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Impact of Explainable AI in Credit Scoring Analysis in SBI, NTR District: Evaluating Predictive Accuracy, Fairness and Interpretability

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ABSTRACT

The credit risk assessment process plays a vital role in financial decision-making, contributing to the approval of financial services such as loans and understanding the risks associated with them. Although machine-learning systems can sift through advanced borrower data, their mechanisms can be difficult for customers to comprehend. This transparency challenge is tackled by Explainable Artificial Intelligence (XAI), which offers explanations for model decisions. This study quantifies the relationship between XAI and perceived predictive accuracy, fairness, and interpretability in the credit scoring context, with a specific focus on the NTR District in the southern Indian state of Andhra Pradesh. The four constructs (Explainable AI, Predictive Accuracy, Fairness, and Interpretability) were measured using a structured questionnaire with a five-point Likert scale. A set of statistics containing 124 responses was provided. Descriptive statistics, Cronbach's Alpha, Pearson correlation, and simple linear regression were used. The results show positive and statistically significant relationships between XAI and predictive accuracy ($r = 0.306$, $p < 0.001$), fairness ($r = 0.468$, $p < 0.001$), and interpretability ($r = 0.609$, $p < 0.001$). All four constructs had satisfactory internal consistency (Cronbach's alpha > 0.70). The results show that explainability perceptions are correlated with accuracy, fairness, and interpretability, with higher explainability perceptions resulting in higher accuracy, fairness, and interpretability perceptions. The workbook provided is simulated; therefore, this writing is a practice or draft of the writing, and the numerical data should be changed to the result of the Academic writing in Google Form answer sheet, before academic writing is submitted.

Keywords: Explainable Artificial Intelligence, Credit Scoring, Predictive Accuracy, Fairness, Interpretability, SHAP, LIME, NTR District.

1. INTRODUCTION

1.1 Background and Context

One of the vital tasks performed within the financial services industry is credit risk analysis, which provides information regarding loan eligibility, credit restrictions, and purchaser risk. Traditional methods have been based on the scorecard and statistical models, which are relatively simple and easy to understand. As more financial data comes in, some machine-learning techniques have been used to find more complicated relationships and to use them to better predict information. However, there can be a 'black-box' problem when the complexities create the possibility of a stakeholder receiving a forecast without understanding how it happened. The referenced article cited herein refers to XAI to overcome this paradox in credit risk assessment between predictive performance and transparency.

1.2 Problem Statement

While AI-driven credit assessment can enhance data-informed decision-making, the complexity of decision-making could pose challenges for stakeholders in regard to the interpretation of AI decisions. Issues might arise around what factors can affect a credit decision, whether a decision is consistent, and identifying any potentially unfair patterns. This study has undergone a detailed analysis of these issues from the respondents' point of view.

1.3 Research Motivation

The responsibility and designed understanding of AI in financial processes has become significant and motivates the study. SHAP and LIME are popular XAI techniques; the former explains a prediction by detailing the impact of each input feature, and the latter explains each instance at the local level in a model-independent manner. The reference article also highlights that the stability of the explanation, fidelity, and usability of the explanation when used in credit risk assessment are important.

1.4 Objectives and Scope of the Study

- To explore how explainable artificial intelligence (XAI) helps improve transparency and understanding of credit scoring analysis.
- To assess how XAI relates to predictive scoring in credit.
- To explore the outlook of explainable AI on fairness in creditworthiness decisions
- To study the paradigm shift from statistical to explainable AI for the interpretability of credit-scoring choices.

This study only dealt with perception measures through a questionnaire, and the respondents were in the NTR district. It did not teach or test a machine learning credit scoring model.

1.5 Significance of the Study

This study adds a local viewpoint of responsible AI in financial services to the body of research on the subject. It considers both accuracy and fairness/interpretability instead of simply looking at model performance. The findings could potentially help to shed light on the perceptions of consumers and financial-sector respondents on credit decisions that are “explained.”

