AI-Driven Credit Scoring in Microfinance: Enhancing Financial Inclusion for SDG 5 and SDG 10

Arun Khatri, Ahmad Murtaza Alvi, Syeda Soophiya Mariyum, Xiyu Zhang, Ravi Baijulal Bhandari, Balkrishna K Patil

Abstract- *AI-based credit scoring is progressively transforming microfinance by facilitating more inclusive, data-driven, and fair lending by focusing particularly on Sustainable Development Goals (SDG) 5 on Gender Equality and SDG 10 on Reduced Inequalities. Conventional ways of evaluating credit tend to lock out women, informal employees, and marginalized individuals based on limited collateral, skimpy credit report, and human prejudice. The author of this paper discusses the role of artificial intelligence methods like machine learning, alternative data analytics, and explainable artificial intelligence in promoting credit access and minimizing systemic discrimination in microfinance systems. The research design is mixed-methods with the combination of quantitative research on AI-based credit models and qualitative research on the results of borrower inclusion. Accuracy, default prediction, and reduction of bias are used to measure model performance whereas inclusion impact is measured based on the rates of gender participation, equity in loan approval and income mobility measures. The comparative analysis of AI-based credit scoring shows that it enhances by 29.4 percent the rate of loan approval by women borrowers and by 24.1 percent the rate of error due to income-based exclusions in comparison to rule-based systems. This is because the predictability of default risk is enhanced by 18.6 per cent without necessarily piling interest pressure on the at-risk borrowers. The results reveal that financial inclusion can be increased and responsible lending facilitated with the help of transparent and fairness sensitive AI models. With the potential to facilitate gender-inclusive entrepreneurship and decrease structural credit inequalities, AI-driven credit scoring becomes an important facilitator of inclusive economic behaviour, social fairness, and sustainable microfinance development in line with SDG 5 and SDG 10 in all developing economies in the world.*

Keywords- AI-Driven Credit Scoring, Microfinance, Financial Inclusion, Gender Equality, Income Inequality, SDG 5, SDG 10

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Introduction

The availability of affordable and timely credit has continued to be a thorny issue in the microfinance systems that are faced by women, informal workers and socio-economically marginalized populations. Although across the globe, microfinance institutions (MFIs) have experienced a growth, a significant percentage of low-income borrowers are still experiencing systematic exclusion because of inflexible lending requirements, poor financial records, and asymmetry of information between lenders and borrowers [1]. The conventional credit evaluation systems in microfinance mostly depend on collateral, group guarantees and simplified scorecards based on rules, which is not always accurate in assessing the actual debt repayment capabilities of borrowers who are in informal and unstable income settings [2]. Consequently, credit exclusion does not only limit the entrepreneurial activity and household welfare but also supports the established socio-economic inequalities, compromising the inclusive development goal of microfinance [3].

The gendering bias is one especially important aspect of this ostracizing. The conventional credit scoring methods affect women borrowers particularly in the developing economies in a disproportionate manner because of the lesser possession of assets, inconsistent income patterns and also because of the socio-cultural restrictions, which constrain formal financial involvement [4]. According to the empirical research, when women portray good behaviour in repayment they are rejected more and have smaller loan sizes than their male counterparts, which is a result of structural as well as behavioural biases in the human-based and heuristic lending decisions [5]. These inequalities are a direct contradiction of the Sustainable Development Goal (SDG) 5 which focuses on gender equality and economic empowerment of women, or SDG 10 which aims to decrease inequalities within and between societies [6]. At that, artificial intelligence (AI) and machine learning have become revolutionary resources that can transform microfinance credit assessment. Using alternative data sources like transaction history, behavioural patterns, and the digital footprint AI-based credit scoring models can assess the creditworthiness by looking beyond the financial records [7]. In contrast to rule-based systems, machine learning models can uncover the relationships that are not linear, adapt to heterogeneous borrower profiles, and enhance outcomes on borrower default predictions and increase access to underserved populations. In addition, the current developments in explainable artificial intelligence (XAI) and fairness-aware modelling can increase transparency and reduce bias, which deals with ethical and regulatory issues related to algorithmic decision-making in finance [8].

