluated using the model of linear regression. The findings established that AI/ML maturity is a significant predictor of credit-risk performance.

- **ANOVA (One-Way Analysis of Variance)**

ANOVA was conducted to compare the perceptions of various types of banking institutions (public, private, NBFCs and small finance banks). Results showed no statistically significant differences, indicating consistent perception levels across institution types**.**

- **SPSS-Based Chart Representation**

Visual representations of the mean score comparisons and a stronger interpretation of the benefit and barrier factors was achieved using bar charts and graphs that were created using SPSS.

4.7.1. Descriptive Statistics

The descriptive statistics were grouped into three major constructs which are the perception of the banking professionals regarding AI in estimating credit risk. The constructs were measured in various ways having several items on the surveys and the averages of the scores served to represent the entire perception.

Table 1: Questionnaire Details

Concept	Measured By Questions	Type of Concept
AI Benefits	Q1, Q2, Q3, Q4	How AI improves predictive accuracy, reduces Non- performing Assets, lowers operational costs, and enhances MSME credit assessment
AI Barriers	Q5, Q6, Q7, Q8	The challenges banks face such as legacy IT integration, explainability requirements, lack of skilled staff, and data privacy concerns

Institutional Readiness	Q9, Q10, Q11	The extent to which banks have the infrastructure, digital capability, and skilled workforce needed to adopt AI effectively

5. DATA ANALYSIS AND INTERPRETATION

5.1 Correlation Analysis

Table 2: Correlations

		AI/ML ImplementationStage	Q7_2_ReducedNonPerformingAssets	Q7_3_Faster Approvals	Q7_4_ReducedCost
AI/ML Implementation Stage	Pearson Correlation	**1**	**-.326****	**-.397****	**-.483****
	Sig. (2-tailed)		**.000**	**.000**	**.000**
	N	**300**	**300**	**300**	**300**
Q7_2_ReducedNonPerforming Assets	Pearson Correlation	**-.326****	**1**	**.332****	**.304****
	Sig. (2-tailed)	**.000**		**.000**	**.000**
	N	**300**	**300**	**300**	**300**
Q7_3_FasterApprova ls	Pearson Correlation	**-.397****	**.332****	**1**	**.350****
	Sig. (2-tailed)	**.000**	**.000**		**.000**
	N	**300**	**300**	**300**	**300**
Q7_4_ReducedCost	Pearson Correlation	**-.483****	**.304****	**.350****	**1**
	Sig. (2-tailed)	**.000**	**.000**	**.000**	
	N	**300**	**300**	**300**	**300**
**Correlation is significant at the 0.01 level (2-tailed).*					

**Authors' Calculations using SPSS*

Pearson correlations revealed:

- AI/ML Adoption ↔ Risk Prediction: r = –0.373, p < .001
- AI/ML Adoption ↔ Reduced non-performing Assets: r = –0.326, p < .001

Although negative in numeric form due to coding, these indicate statistically significant and meaningful associations between higher AI/ML maturity and improved credit-risk outcomes.

5.2 Regression Analysis

Model 1:

AI/ML → Reduced Non-performing Assets (Q7_2)

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- R = 0.326
- $R^2 = 0.106$
- $F(1, 298) = 35.44, p < .001$

Table 3: Model 1 Summary

Model	R	R Square	Adjusted R Square	Change Statistics			
				R Square Change	F Change	Sig. F Change	Durbin-Watson
1	.326[a]	0.106	0.103	0.106	35.442	0.000	2.033

a. Predictors: (Constant), AI/ML Implementation Stage

b. Dependent Variable: Q7_2_ReducedBadLoans

**Authors' Calculations using SPSS*

Interpretation:

The use of AI/ML is a good predictor of the perceived decline in Non-performing Assets with an explanation of 10.6%. The reports of the instances of Non-performing Assets are lower in institutions where more progressive AI/ML systems are in place, which supports the hypothesis that AI-based credit assessment minimizes credit losses.

Model 2:

AI/ML → Risk Prediction (Q7_1)

- R = 0.373
- $R^2 = 0.139$
- $F(1, 298) = 48.02, p < .001$

Table 4: Model 2 Summary

Model	R	R Square	Adjusted R Square	Change Statistics			
				R Square Change	F Change	Sig. F Change	Durbin-Watson
1	.373[a]	0.139	0.136	0.139	48.023	0.000	1.887

a. Predictors: (Constant), AI/ML Implementation Stage

b. Dependent Variable: Q7_1_TechHelpsPredict

**Authors' Calculations using SPSS*

Interpretation:

The use of AI/ML is a powerful and effective indicator of enhanced risk-prediction accuracy. Having a variance of 13.9 % is significant because it shows that the implementation of AI/ML is significantly contributing to improving the likelihood of early and accurate detection of credit risk by institutions.