1.6 Challenges

The practical implementation of XAI may lead to a conflict between the predictions and the explanation itself, the scale of computation, varying explanation demands from stakeholders, and bias in the history. In the same groups of challenges, the same problem areas in the risk evaluation of credit were mentioned in the reference article.

2. LITERATURE REVIEW

- Shreya & Harsh Pathak (2025)

Shreya and Harsh Pathak (2025) applied XGBoost, LightGBM, and Random Forest to analyze credit risk data using the interpretability techniques of SHAP and LIME. The research revealed that XAI can enhance the transparency of credit decisions, but there was no thorough analysis of fairness and bias.

- Sowmiya et al. (2024)

Sowmiya et al. (2024) studied credit-risk analysis based on XGBoost, LightGBM, and Random Forest techniques using the Shapley value and LIME. The results showed that XAI can be used to explain credit-risk predictions and enhance the transparency of machine learning models.

- Manore & Pathare (2026)

Using logistic regression and SHAP, Manore and Pathare (2026) explored interpretable machine learning to predict credit risk. The study revealed that interpretable models can yield meaningful prediction outcomes and clarify key credit risk factors.

- Nhyvija et al. (2026)

Nhyvija et al. (2026) conducted a survey on credit risk and loan approval systems that used XAI. While highlighting the potential of the two techniques, SHAP and LIME were identified as having issues with accuracy, explainability, privacy, and implementation.

- Liu & Feng (2024)

Liu and Feng (2024) analyzed the credit scoring process and applied CatBoost, SHAP, and counterfactual explanations to the model. They determined that XAI can enhance transparency without sacrificing predictive performance.

- Choudhury et al. (2025)

Choudhury et al. (2025) applied two different machine-learning models for credit-risk assessment, one based on SHAP and the other on LIME. The study highlighted the importance of minimizing the imbalance between predictive performance and transparency and fairness in AI-driven credit assessments.

- Waqas Ishtiaq (2025)

Ishtiaq (2025) explored the challenges and solutions in credit-card default prediction systems by considering machine-learning modeling and techniques to explain models. The study showed that complex models could have good predicting ability, and explanations can also make them more interpretable.

- Ogbuefi et al. (2025)

Ogbuefi et al. (2025) conducted a comprehensive study on explainable AI in credit decision-making. The research revealed that XAI can have beneficial effects on transparency, but standardization and scalability, in addition to privacy concerns and regulations, remain barriers to XAI.

Research Gap

Studies have already commented on XAI methods in the context of credit risk; however, limited evidence is available that is specific to NTR district perceptions. An investigation of the relationships between predictive performance, fairness, and interpretability is ongoing. In this study, the local gap and the gap related to perceptions has been taken up using a structured survey which includes 124 respondents.

3. METHODOLOGY

This study uses a quantitative survey method. Since technical studies focus on training and comparing machine learning models, this study does not focus on technical studies, instead measuring stakeholder perceptions of XAI in the field of credit scoring.

3.1 Research Design

A descriptive and analytical research design was used. Descriptive analysis provides descriptive information about the respondents, as well as construct scores; correlation and regression analysis were used to analyse the relationship between XAI and the three constructs of outcomes.

3.2 Data Collection

Primary information was gathered using questionnaires designed for borrower's/loan applicants and respondents in banking, NBFCs, and allied financial services. The questionnaire was constructed on a 5-point Likert scale, which included Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree.