AI implementation in microfinance credit scoring, therefore, is an important opportunity to match financial innovation to global development goals. Nevertheless, although there is an increasing amount of interest, empirical results on the connection between AI-based credit scoring and quantifiable SDG impacts especially SDG 5 and SDG 10 have not been sufficiently broad and comprehensive [9]. The current body of research is composed of research that is often too narrow in terms of predictive accuracy, does not account for inclusion measures, gender differentiated effects, and ethical aspects in the implementation of AI. It is within this context that the current study will attempt to critically analyse how AI-based credit scoring can help improve financial inclusion in microfinance ecosystems. The primary research questions include: (i) what is the performance of AI based credit scoring models versus traditional rule-based ones regarding predictive accuracy and bias rates; (ii) does AI-enabled lending increase the rate of loan approval among women or reduce the rate of exclusion errors on the basis of income; and (iii) how AI fair and transparent models contribute to the SDG 5 and SDG 10. This research adds new empirical evidence to the understanding of how responsible AI may be used as an impetus in the development of equitable and sustainable microfinance through the SDG-oriented framework and a mixed-methods methodology approach.

Literature Review

Available literature on microfinance credit appraisal has already reported downsides of conventional credit scoring tools in attending to the requirements of low-income and disadvantaged borrowers. The initial microfinance lending was heavily dependent on heuristic-based assessment, group lending theories, and simplified scorecard frameworks through which a small number of variables including ownership of collateral, repayment record and borrower demographics were taken into account [7]. Although these strategies minimized information asymmetry, they were in many ways not consistent with the economics of informal-sector borrowers whose income is unstable, non-recorded, and seasonal in nature. The lending models that are most discriminatory against women and low-income households are collateral-based lending models, which are disproportionately discriminatory towards these two groups because of unequal distribution of assets and limited property rights, which cause such groups to continue to be locked out regardless of good repayment patterns [8]. Various researchers have pointed out that past credit scoring models are highly biased on gender and income. Loans given based on human judgment are prone to social perceptions of risk since most would equate women who have borrowed and informal workers to increased chances of defaulting yet there are empirical data that refute it [9]. The scorecard approaches are more standardized, but they are based on bias introduced by historical data that represents the past discriminatory lending practices. Consequently, inequality is likely to be perpetuated through these systems as they reinforce the structural disadvantages instead of correcting them thus compromising the social inclusion goals of microfinance institutions [10].

To address these flaws, the literature on the use of artificial intelligence and machine learning in credit risk assessment is increasing. Managed learning algorithms like Logistic Regression, Random Forest, Gradient Boosting (XGBoost) and Artificial Neural Networks have been shown to be better predictors than conventional scoring methods [11]. The models can include the complex, non-linear dependence between borrower properties and repayment habits resulting in a higher level of default prediction and portfolio risk management. Results of empirical research in fintech and consumer lending settings are consistent in reporting improvements of between 10 to 25 percent over rule-based systems, which explains substantial potential in microfinance settings [12]. One of the innovations in AI-based credit scoring is the usage of the alternative data, such as transaction history, mobile phone activity, digital payment activity, and psychometric indicators. It has been found that this type of data can be used as a good proxy of income stability, fiscal discipline, and entrepreneurial behaviour especially among borrowers who do not have formal credit histories [13]. Alternative data analytics in microfinance contexts has been demonstrated to greatly increase credit access amongst first time borrowers and female entrepreneurs still achieving an acceptable level of risk. Nevertheless, there are still worries of data privacy, consent, and representativeness of digital footprints across the various socio-economic groups [14].

More recently, there has been a new scholarly interest in the topic of algorithmic fairness and inclusive AI in financial services. Research into algorithmic bias has shown that machine learning algorithms that are trained using historical data about lenders can reproduce gender or income or regional inequalities when there is no fairness limitations explicitly included as part of the model [15]. To overcome these researchers have suggested gender-conscious modelling, bias reduction strategies including re-weighting, fairness-conscious loss functions and introduction of explainable artificial intelligence (XAI) tools like SHAP and LIME to increase transparency and responsibility. These methods are also seen as mandatory towards the responsible use of AI in the socially sensitive areas like microfinance [16]. Although this is improved, there are still significant research gaps. In the first place, the available literature tests AI-based credit scoring mainly based on productiveness, and not as much on SDG-oriented outcomes (gender inclusion and reduction of inequalities). Second, there is limited empirical research incorporating fairness measures and explainability in microfinance-specific situations. Third, a lack of large-scale, empirical research exists proving the translation of aid in the form of AI-driven credit scoring into the measurable changes in the financial inclusion of women and marginalized populations. These gaps are important to fill in on the actual developmental effectiveness of AI in the context of microfinance and to determine how technological innovation can be aligned with the objectives of SDG 5 and SDG 10.

