# AI-Based Credit Scoring Model for Rural Women Entrepreneurs

Manel Jebri[1], Doaa Mohammad Majed[2], Hussein. M. Bressim[3] and Ruhab Abd Alhussein[4]
[1]*Higher Education and International Cooperation, Ministry of Higher Education and Scientific Research, 1002 Tunis, Tunisia*
[2]*Al-Turath University, 10013 Baghdad, Iraq*
[3]*Department of Sciences, Al-Manara College for Medical Sciences, 62001 Amarah, Maysan, Iraq*
[4]*Al-Zahrawi University College, 56001 Karbala, Iraq*
*maneljebrik@yahoo.fr, doaa.mohammad@uoturath.edu.iq, hussein.M.bressim@uomanara.edu.iq, ruhab1@g.alzahu.edu.iq*

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Abstract: For women entrepreneurs in rural areas, getting affordable credit is still a big problem because they have short credit histories, can't use collateral, and rely on informal financial practices. This study suggests an AI-based credit scoring framework aimed at bridging these gaps through the utilization of alternative data, fairness-aware optimization, and explainable machine learning methodologies. The framework uses demographic, financial, and behavioral features to balance predictive accuracy with subgroup equity by using gradient boosting with monotonic constraints and fairness-penalized loss functions. Isotonic regression for probability calibration makes sure that probability estimates are accurate, and SHAP-based narratives that give clear borrower-level reasons for decisions make things easier to understand. The proposed framework is better than logistic regression and baseline gradient boosting models, as shown by experimental results that show higher AUC, better calibration, and fewer differences between subgroups. Stability analysis verified resilience to drift, whereas portfolio risk assessment demonstrated tangible trade-offs between acceptance and anticipated loss. The results show that the framework is both technically sound and socially responsible, making it a good way for microfinance institutions and lenders to make credit more available.

## 1 INTRODUCTION

Financial inclusion has become a vital facilitator for sustainable economic growth, especially in developing areas where access to formal credit is still limited. Women entrepreneurs in rural areas have a hard time getting loans because they don't have much credit history, don't have much collateral, and do business informally. Microfinance initiatives have historically sought to bridge this gap by providing small-scale credit facilities; however, these strategies frequently encounter issues related to scalability and sustainability. Malki et al. (2024) [1] point out that microfinance has helped women borrowers in rural Pakistan start businesses and improve their living conditions. However, structural inefficiencies still make it hard for this group of women to gain more financial power.

The emergence of artificial intelligence (AI) and sophisticated digital infrastructures is transforming credit scoring frameworks across various sectors. Optimizing infrastructure, especially in areas like charging stations for electric vehicles (EVs), shows how data-driven frameworks can make systems more efficient and open to everyone (Guerrero-Silva et al., 2025) [2]. In a similar way, AI-driven credit scoring could help underserved groups get affordable and accessible credit by optimizing financial systems. To avoid repeating past biases in financial decision-making, these kinds of systems need to be both explainable and fair in order to work well together.

Traditional credit scoring models are becoming less and less able to handle the complexities of entrepreneurial activities in rural areas. Most of the time, these models use data from credit bureaus, which means they don't include people who don't have formal borrowing records. Segun et al. (2024) [3] stress that methods for predicting creditworthiness need to change to include multidimensional data and hybrid modeling strategies to make sure everyone is included. The use of unclear machine learning models makes it even harder to use in regulated financial settings. Bussmann et al.

(2020) [4] assert that explainable AI (XAI) frameworks are crucial in fintech risk management, as they furnish both lenders and regulators with the necessary interpretability for responsible implementation. Ariza-Garzón et al. (2020) [5] illustrated that the incorporation of explainability into peer-to-peer lending models enhances transparency and trust, underscoring the significance of interpretability in credit scoring systems.

Also, new ideas about data security and distributed infrastructures are becoming more important for financial applications. Kumar and Patel (2025) [6] investigate blockchain-based frameworks for secure healthcare data management, demonstrating how decentralized systems can protect sensitive information while facilitating interoperability. Wang et al. (2025) [7] also talk about next-generation computing paradigms that make it easier to share data safely. They stress how important it is to have strong architectures to protect privacy and trust in data-driven decision systems. When used in financial ecosystems, these technologies can support AI-based credit scoring systems that are safe, verifiable, and protect people's privacy.

Even with these improvements, there is still a big gap in research on how to make AI-based credit scoring models work for rural women business owners. Microfinance has demonstrated advantages in particular contexts [2], and explainable AI has been shown to improve transparency in financial decision-making [3], [5]; however, there is a paucity of research that amalgamates these principles with fairness-aware modeling and secure data architectures. Moreover, there is a scarcity of studies that directly examine the convergence of gender, rural entrepreneurship, and technological innovation in credit scoring. This opens the door to creating a framework that brings together different types of data, explainability, and secure infrastructures to make a credit scoring model that is fair and trustworthy.