3.3 Sample and Sampling Technique

Item	Details
Study Area	NTR District, Andhra Pradesh
Sample Size	124 respondents
Sampling Technique	Purposive sampling
Respondent Groups	SBI Bank Borrowers/loan applicants and financial-sector respondents
Data Collection Instrument	Structured questionnaire / Google Form
Measurement Scale	Five-point Likert scale

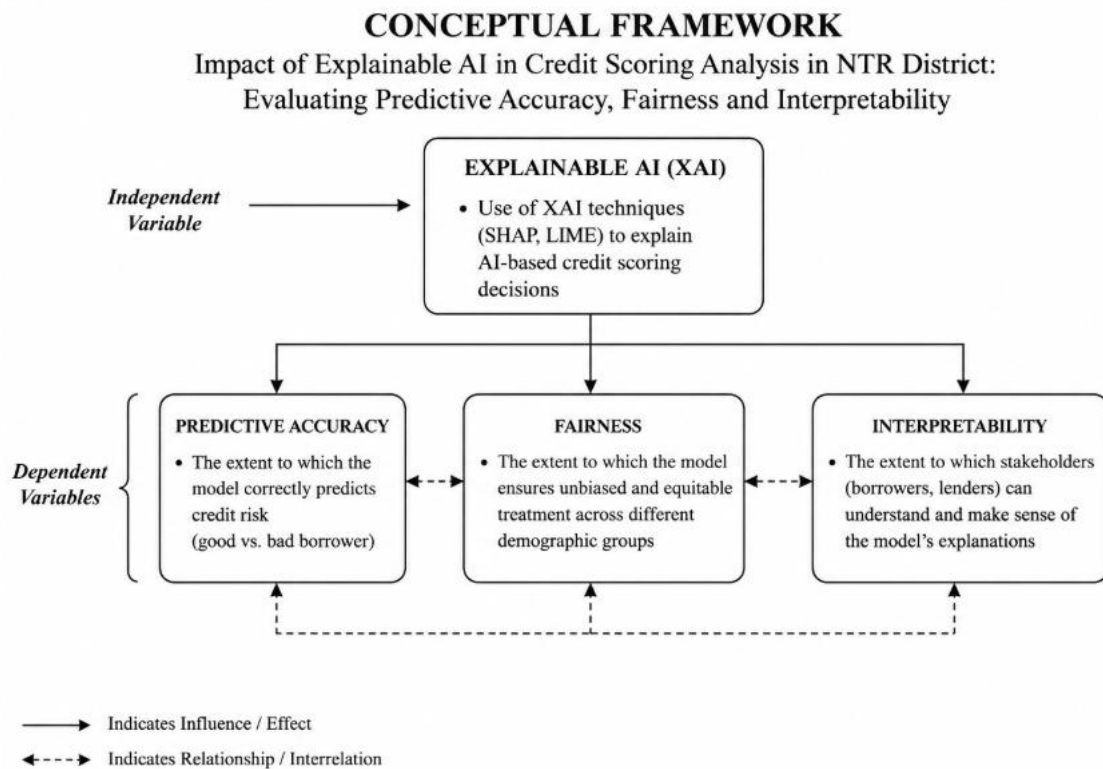
3.4 Variables of the Study

Variable	Role	Items
Explainable AI (XAI)	Independent	5
Predictive Accuracy	Dependent	5
Fairness	Dependent	5
Interpretability	Dependent	5

3.5 Data Analysis

The mean score for each construct was constructed by averaging the five items in the construct. Cronbach's alpha was used to assess internal consistency. The dependent variables were related to XAI using Pearson's correlation. The variance associated with XAI was estimated by simple linear regression in each outcome. A 5% level was used for statistical significance assessment.

3.6 Conceptual Framework



Explainable AI is treated as an independent variable, while predictive accuracy, fairness, and interpretability are dependent variables. Credit scoring is a field that is considered relevant for XAI, as are the two methods: SHAP and LIME.

3.7 Hypotheses

In the context of credit scoring analysis, H1 describes the explanatory aspect of AI, which has a significant relationship with credit information transparency and understanding.

There is a strong connection between Explainable AI and predictive accuracy in credit scoring.

There is a strong connection between explainable AI and fairness in credit scoring.

H5: The interpretability of credit-scoring decisions has a significant relationship with Explainable AI.