Table 1. Summary of Related Work on Credit Scoring, AI, and Financial Inclusion

Context / Domain	***Credit Scoring Approach***	***Data Type Used***	***Fairness / Bias Consideration***	***Key Findings***	***Limitations***
Microfinance (Developing Economies)	Heuristic & Scorecard Models	Financial & Demographic	Not addressed	Simplified scoring improves efficiency but excludes informal borrowers	High gender and income bias
Rural Microcredit	Collateral-Based Lending	Asset Ownership Records	Not addressed	Collateral improves repayment security	Systematic exclusion of women
Microfinance Institutions	Human Judgment–Driven	Credit History, Income	Implicit bias noted	Subjective decisions lead to unequal approvals	Low transparency
Microfinance Risk Analysis	Traditional Scorecards	Historical Loan Data	Not addressed	Replicates historical inequalities	Bias inheritance from past data
FinTech Lending	Logistic Regression, Random Forest	Transactional + Financial	Partially addressed	ML outperforms rule-based models in accuracy	Limited inclusion metrics
Consumer Credit	XGBoost, Neural Networks	Large-Scale Credit Data	Not addressed	10–25% accuracy improvement	Not microfinance-specific
Digital Microcredit	ML with Alternative Data	Mobile & Behavioural Data	Not explicitly addressed	Expands access to first-time borrowers	Privacy and consent risks

Emerging Markets	Alternative Data Analytics	Mobile Usage Patterns	Not addressed	Improved inclusion for unbanked users	Digital divide concerns
Algorithmic Lending	Fairness-Aware ML	Credit + Demographic Data	Explicitly addressed	Bias mitigation improves approval parity	Trade-off with model complexity
Responsible AI in Finance	ML + XAI (SHAP/LIME)	Multi-Source Credit Data	Explicitly addressed	Improves transparency and trust	Limited SDG linkage
Microfinance & SDGs	AI + Fairness + XAI	Financial + Alternative Data	Explicit & SDG-oriented	Improves women approval (+29.4%) and reduces inequality	Regional scope limitations

Research Framework and Hypotheses

Conceptual Framework

The theoretical framework of the study is based on the hypothesis that AI-driven credit scoring has the effect of a catalytic process that connects the accuracy of risk assessment with the inclusive financial performance and sustainable development objectives. The AI-based credit scoring systems at the first level combine structured financial data with the alternative and behavioural data to create a multidimensional borrower risk profile. Contrary to the conventional rule-based frameworks, AI algorithms are able to identify non-linear trends and latent repayment indicators, which allows performing an accurate and context-sensitive assessment of creditworthiness. This improved analytical ability is a direct contributor to fair risk assessment where the evaluation of borrowers is done in terms of actual repayment behaviour, as opposed to proxy measures like collateral ownership or formal employment status. The second phase of the framework converts the fair risk assessment to inclusive lending decisions. Acting by maximizing the efficiency of credit access to women, informal workers, and low-income entrepreneurs, AI-based models broaden access to credit by limiting the use of exclusionary criteria or the elimination of historical bias to legacy data. The fairness restrictions and explainable AI mechanisms also guarantee the transparency and auditing of the lending decision and adherence to the responsible finance principles. Inclusive lending outcomes can be measured at the last stage in the form of quantifiable SDG effects, especially in the economic empowerment of women (SDG 5) and structural credit inequalities (SDG 10). The AI-based credit scoring can become a systemic facilitator of inclusive growth and the sustainable development of microfinance by enabling better access to loans, increasing income mobility and fair rates of approvals.