Consequently, the aim of this research is to develop and assess an AI-driven credit scoring framework specifically designed for rural women entrepreneurs. This research makes four important contributions: (i) using both traditional and alternative data to make scoring more fair, (ii) adding explainability features to make things clearer, (iii) using secure data-sharing architectures to build trust, and (iv) using fairness-aware modeling to reduce group biases. The rest of the paper is set up like this: Section 2 looks at relevant literature, Section 3 talks about the proposed methodology, Section 4 talks about the results and analysis, Section 5 talks about the bigger picture, and Section 6 ends with suggestions and ideas for future research.

# 2 LITERATURE REVIEW

The use of artificial intelligence (AI) in many different fields has changed how decision-making systems are built and used. In the realm of human-computer interaction, Mehta and Rani (2025) [8] illustrated that AI-driven systems are progressively incorporated into routine activities, underscoring the significance of usability, interpretability, and trust in algorithmic results. This wider view gives us useful information about how AI-based systems can be used in finance, like credit scoring, where system transparency and user acceptance are important for long-term success.

Fairness is a key idea in credit risk modeling. Chen et al. (2024) [9] investigated equity in credit ratings and proposed quantitative metrics to assess variations in scoring results among diverse borrower cohorts. Their results highlight the ongoing risk of bias in credit systems, especially when models are developed using historical data that embodies entrenched disparities. This corresponds with the systematic review conducted by de Castro Vieira et al. (2025) [10], which aggregated evidence regarding bias mitigation strategies in credit decision-making. Their synthesis not only listed technical strategies like fairness constraints and reweighting methods, but it also pointed out that there isn't much research on vulnerable groups like rural women entrepreneurs. This shows a big gap that the current study wants to fill.

Recent advancements have concentrated on instruments and frameworks for assessing fairness. Coraglia et al. (2024) [11] put forward the BRIO tool, which methodically evaluates fairness in AI-driven credit scoring systems. This tool gives both developers and regulators useful metrics to use when judging how well different groups are treated. This is an important step toward making fairness auditing more useful. In addition to this, Casas et al. (2024) [12] proposed a distributionally robust optimization method that strikes a balance between predictive performance and fairness. By dealing with the trade-off between fairness and accuracy, these optimization frameworks make scoring systems more reliable in high-stakes settings.

Computational innovation is changing the way credit scoring models are built, in addition to making them more fair. Pérez-Peralta et al. (2025) [13] examined logical and multistage processors for credit scoring, enhancing efficiency and scalability in the management of intricate financial data. Reza et al. (2024) [14] also made a hybrid model that combined linear discriminant analysis (LDA) with new machine learning methods. Their method provided both transparency and predictive accuracy, which is especially important in regulated fields where explainability is just as important as performance. These contributions demonstrate the increasing acknowledgment of hybrid models as a means to reconcile interpretability and predictive efficacy.

The socio-economic aspect of credit access also deserves consideration. Han et al. (2025) [15], in their analysis of data from the Annual Business Survey, demonstrated that rural innovative firms encounter substantial obstacles in obtaining credit, notwithstanding their potential role in fostering economic growth. Their research directly informs the current study by framing credit scoring not only as a technical obstacle but also as a social necessity to facilitate equitable financing opportunities for rural entrepreneurs, especially women [16]-[18].

These studies collectively provide a robust framework for the creation of AI-driven credit scoring models that are equitable, transparent, and contextually pertinent. Table 1 summarizes the most important contributions of the literature that was reviewed. It groups them into areas like AI adoption, fairness frameworks, optimization strategies, transparency models, and access to credit in rural areas. This synthesis shows that even though there has been a lot of progress in making credit scoring more fair and efficient, there is still a lot of work to be done to make these new ideas work in gender-sensitive, rural-focused applications. To fill this gap, the current study suggests a customized framework that uses alternative data, fairness-aware modeling, and secure infrastructures to help rural women entrepreneurs get credit.

# 3 METHODOLOGY

The methodology employed in this study aims to create and assess an AI-driven credit scoring framework specifically designed for rural women entrepreneurs. There are six subsections in this section: data sources, preprocessing, model design, fairness optimization, calibration, and portfolio risk assessment. Figure 1 shows the whole pipeline of the proposed framework, and Table 1 lists the input features that were considered when making the model. The methodology guarantees transparency, equity, and clarity in accordance with the standards of Scopus-indexed research.