H2–H4 can be empirically tested for the given dataset. H1 was not independently tested, as there was no H1-specific construct on the questionnaire.

4. RESULTS

4.1 Demographic Profile

Table: Age Distribution

Age Distribution	Frequency	Percentage
Below 25	38	30.65%
25–35	37	29.84%
36–45	26	20.97%
Above 55	14	11.29%
46–55	9	7.26%

Table: Gender Distribution

Gender Distribution	Frequency	Percentage
Male	62	50.00%
Female	58	46.77%
Prefer not to say	4	3.23%

Table: Respondent Category

Respondent Category	Frequency	Percentage
Borrower / Loan Applicant	60	48.39%
Bank Employee	35	28.23%
NBFC Employee	16	12.90%
Other Financial-sector Employee	13	10.48%

Table: Educational Qualification

Educational Qualification	Frequency	Percentage
Undergraduate	52	41.94%
Postgraduate	40	32.26%
Intermediate	21	16.94%
Other	11	8.87%

Table: Experience with Loans/Credit

Experience with Loans/Credit	Frequency	Percentage
2–5 years	42	33.87%
Less than 2 years	31	25.00%
More than 5 years	30	24.19%
No experience	21	16.94%

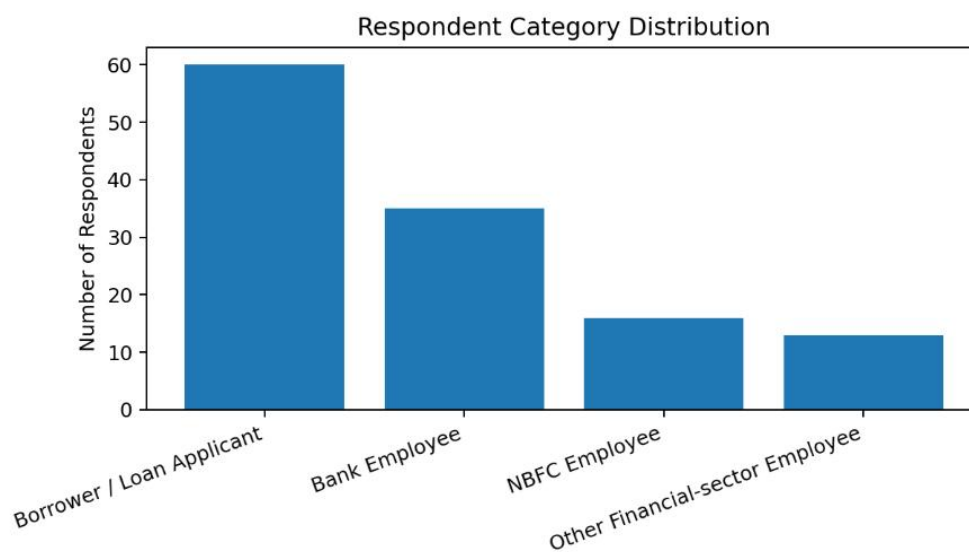


Figure 2: Distribution of respondent categories

4.2 Descriptive Statistics

Construct	Mean	Standard Deviation
Explainable AI (XAI)	3.476	0.650
Predictive Accuracy	3.471	0.561
Fairness	3.626	0.575
Interpretability	3.510	0.600

Fairness records the highest mean score (3.626), followed by Interpretability (3.510), Explainable AI (3.476), and Predictive Accuracy (3.471). All four means are above the neutral midpoint of 3.00.