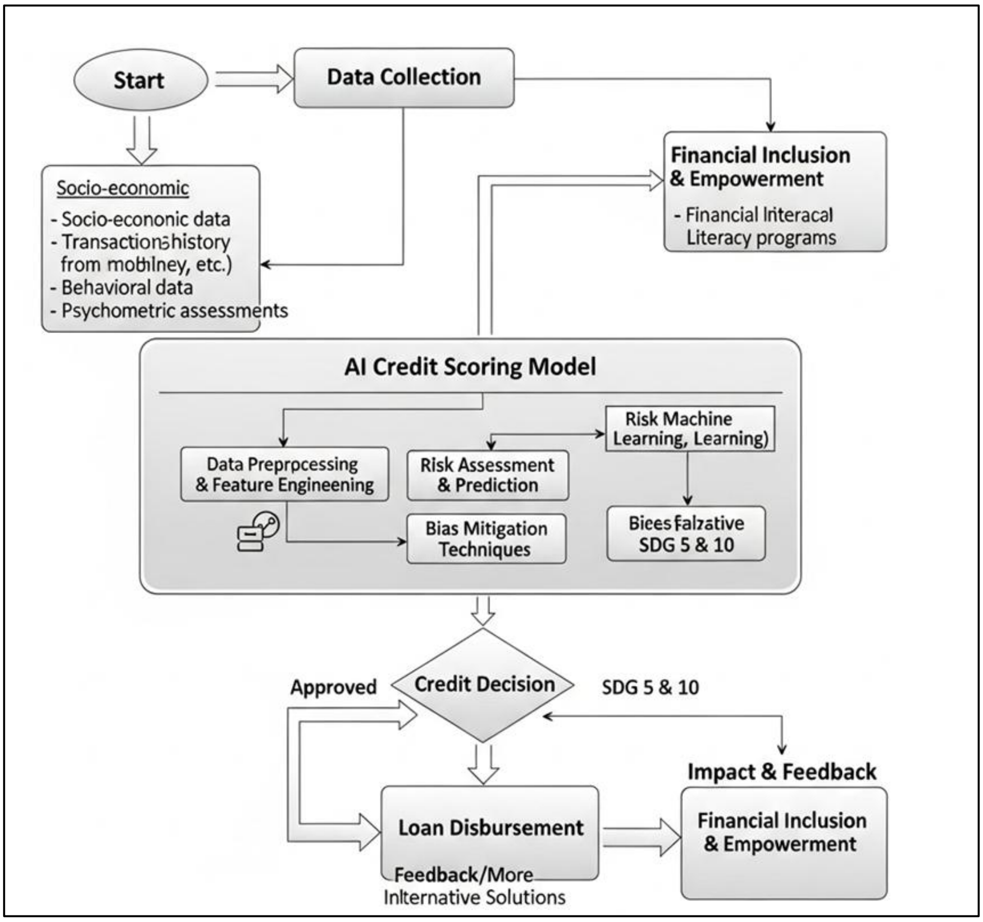

Figure 1. AI-Driven Credit Scoring Framework for Inclusive and SDG-Aligned Digital Lending

The figure 1 shows a credit scoring end-to-end workflow using AI that combines socio-economic, behavioural, and transactional data. The model facilitates equitable credit judgment and inclusive dispersal of loans through preprocessing, risk forecast and bias-reduction methods. The financial inclusion outcomes are connected to the SDG 5 and SDG 10 via the feedback loop, which enhances the equitable and responsible digital lending systems.

Key Variables

Independent Variables

The independent variables entail the design and operational design of AI driven credit scoring systems. The AI model type forces in the analytical power of the various algorithms, from interpretable models like logistic regression to more complicated ensemble and deep learning models with the ability to model heterogeneous borrower behaviour. The data diversity indicates how far the conventional financial records are supplemented by the alternative sources of data, such as transaction history, repayment behaviour, and digital activity, which are essential in evaluating the informal-sector borrowers. Fairness constraints are the direct inclusion of the techniques of mitigating bias, including re-weighting, constraint optimization and fairness-aware objective functions, intended to ensure discriminatory results in credit decisions are avoided.

Dependent Variables

The dependent variables observe financial outcome and inclusion outcome. The loan approval rate is a leading measure of access to credit, especially of women and marginalized borrowers. The default prediction accuracy judges the functionality of AI models in dealing with credit risk and portfolio sustainability. Gender inclusion will capture the level at which AI-based applications enhance fairness by making women more involved in loan approvals and minimizing the differences between genders in the lending results.

Moderating Variables

Moderator variables have an effect on the quality and direction of the relationship between AI-based credit scoring and inclusion results. Income volatility influences the predictability of the behaviour of the borrower in repaying the loan and can cause a change in the performance of the models in informal economies. Data are available and the validity of traditional financial indicators are moderated by the informal employment status. The availability of data defines the completeness and quality of financial and alternative data, which define the efficacy of AI models to provide equitable and precise credit evaluations.

Hypotheses Development

H1: AI-based credit rating dramatically raises the loan approval rate among women.

