AIJFR
Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

AI-Driven Credit Scoring and Financial Inclusion: Performance, Fairness, And Transparency in Alternative-Data Lending

Aarav Vikas Dang

Surat, Gujarat, India
Email: aravvikasdang@gmail.com

Abstract

Access to formal credit remains uneven, especially for individuals with limited or no credit histories. Such "thin-file" borrowers are routinely excluded from conventional bureau-based credit scoring that depends on past repayment records and formal financial footprints. Advances in artificial intelligence (AI) and machine learning (ML) allow lenders to incorporate richer, consented alternative data into credit assessment, offering a pathway to improve both default prediction and financial inclusion. This paper evaluates whether AI-driven credit scoring models improve loan default prediction and expand credit access compared with traditional statistical approaches. Using a combination of bureau variables and alternative indicators—including mobile payments, UPI transaction stability, utility-bill regularity, and telecom-based behavioral aggregates—the study examines predictive performance, approval lift among underserved borrowers, fairness trade-offs across demographic groups, and transparency requirements for responsible deployment. Overall results show that ML models (particularly gradient boosting and hybrid ensembles) deliver higher predictive accuracy than logistic-regression baselines and raise approval rates for thin-file applicants without a proportional rise in default risk. However, improvements in access do not automatically translate into equitable outcomes; residual disparities remain, highlighting the need for fairness-aware governance. Explainability tools improve decision transparency but may exhibit instability under class imbalance and data drift that are common in thin-file portfolios. The paper concludes by proposing operational and policy guardrails—fairness audits, interpretable decision rationales, standardized adverse-action notices, and strict data-protection practices—to ensure that AI-based credit scoring advances inclusion while maintaining accountability and consumer trust.

Keywords: Alternative data, artificial intelligence, credit scoring, fairness, financial inclusion, machine learning, transparency.

1. Introduction

Access to credit is a cornerstone of household resilience and small-business growth. Yet even in rapidly digitizing economies, large segments of the population remain excluded from formal lending because they lack bureau histories. Traditional credit scoring systems, typically based on logistic regression or scorecards derived from repayment histories and income proxies, are effective for long-standing borrowers but systematically exclude first-time credit seekers and informal-sector workers. This exclusion creates persistent barriers for thin-file borrowers, particularly in emerging markets where formal borrowing is not universal.

AI-driven credit scoring offers an alternative. ML models can learn non-linear patterns from heterogeneous datasets and incorporate consented alternative data—such as digital payments, utility regularity, and mobile-usage aggregates—that may reveal repayment discipline even without bureau depth. Empirical work shows that digital footprints and telecom signals can match or complement bureau scores, and that combining both sources improves prediction for thin-file segments [1], [2].

However, replacing conventional scoring with AI is not purely technical. AI models may encode historical bias present in training data, and complex models reduce interpretability and contestability of decisions [3]. Regulators are also increasingly classifying credit scoring as a high-risk AI application, requiring fairness and transparency safeguards [4].

Assumptions for this study (explicit): Target geography/segment is India, with retail borrowers who have limited bureau history, including semi-urban and rural users with UPI adoption. Available data includes bureau records, UPI transaction summaries, telecom behavioral aggregates, and utility payment regularity.

Objectives: (1) Compare predictive performance of AI-based models with traditional scoring for thin-file borrowers. (2) Quantify inclusion effects (approval lift) enabled by alternative data. (3) Evaluate fairness and transparency trade-offs and propose governance practices.

2. Literature Review

2.1 Traditional Credit Scoring and Its Limitations

Traditional scoring relies on bureau data, repayment history, liabilities, and verified income. While transparent and auditable, these methods fail where bureaus are sparse. Thin-file borrowers cannot be reliably scored using historical repayment features, producing systematic exclusion [1].

2.2 AI and Machine Learning in Credit Scoring

Modern ML methods outperform linear baselines by capturing non-linear patterns and interactions. Digital footprints derived from online behavior can predict default risk comparably to bureau scores, and hybrid models combining both outperform either source alone [1]. Telecom-based behavioral features—call patterns, contact diversity, and activity regularity—have strong predictive power in thin-file contexts, sometimes outperforming bureau models in cross-time tests [2].

2.3 Alternative Data Sources and Inclusion

Alternative data enables scoring beyond traditional financial histories. Empirical work using call-detail networks and social-interaction features shows that alternative data adds measurable lift in accuracy and portfolio profit while expanding access [5]. Studies of fintech lending also report approval increases for underserved segments without large deterioration in defaults, supporting the inclusion potential of non-traditional signals [6].

2.4 Fairness, Discrimination, and Consumer Protection

Predictive gains do not guarantee fair outcomes. Evidence from algorithmic consumer lending shows that disparities can reduce but often persist due to proxy variables and biased training distributions [3]. Therefore, fairness evaluation must accompany deployment, particularly for vulnerable groups.

2.5 Explainability and Transparency

Explainable AI methods such as SHAP and LIME can provide local and global rationales for decisions [7]. Yet interpretability can degrade under class imbalance and drift—conditions common in credit scoring—reducing the stability of explanations [8].

2.6 Open Banking, UPI, and Regulatory Context

Open banking and India's UPI ecosystem increase data portability for thin-file borrowers by providing transaction histories that can substitute for missing bureau depth. Such systems may widen access but also raise privacy and consent concerns, requiring careful governance. High-risk AI frameworks emphasize transparency, bias testing, and human oversight for credit scoring [4].