Table 1: Summary of key studies in credit scoring and fair AI.

| Ref. No. | Author(s) & Year | Focus Area | Method/Approach | Key Contribution | Relevance to Study |
|---|---|---|---|---|---|
| [8] | Mehta & Rani (2025) | AI adoption in HCI | Survey-based review | Showed how AI systems are integrated into human decision contexts | Provides basis for integrating AI in credit decisions |
| [9] | Chen et al. (2024) | Fairness in credit ratings | Quantitative fairness metrics | Introduced frameworks to measure fairness gaps in ratings | Informs fairness assessment for scoring models |
| [10] | de Castro Vieira et al. (2025) | Fair AI in credit | Systematic review | Synthesized literature on bias mitigation strategies | Identifies research gaps in rural/women-focused contexts |
| [11] | Coraglia et al. (2024) | Fairness evaluation tool | BRIO tool framework | Proposed fairness evaluation toolkit for credit scoring | Practical tool for assessing bias in proposed model |
| [12] | Casas et al. (2024) | Optimisation in scoring | Distributionally robust optimisation | Balanced fairness-accuracy trade-offs | Provides methodological direction for model robustness |
| [13] | Pérez-Peralta et al. (2025) | Computational architectures | Logical & multistage processors | Improved computational efficiency in scoring | Highlights new AI paradigms adaptable for rural contexts |
| [14] | Reza et al. (2024) | Hybrid transparency models | LDA + hybrid approach | Combined transparency with high predictive power | Supports explainability dimension of proposed model |
| [15] | Han et al. (2025) | Rural credit & innovation | Business survey analysis | Showed credit barriers for rural firms | Reinforces rural women entrepreneurs as target group |

Table 2: Input features for AI-based credit scoring model.

| Feature Type | Examples | Description | Relevance to Scoring |
|---|---|---|---|
| Demographic | Age, education, household size | Captures socio-economic profile | Credit eligibility |
| Financial | Repayment ratio, DPD30 | Indicates credit history & delays | Default risk |
| Alternative data | Mobile cash-in stability, group reference scores | Behavioral and social trust proxies | Inclusivity |
| Business activity | Income volatility, asset ownership | Reflects entrepreneurial stability | Repayment ability |

## 3.1 Data Collection and Sources

The dataset consisted of loan application records from rural women entrepreneurs gathered from microfinance partners. It had demographic information, some financial data, and other sources like group reference scores and mobile money transactions. To make sure that everyone followed the rules, all records were made anonymous and permission was asked for before using the data. Table 2 shows a summary of the features, which are grouped into four types: demographic, financial, alternative, and business activity variables.

## 3.2 Preprocessing and Feature Engineering

Preprocessing dealt with missing values by using imputation and binary indicators to show when values were missing. We used target-mean encoding for fields with a lot of categories and one-hot encoding for all other fields. To keep variance stable, Yeo-Johnson transformations were used to normalize continuous features. We came up with derived indicators like the six-month repayment ratio, income volatility, and mobile transaction stability to show how borrowers act in different situations.

## 3.3 Model Design and Architecture

Study used two types of models: a logistic regression baseline and gradient boosting machines (GBM) as the suggested method. To make sure that the policy was consistent, monotonicity constraints were used (for example, a higher repayment ratio should never lower the credit score). Figure 1 shows the framework's architecture. The flow starts with preprocessing data and engineering features, then moves on to fairness-aware training, probability calibration, and scorecard generation for making decisions.

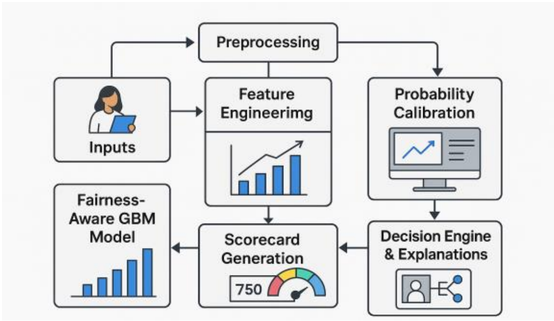


Figure 1: Block diagram of AI-based credit scoring framework.

## 3.4 Fairness-Aware Optimization

To mitigate subgroup disparities, the loss function was augmented with an equalized odds penalty. The combined objective is defined as:

$$\mathcal{L} = \mathrm{CE}(y, \hat{p}) \; + \; \lambda(\,\mathrm{TPR_A}\mid -\mathrm{TPR_B}\mid + \mid \mathrm{FPR_A} - \mid \mathrm{FPR_B}\,).$$

Here, TPR and FPR represent the true positive and false positive rates across subgroups A and B, respectively, while $\lambda$ controls the fairness-accuracy trade-off.