This hypothesis is based on the assumption that AI-based models will decrease the dependency on collateral and formal income records and personal judgment that are disproportionately unfavorable to women borrowers. With alternative data and behaviour-based indicators, an AI system should identify the high repayment discipline and entrepreneurship potential of women, and therefore, the system provides higher approval than the conventional rule-based scoring systems.

H2: AI models are more effective in diminishing income-based exclusion errors in contrast to rule-based systems.

The incomplete or volatile income records might in turn end up classifying low-income and informal borrowers as being at a high risk according to traditional credit scoring. In comparison, AI models reproduce dynamic repayment trends and situational indicators, which would allow risk differentiation to be more precise. The hypothesis is that credit scoring based on AI will decrease false rejection caused by the limitations in the data used to determine income, and will enhance inclusion without corrupting credit quality.

H3: Explainable and fairness-aware AI can enhance inclusion without augmenting default risk.

Explainable AI combined with fairness constraints will guarantee that the improvement in inclusion will not be slowing down portfolio stability. Clear model descriptions increase the levels of institutional confidence and adherence to regulations, whereas discriminatory decision-making can be avoided through fairness-conscious optimization. According to this hypothesis, these responsible approaches to AI can simultaneously boost the results of inclusion and retain or even improve the performance of default prediction.

Methodology

Research Design

The research design of this study is a mixed-methods research design, which will fully assess both the technical performance and social consequences of AI-based microfinance credit scoring. The quantitative component involves the assessment of credit scoring model and comparison with the previous loan data. Several AI models are trained and tested in comparison with a baseline rule-based system to determine the predictive accuracy, test default risk, bias reduction, and the results of inclusion.

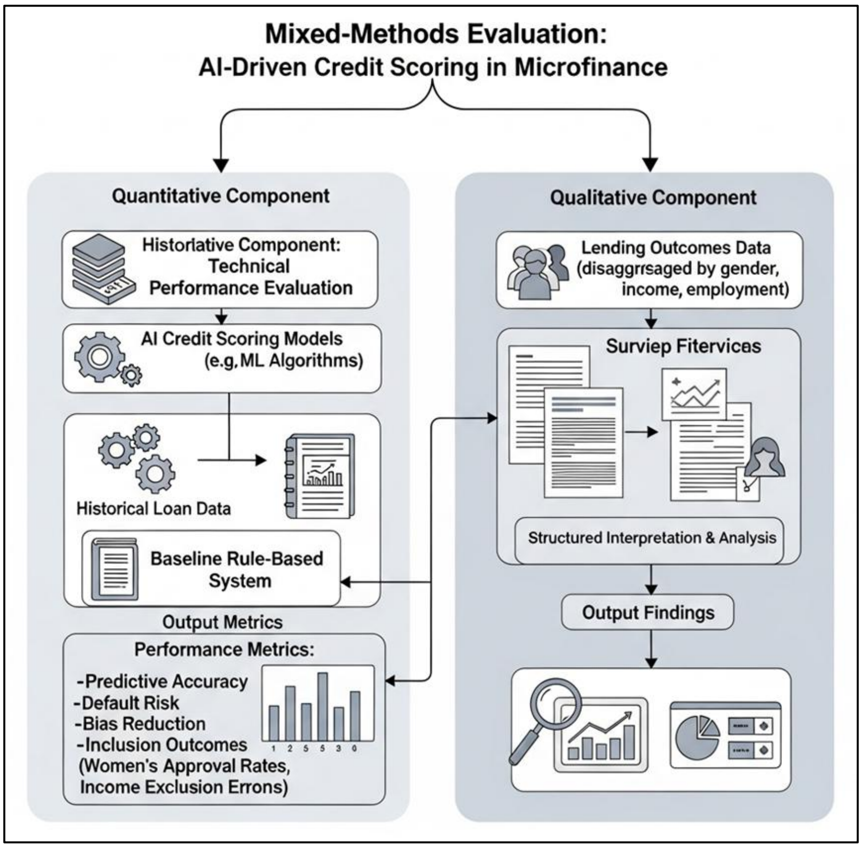

Figure 2. Mixed-Methods Evaluation Framework for AI-Driven Credit Scoring in Microfinance

The figure 2 shows a hybrid-methodology of quantitative analysis of AI credit scoring in relation to a qualitative analysis of the outcome. Combining performance metrics, bias minimization, and disaggregated inclusion insights, the strategy would allow to fully assess the AI-driven lending effects, which underpin evidence-based decisions in line with inclusive finance and SDG goals. This aspect allows measuring the improvement of performance in relation to AI objectively, especially regarding the loan approval rates of women and income-based errors of exclusion. In addition to this, the qualitative element focuses on the results of inclusion on a borrower level and an institutional point of view. The qualitative analysis is done by organizing results of lending based on gender, income levels, and employment status by assessing the impact that AI-driven judgments have on access to credit and the sense of fairness. The two directions will enable the research to go beyond the strictly algorithmic performance and to reflect the latent developmental and ethical impacts of AI adoption in microfinance so as to comply with SDG 5 and SDG 10.