2.7 Research Gaps

Key gaps remain: limited causal evidence on borrower welfare from AI-enabled credit expansion; persistent fairness trade-offs between accuracy and inclusion; insufficient validation of interpretability stability in thin-file portfolios; and lack of operational governance models tailored to emerging markets.

3. METHODOLOGY

This study employs a comparative modeling design evaluating traditional and AI-driven credit scoring approaches for default prediction and inclusion outcomes. The design integrates bureau and alternative data to evaluate incremental value.

Data sources include structured bureau variables (repayment history, liabilities, income proxies) and consent-based alternative data: UPI/digital payment activity, utility payment regularity, and telecom behavioral aggregates. All data are anonymized and processed under consent and data-minimization principles.

Models evaluated are Logistic Regression (LR) and Linear Discriminant Analysis (LDA) baselines, Random Forest (RF), Gradient Boosting (XGBoost), Deep Neural Networks (DNN), and a Hybrid Ensemble combining bureau and alternative features.

Evaluation includes predictive accuracy (AUC-ROC, Precision–Recall, F1), inclusion outcomes (thin-file approval lift, default change), fairness (demographic parity, equalized odds, calibration by subgroup), and transparency (SHAP/LIME explanations and stability across time and subgroups).

The analytical procedure consists of preprocessing, 70/30 train–test split with 5-fold cross-validation, bureau-only vs. alternative-only vs. hybrid training, and robustness checks via subgroup and out-of-time validation.

4. RESULTS AND ANALYSIS

AI models outperform traditional models on default prediction. Gradient boosting and hybrid ensembles show the largest lift, indicating complementarity between bureau depth and alternative behavioral signals.

Approval rates for thin-file borrowers rise substantially under AI scoring, while default rates increase only marginally. Parity gaps narrow but do not fully disappear.

SHAP analyses highlight transaction regularity, utility timeliness, and behavioral consistency as major predictors. Explanation stability is weaker for alternative-only models under imbalance.

Table 1a. Comparative Performance of Traditional vs. AI-Driven Models (Part 1)

Model Type	Data Used	AUC-ROC	Thin-File Approval Lift
LR	Bureau only	0.68	+5%
LDA	Bureau only	0.65	+4%
RF	Bureau + Alternative	0.80	+22%
XGBoost	Bureau + Alternative	0.83	+28%
DNN	Alternative only	0.84	+30%
Hybrid Ensemble	Bureau + Alternative	0.85	+30%

Table 1b. Comparative Performance of Traditional vs. AI-Driven Models (Part 2)

Model Type	Default Rate Change	Fairness Gap Reduction	Explanation Stability
LR	Baseline	Minimal	High
LDA	Baseline	Minimal	High
RF	+2%	Moderate	Moderate
XGBoost	+2.5%	High	Moderate
DNN	+3%	Moderate	Low
Hybrid Ensemble	+2–3%	High	Moderate–High

5. DISCUSSION

The results indicate that alternative data improves risk differentiation where bureau depth is limited. Hybrid ensembles provide the strongest accuracy and subgroup calibration, suggesting that alternative signals are most valuable when used to complement bureau records.

Inclusion gains in the Indian context are practically important because UPI footprints can serve as a functional credit history. However, fairness improvements are partial, showing that models trained on historical outcomes still reflect inherited biases. This motivates continuous bias monitoring and calibrated decision thresholds.

Explainability tools enhance transparency for lenders and supervisors, but instability under class imbalance implies that operational use must include audits of explanation drift. In environments where credit scoring is treated as high-risk AI, compliance depends on documentation, bias controls, and contestability in addition to performance.

6. CONCLUSION

AI-driven credit scoring improves predictive accuracy and expands access for thin-file borrowers without a proportional rise in default risk. Hybrid models leveraging bureau and alternative data deliver the most robust outcomes. Yet fairness gaps persist and require active oversight through audits and governance. Explainability is necessary for trust and compliance, but stability must be validated under imbalance and drift typical of thin-file portfolios. Future work should measure long-term borrower welfare, explore privacy-preserving ML, and develop drift-aware fairness frameworks.

7. ACKNOWLEDGEMENTS

The author thanks mentors, peer reviewers, and colleagues for feedback on earlier drafts of this work.

References

1. Berg, T., Burg, V., Gombovic, A., and Puri, M., On the rise of FinTechs: Credit scoring using digital footprints, Review of Financial Studies, 33(7), 2020, 2845–2897.
2. Bjorkegren, D., and Grissen, D., Behavior revealed in mobile phone usage predicts credit repayment, World Bank Economic Review, 34(3), 2020, 618–634.
3. Bartlett, R., Morse, A., Stanton, R., and Wallace, N., Consumer-lending discrimination in the FinTech era, Journal of Financial Economics, 143(1), 2022, 30–56.
4. European Union, Artificial Intelligence Act, Official Journal of the European Union, 2024.
5. Oskarsdottir, M., Bravo, C., Sarraute, C., Vanthienen, J., and Baesens, B., The value of big data for credit scoring: Enhancing financial inclusion using mobile phone data and social network analytics, Applied Soft Computing, 91, 2020.
6. Alok, S., Ghosh, P., Kulkarni, N., and Puri, M., Financial inclusion and alternate credit scoring, Journal of Money, Credit and Banking, 2022.

7. Bussmann, N., Giudici, P., Marinelli, D., and Papenbrock, J., Explainable machine learning in credit risk management, Computational Economics, 57(1), 2021, 203–216.
8. Bertomeu-Sanchez, S., Bravo, C., and Maldonado, S., Interpretable machine learning for imbalanced credit scoring datasets, European Journal of Operational Research, 304(1), 2023, 147–162.