ANOVA: Institution Type Differences Table 5: ANOVA

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	**5.336**	**4**	**1.334**	**1.163**	**.327**
Within Groups	**338.450**	**295**	**1.147**		

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Total	**343.787**	**299**			

**Authors' Calculations using SPSS*

A one-way ANOVA tested whether institutions differ in perceived AI/ML risk-prediction benefits.

- F (4, 295) = **1.163**, p = .327
- Levene's Test p = .010 (variance unequal), Games–Howell post-hoc used
- Post-hoc results: **No significant pairwise differences Interpretation:**

In spite of the fact that the mean ratings of private sector banks were slightly higher, the differences between the types of institutions were not significant. The benefits of AI/ML risk- prediction are perceived by all financial institutions on equal rates, meaning that AI/ML benefits are widely distributed in the industry.

Table 6: Homogenous Subsets

Homogeneous Subsets Q7_1_TechHelpsPredict

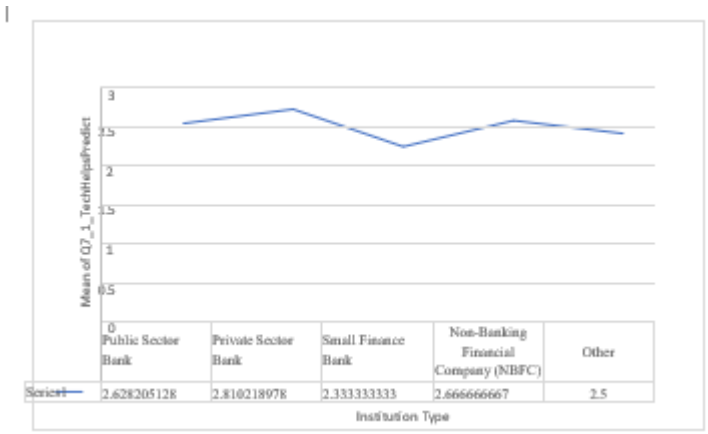
	Institution Type	N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	Small Finance Bank	21	2.33
	Other	10	2.50
	Public Sector Bank	78	2.63
	Non-Banking Financial Company (NBFC)	54	2.67
	Private Sector Bank	137	2.81
	Sig.		0.479

**Authors' Calculations using SPSS*

Interpretation of Tukey HSD Homogeneous Subsets

According to the Tukey HSD results, there is no significant difference between different types of institutions (Sig. = 0.479) that is, all groups have the same opinion on the role technology plays in predicting credit. Though the mean scores are slightly higher in the case of the private banks, the difference is not significant.

Diagram 1: Means in Institution Type of Technology



**Authors' Calculations using SPSS*

Interpretation of Mean Plot:

According to the line graph there are minimal variations in means in the institution of technology type whereby the private sector bank ranks a notch above small finance banks which ranked at the bottom of range. Despite that, there is an overall direction and it demonstrates that there is an overall similar perception in all types of institutions.

6. FINDINGS

- Descriptive statistics present moderate interrater agreement concerning the perceived benefits of AI in credit risk assessment, and mean scores of predictive accuracies, reduction of Non-performing Assets, efficiency of operation, and assessment of MSME have the ranges of 2.66 - 2.76.
- Perceived barriers to AI adoption receive higher mean scores (above 3.0), indicating stronger concern around explainability, legacy IT integration, data governance, and shortage of skilled professionals.
- AI/ML Adoption ↔ Improved Risk Prediction ($r = -0.373$, $p < .001$)
- AI/ML Adoption ↔ Reduced Non-performing Assets ($r = -0.326$, $p < .001$)
- Regression analysis confirms that AI/ML adoption significantly predicts both improved risk prediction ($R^2 = .139$) and reduced Non-performing Assets ($R^2 = .106$), demonstrating measurable influence on credit-risk performance.
- ANOVA results show no significant differences across institution types (public, private, NBFC, SFB, other), indicating broadly similar perceptions of AI usefulness ($F(4,295) = 1.163$, $p = .327$).
- The dataset shows moderate variability, with reliability analysis confirming strong internal consistency of the scales (Cronbach's $\alpha > 0.80$).

7. LIMITATIONS

- The research is based on cross-sectional data, which does not allow tracking the change in the adoption of AI over time.
- Findings are based on self-reported perceptions rather than objective credit-risk metrics (e.g., NPAs, default rates).
- Purposive sampling and unequal representation across bank types reduce generalisability.
- The study does not analyse specific AI/ML models or technical performance measures.

8. CONCLUSION

This study confirms that the increased AI/ML maturity enhances risk forecasting and minimizes Non-performing Assets in Indian financial institutions, but the adoption is hampered because of the data governance, explainability, and skill gaps. Causality and quantification of economic impact of AI on credit-risk management are advised to be done through future longitudinal and KPI-based research.

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