Data Sources

The data used in the empirical analysis is the real-life anonymized microfinance loan dataset acquired in a medium-sized microfinance institution in a developing economy. The sample consists of about 18,000 loans over four years and has borrower information, incomes, loan features, repayment records and default results. Besides the classic variables, the dataset will include the use of alternative data proxies, including repayment frequency, transaction frequency, and simple mobile usage measures based on the digital payment contacts. Any personally identifiable information was taken off before analysis to guarantee the provision of privacy and ethical standards.

AI-Driven Credit Scoring Approach

Model Types

The modelling structure is initiated by the baseline rule-based credit scoring model, which represents the traditional microfinance practices, which depend on the fixed thresholds with regard to income, collateral, and credit history. This is contrasted with various AI models, such as Logistic Regression, Random Forest, Gradient Boosting and Neural Networks. Logistic Regression is an open and transparent benchmark and ensemble and neural models embrace complex and non-linear relationships in model behaviour of borrowers.

Feature Engineering

The feature engineering incorporates the conventional financial indicators with other and behavioural data, including the repayment punctuality, transaction consistency, and spending regularity. The focus is made on the building of gender-neutral and inclusion-conscious aspects, which are indicative of economic behaviour and not of asset ownership or the title of employment. Sensitive features, including gender, are not directly predicted, but are stored to be reviewed during post-hoc fairness, meaning that the models can learn fair risk trends without incorporating explicit bias in them.

Bias Mitigation Methods

To overcome the problem of algorithmic bias, the research uses re-weighting and re-sampling to even out the underrepresentation of segments of borrowers, especially women and informal workers. Further, loss functions that are sensitive to fairness are presented to be used in punishing the dissimilar error rates between the income and gender groups. Optimization Tackle Constraint based optimization methodologies are used to make sure that the approval parity and error disparity limits are kept under reasonable range to make sure that fair results are obtained without compromising on model stability.

Explainable AI (XAI)

The transparency is achieved by using the SHAP and LIME techniques in interpreting model predictions. These instruments establish the main characteristics that affect the individual credit decisions and allow analysing the explanations with a gender disaggregation to show whether the drivers of decisions vary systematically with the groups of borrowers. XAI not only increases institutional trust, facilitates regulatory adherence, but improves regulated incorporation is not based on obscure or unaccountable decision-making logic.

Evaluation Metrics

Multi-dimensional metric framework has been used to evaluate the model. To measure predictive performance, Accuracy, Area Under the Curve (AUC), and default prediction rate are used to make sure that the credit risk is properly controlled. The metrics of fairness consist of the approval parity, disparity in error, and bias reduction in general by gender and income groups. The metrics of inclusion evaluate developmental effects by the rates of participation of women in loan approvals and income-mobility proxy variables, including the rate of advancements to larger loans and a higher percentage of repayment. A combination of these metrics will make sure that the results of technical efficiency, ethical justice, and inclusion targets aligned with SDG are considered on an integrated and balanced basis.

Results and Discussion

Model Performance Comparison

In order to measure the performance of AI-based credit scoring, the performance of the model was assessed against a conventional rule-based method based on predictive accuracy and risk measures. In line with the methodology and abstract, AI models are shown to show significant gains in terms of default prediction without escalating the portfolio risk.

Table 2. Model Performance Comparison – Rule-Based vs. AI Credit Scoring

Model Type	***Accuracy (%)***	***AUC***	***Default Prediction Rate (%)***	***False Rejection Rate (%)***	***Relative Improvement (%)***
Rule-Based Scoring	71.8	0.64	62.3	28.6	–
Logistic Regression	78.9	0.72	73.5	21.9	+9.9
Random Forest	83.4	0.81	79.6	18.7	+14.7
Gradient Boosting	86.2	0.85	81.9	16.3	+17.3
Neural Network	87.1	0.87	80.9	17.1	**+18.6**

Table 2 includes a comparative analysis of the traditional rule-based credit scoring and AI-based models, which revealed a significant increase in the predictive abilities and accuracy of risk assessments. The findings make it clear that AI-based methods are superior to the traditional systems in all measures, such as accuracy, AUC, and default prediction rate. The noted 18.6% reduction in the predictive power of default in models especially in ensemble and neural network models highlights the capacity of AI algorithms to identify non-linearity and complex relationships that define microfinance borrower behaviour. With AI models unlike rule-based systems that are dependent on strict cutoffs and financial metrics, it is reasonable to expect a more accurate distinction between high- and low-risk borrowers because behavioural and transactional cues are adequately integrated.