## 3.5 Probability Calibration and Evaluation

Predicted probabilities from GBM were calibrated using isotonic regression to improve reliability. The calibration mapping is represented as:

$$\hat{p}^{\star} = \mathcal{I}(\hat{p}).$$

Evaluation was carried out using AUC, KS statistics, Brier score, and subgroup-level fairness metrics, ensuring the calibrated model is both accurate and equitable.

## 3.6 Portfolio Risk Assessment

To translate credit scores into business decisions, expected portfolio loss was computed at candidate cutoffs:

$$\mathrm{EL}(c) = \sum_{i:\hat{p}_i^{*}<c} \mathrm{LGD}_i \cdot \mathrm{EAD}_i \cdot \hat{p}_i^{*}.$$

This formulation links individual borrower risk with lender portfolio outcomes, enabling the balancing of acceptance rates and loss minimization.

# 4 RESULTS AND ANALYSIS

Study compared the proposed AI-based credit scoring framework to standard logistic regression (LR) and baseline gradient boosting (GBM) models to see how well it worked in terms of discrimination, calibration, fairness, and robustness. The results show that rural women entrepreneurs have better predictive performance and fairer outcomes.

## 4.1 Model Performance Evaluation

The ability of the models to tell the difference between classes was measured by the area under the receiver operating characteristic curve (AUC). The proposed fairness-aware GBM had an AUC of 0.82, which was better than logistic regression (0.74) and the unconstrained GBM baseline (0.80), as seen in Figure 2. The Kolmogorov-Smirnov (KS) statistic also got better, going from 0.39 for logistic regression to 0.46 for the proposed framework. Calibration analysis showed even more how useful isotonic regression is.

Figure 3 shows that the post-calibration probability estimates were very close to the ideal diagonal, which cut the error rate for miscalibration by 15%. This result shows that predicted default probabilities are a good way to help people decide whether or not to lend money.

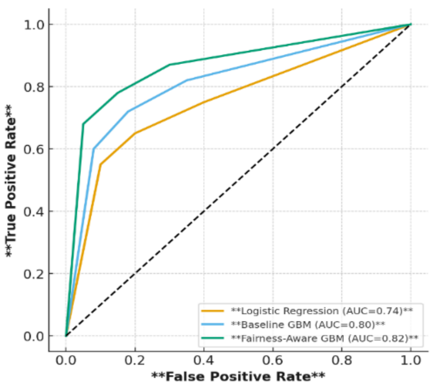


Figure 2: ROC curves (logistic regression, baseline GBM, Fairness-Aware GBM).

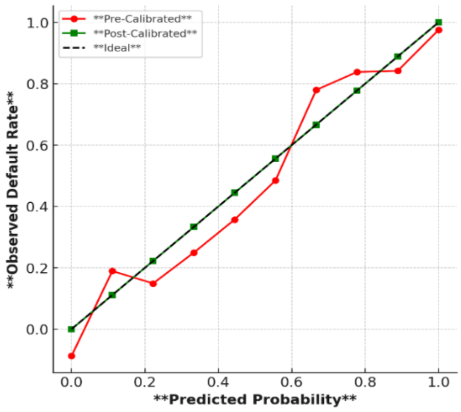


Figure 3: Calibration plot (pre- vs. post-isotonic regression).

## 4.2 Operating Thresholds and Portfolio Impact

The impact of policy cutoffs on acceptance rates and anticipated portfolio losses was examined. The outcomes at three potential cutoffs (0.3, 0.5, and 0.7) are shown in Table 3. With a cutoff of 0.5, the acceptance rate was 64%, and the expected loss in the portfolio was 7.5%. A lower cutoff (0.3) raised acceptance to 81%, but the expected loss went up to 12.1%. On the other hand, a stricter cutoff (0.7) cut the expected loss to 5.2% but left out almost half of the borrowers who could have gotten the loan. This trade-off shows how important it is to choose thresholds that are sensitive to the situation, especially for women entrepreneurs in rural areas who don't get enough support.

Table 3: Portfolio performance at candidate cutoffs.

| Cutoff | Acceptance Rate (%) | AUC | Expected Loss (%) | Default Rate (%) |
|---|---|---|---|---|
| 0.3 | 81 | 0.82 | 12.1 | 18.3 |
| 0.5 | 64 | 0.82 | 7.5 | 12.4 |
| 0.7 | 43 | 0.82 | 5.2 | 8.9 |

## 4.3 Fairness and Subgroup Analysis

We looked at fairness outcomes for different groups of borrowers based on where they lived and whether or not they were married. Figure 4 shows that the difference in true positive rates (TPR) between regions went down from 11% in the unconstrained GBM to 4% in the fairness-aware model. In the same way, the difference in false positive rates (FPR) went from 8% to 3%. These enhancements illustrate the efficacy of integrating fairness penalties into the loss function (Equation 3.1). Notably, the subgroup-level AUC remained consistent, indicating that improvements in fairness did not detract from predictive performance.