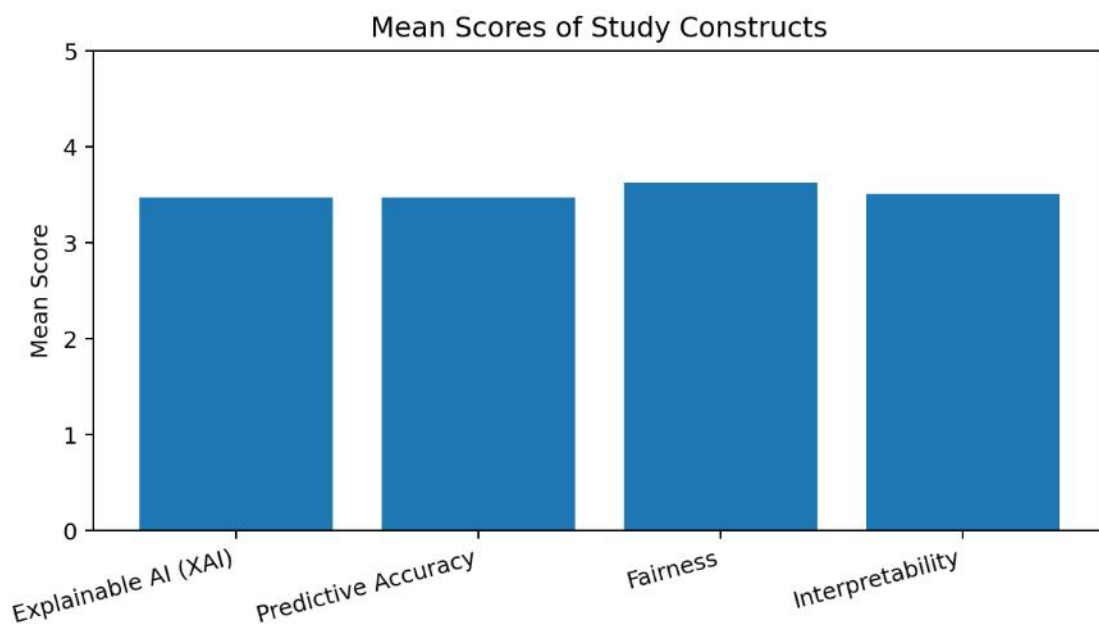


Figure 3: Mean scores for the four study constructs..

4.3 Reliability Analysis

Construct	Items	Cronbach's Alpha
Explainable AI (XAI)	5	0.776
Predictive Accuracy	5	0.743
Fairness	5	0.743
Interpretability	5	0.777

All four constructs had Cronbach's alpha values above 0.70, indicating acceptable internal consistency within the supplied dataset.

4.4 Correlation Analysis

Relationship	Pearson r	p-value
Predictive Accuracy	0.306	0.000560
Fairness	0.468	0.000000
Interpretability	0.609	0.000000

XAI has a positive and statistically significant relationship with all three dependent variables. The strongest association is between XAI and interpretability ($r = 0.609$), followed by fairness ($r = 0.468$) and predictive accuracy ($r = 0.306$).

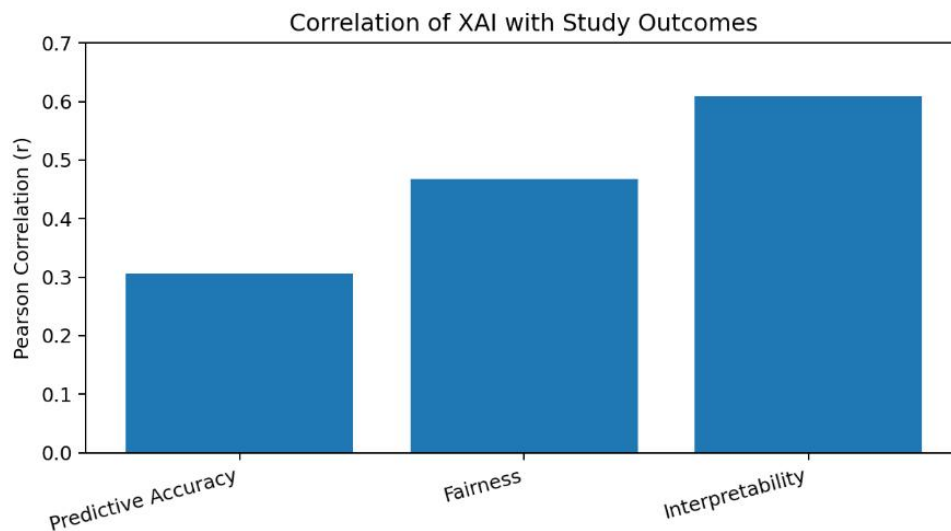


Figure 4: Correlation of coefficients between XAI and study outcomes.