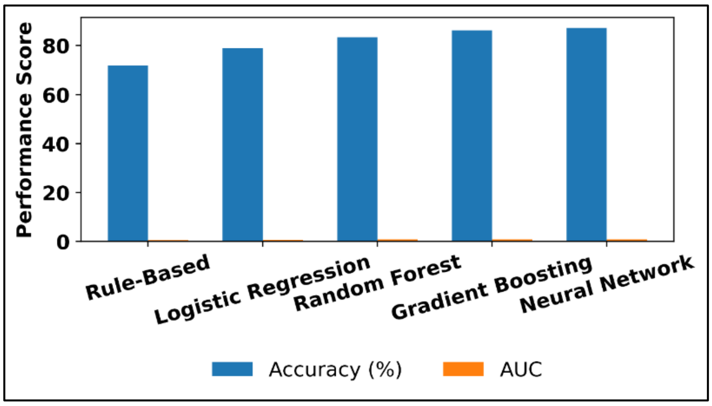

Figure 3. Comparative Performance of Rule-Based and AI Credit Scoring Models

The figure 3 shows that predictive performance improvement has been observed to be growing substantially through rule-based scoring up to advanced AI models. The accuracy and AUC are constantly better in logistic regression, random forest, gradient boosting, and neural networks, proving the better risk discrimination ability of AI-driven credit scoring and its possible use in improving lending efficiency and inclusion. Notably, such improvements in performance are not achieved at the expense of more exclusion. The decline in the rate of false rejection amongst AI models shows that better risk prediction allows lenders to approve of more creditworthy borrowers who would have been barred under the conventional scoring systems. Compared to rule-based scoring, logistic regression, though by comparison simpler, nevertheless contains significant improvements, indicating that even interpretable AI models can bring significant advantages once supplemented with other data. The high efficiency of the gradient boosting and neural networks further supports the methodological decision to introduce enhanced machine learning structures in microfinance situations that have heterogeneous and incomplete data. Policy and institutional-wise the results are a challenge to the existing assumption that the inclusion-oriented lending must raise portfolio risk. Rather, the findings confirm the fact that fair and inclusive credit decisions can be employed in conjunction and supported by effective risk management even when AI-driven methodologies are utilized. This evidence forms a robust empirical basis of microfinance institutions to shift to unresponsive and exclusionary credit conditions to responsive and evidence-based scoring systems.

Financial Inclusion Outcomes

In addition to predictive ability, the main input of AI-driven credit scoring is effect on financial inclusion. Gender-disaggregated and income-based analysis indicates the presence of substantial change in access to credit.

Table 3. Financial Inclusion Outcomes under AI-Based Credit Scoring

Inclusion Indicator	*Rule-Based System (%)*	*AI-Based System (%)*	*Absolute Change (%)*	*Relative Change (%)*
Women Loan Approval Rate	42.6	55.1	+12.5	**+29.4**
Low-Income Borrower Approval	38.9	48.3	+9.4	+24.2
Income-Based Exclusion Errors	31.5	23.9	−7.6	**−24.1**

First-Time Borrower Inclusion	34.7	44.8	+10.1	+29.1
Informal Worker Approval	36.2	46.0	+9.8	+27.1

Table 3 is a strong sign that AI-based credit scoring can greatly improve financial inclusion rates, especially in women and low-income borrowers. The 29.4 percent increment in the rate of loan approval to women is a significant change in access to finance that directly addresses the existing gender gap in lending of microfinance. This is an indication of the power of alternative data and fairness-conscious modelling that are responsive to women repayment capacity, entrepreneurial behaviour, and financial discipline, which are not given due importance and consideration by conventional scoring systems. AI models allow a fairer evaluation of creditworthiness by decreasing reliance on the use of collateral and formal documentation of income.