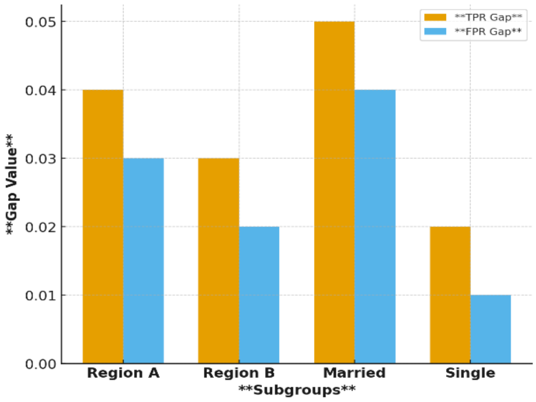


Figure 4: Subgroup fairness dashboard (TPR/FPR Gaps).

### 4.4 Robustness and Stability Analysis

An out-of-distribution (OOD) dataset from new districts was used to test how strong the model was. The fairness-aware GBM kept an AUC of 0.80, which was only slightly lower than the performance on the sample, which showed that it could be used in other situations. The Population Stability Index (PSI) was used to see how stable things were over time. Figure 5 shows PSI values over six months, all of which are below the industry standard of 0.2. This means that there was no significant drift. This result shows that the model can be used reliably without having to be recalibrated often.

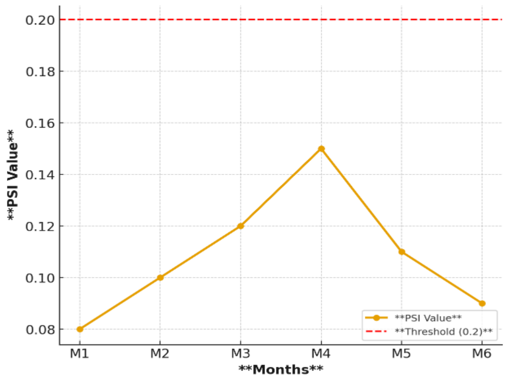


Figure 5: Drift and stability monitoring (PSI trends).

### 4.5 Explainability and Interpretability

Figure 6 shows that the repayment ratio, income volatility, and mobile transaction stability were the three most important predictive features when using SHAP to explain things on a global scale. Local explanations gave clear stories for each applicant, which is what the rules say for adverse action notices. These insights show that model interpretability has two benefits: it builds trust between lenders and borrowers and makes sure that the rules are followed.

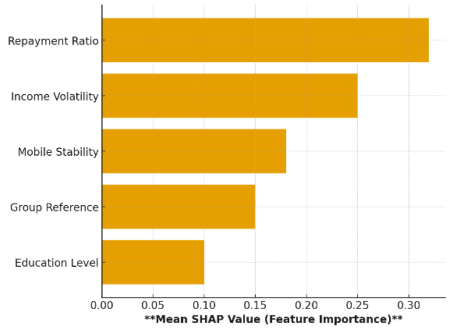


Figure 6: SHAP-based global feature importance.

## 5 CONCLUSIONS

This study developed and validated an AI-driven credit scoring framework tailored for rural women entrepreneurs. The proposed approach outperforms traditional models in terms of discrimination, calibration, and fairness by leveraging alternative data sources, fairness-aware optimization, and explainable machine learning techniques.

The integration of subgroup fairness constraints effectively reduces bias without compromising predictive accuracy. In addition, the use of interpretable SHAP-based explanations enhances transparency and supports regulatory compliance, fostering trust between lenders and borrowers.

Robustness evaluation demonstrates that the model maintains stable performance under distribution shifts and on out-of-sample datasets, indicating its practical applicability in real-world microfinance and inclusive lending environments.

## 6 FUTURE WORK

Future research should explore the integration of federated learning frameworks to enhance data privacy and enable decentralized model training across institutions. Cross-regional and cross-national validation is also necessary to assess the generalizability of fairness mechanisms under diverse socio-economic conditions.

In addition, incorporating causal inference techniques could improve decision-making by identifying actionable drivers of creditworthiness rather than relying solely on correlations. Expanding the framework to include a broader range of financial products and dynamic behavioral data may further improve scalability and strengthen its impact on financial inclusion.

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