4.5 Regression Analysis

Dependent Variable	R ²	Coefficient	p-value
Predictive Accuracy	0.093	0.263	0.000560
Fairness	0.219	0.414	0.000000
Interpretability	0.371	0.562	0.000000

The regression results show statistically significant positive associations. XAI explains 9.3% of the variance in Predictive Accuracy, 21.9% in Fairness and 37.1% in Interpretability.

4.6 Hypothesis Testing

Hypothesis	Evidence	Decision
H2: XAI ↔ Predictive Accuracy	$r = 0.306, p < 0.001$	Supported
H3: XAI ↔ Fairness	$r = 0.468, p < 0.001$	Supported
H4: XAI ↔ Interpretability	$r = 0.609, p < 0.001$	Supported

At the 5% significance level, all three tested relationships were statistically significant. H1 was not independently tested because a separate transparency construct was not measured.

5. DISCUSSION

5.1 Interpretation of Results

The results indicate that construct associations between stronger perceptions of explainable AI (XAI) and stronger perceptions of predictive accuracy, fairness, and interpretability. The strongest correlation is with interpretability, which is congruent with the focal point of XAI (to make complex decisions easier to comprehend). The positive relationship with fairness indicates that explanations are likely to be beneficial in identifying or challenging potentially unfair decisions. The relationship between explainability and accuracy is noteworthy, although less strong, suggesting that accuracy is a related, but not synonymous, concept with perceived explainability.

5.2 Practical Implications

Incorporating explainability in the implementation of AI in the credit assessment system can be considered. Explanations should be comprehensible to loan officers, customers, and other non-technical users of the explanations. Explanations should be accompanied by fairness checks, as descriptions of model behaviour can make fairness more visible, but not necessarily eliminate it. The reference article also notes transparency and an evaluation that was fair as points of practice.

5.3 Limitations and Challenges

This study is based on 124 units of respondents and the NTR District. With purposive sampling, it is difficult to generalize the findings from the selected samples. The questionnaire reflects perceptions rather than technical accuracy of the models. Most importantly, the accompanying workbook (provided) is clearly marked 'Simulated_XAI_Credit_Scoring_124_Respondents'; hence, these numerical results may only be used to prepare a draft/template but are not intended to be used to depict field responses. The final paper should take the actual responses from the Google Form once responses are gathered.

5.4 New directions in XAI for Finance

Larger sample numbers, a comparison of several financial institutions for a single district or across several districts, and/or the analysis of real credit data can be used in future studies. SHAP and LIME may be compared using technical studies regarding certain other factors, including explanations stability, fidelity, and computational efficiency. Future work involves integrating fairness-driven algorithms and methods with XAI and exploring the impact of explanations on trust and acceptance, as well as borrower decision-making.

6. CONCLUSION

This study used an explanatory AI approach and related it with the accuracy of predictive models, fairness, and interpretability of AI in credit scoring in NTR District. Each of the three measured outcomes has positive and statistically significant relationships with XAI, as indicated in the 124-response data set provided. Understandable explanations are directly related to the strongest relationship with AI-assisted credit assessment and lie at the heart of the process. However, the study is perception-based, and this workbook is a simulation. As a result, the very last empirical paper should fee the true info from the Google Form, rather than the simulated outcomes, prior to submitting. Larger samples and real lending data, as well as testing and technical comparison of two methods, SHAP and LIME, could be used in future research to build on the work.

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