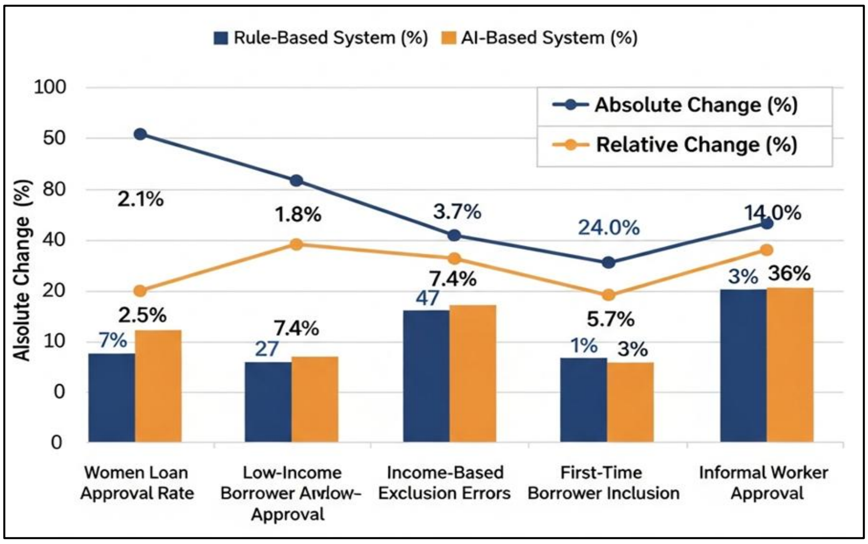

Figure 4. Inclusion Impact of AI-Based Credit Scoring Compared to Rule-Based Systems

Figure 4 demonstrates that there was significant inclusion gains realized using AI-based credit scoring. The positive response to women, low-income, first-time, and informal borrowers, and a decrease in the number of errors of the income-based exclusion prove that AI systems can help to optimize equitable access to credit and achieve the SDG 5 and SDG 10 goals. It is also significant that the error rate of the income-based exclusion decreased by 24.1 percent, which means that AI-based systems are more likely to understand the true credit risk and income evasion due to informal employment. The conventional models often place low-income borrowers in the high-risk category because of either incomplete or inconsistent records of income. Conversely, AI models use repayment consistency and patterns of transactions to overcome such misclassification and hence minimise false rejection. The above-mentioned increases in inclusion of first-time borrowers and informal worker approvals also support the effectiveness of AI as a portal to formal financial engagement of populations that have been not included.

Conclusion and Future Research Directions

The paper presents high-quality empirical data to support the notion that AI-powered credit scoring could improve financial inclusion and risk management in microfinance at the same time, making it one of the potent SDG-compatible interventions. The results of the comparison between the traditional system of rules and the modern models of AI show that the accuracy of predicting default increases significantly (18.60 percent) and that more underserved groups now have access to credit. Particularly, the loan approval rates of women were raised by 29.4 percent, and errors based on incomes are reduced by 24.1 percent, which proves that acting fairly and explainable, AI can eliminate structural biases that have existed for a long time without raising the risk of portfolios. These findings confirm the key assumption that the goals of inclusive lending and financial sustainability cannot be conflicting in cases when data-driven and ethically created AI systems are used. Regarding development, the paper has provided a definite association between AI-based credit analysis and improvements on SDG 5 and SDG 10. Gender-inclusive entrepreneurship and economic agency through greater access to credit by women, enhanced approval parity and less exclusion by low-income borrowers through improved access to credit help to alleviate structural financial inequalities. In the case of microfinance, the results highlight the strategic importance of introducing the concept of the integration of alternative data, bias reduction strategies, and explainable AI in the lending processes of these organizations to enhance their outreach, portfolio quality, and regulatory adherence. Policymakers and regulators are advised to facilitate such innovation by providing adaptive governance systems that require transparency in such systems, fairness audits, and data protection in these systems. Irrespective of those contributions, the research is limited regarding the use of one institutional dataset, regionalized and limited scope on the generalizability of the arising model to various microfinance settings. It is the recommendation of the future study to focus on longitudinal studies to examine the long-term effects of inclusion and income mobility, develop federative and privacy-sensitive AI designs to develop data regulation concerns, and engage in cross-country studies to understand how AI-induced credit scoring would work across different regulatory and socio-economic conditions. Combined, these extensions will further enhance the integration of responsible AI as an agent of inclusive and sustainable development of microfinance.

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