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AI-Powered Alternative Credit Scoring System for MSMEs and Individual Borrowers in India

Ghanshyam Chand Yadav[1*], Vatsalya Pandey[2], Kunal Mishra[3]

[1]Assistant Professor, Department of Commerce, Delhi College of Arts and Commerce, University of Delhi, New Delhi, India.
[2,3]Student, Department of Commerce, Delhi College of Arts and Commerce, University of Delhi, New Delhi, India.
*Corresponding

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Abstract

Access to credit continues to be an endemic problem in India, especially concerning micro, small and medium enterprises ("MSMEs") and the expanding segment of individual borrowers who function outside the traditional financial system. While gig workers, first-time borrowers and entrepreneurs operating in the informal sector are all actually creditworthy, they cannot be identified by lenders because their financial behaviour is not captured in the traditional credit bureau systems. To address this significant problem, this paper proposes an AI-based alternative credit scoring prototype for the Indian market, using digital financial indicators from Unified Payments Interface ("UPI"), Goods and Services Tax Network ("GSTN") compliance data, and operational business metrics. The AI system has been independently validated using two separate Gradient Boosting classifiers with Isotonic Calibration, trained on 5,000 synthetic records of individual borrowers and MSMEs in India. The individual models yielded Area Under Curve ("AUC") and Brier scores of 0.7650 and 0.1950, respectively, while MSME models yielded AUC and Brier scores of 0.7840 and 0.1840.

In addition to predictive accuracy, the system has integrated SHAP-proxy explainability for transparency at the borrower level, a three-tier probability of default decision-making framework, portfolio-level Expected Loss simulations using EL = PD x LGD x EAD, and a Disparate Impact Ratio governance dashboard. The portfolio level results indicated that the Expected Credit Loss was reduced by 51.7% over randomly selected accounts. All four design dimensions are aligned with the Reserve Bank of India FREE-AI framework, the Digital Lending Directions (2022) and the Digital Personal Data Protection Act (2023). The study addresses five documented research gaps in the Indian AI credit scoring literature and offers a replicable, regulatorily compliant blueprint for responsible AI deployment in India's lending ecosystem.

Keywords: *Artificial Intelligence (AI); Credit Scoring; MSMEs*

INTRODUCTION

Background

India's MSME sector is the backbone of the national economy, contributing approximately 30% of GDP, employing over 110 million people and accounting for close to 48% of total export earnings (MoMSME, 2022). Yet despite this outsized economic role, MSMEs face a chronic and well-documented credit gap estimated at Rs. 25 to 30 lakh crore (SIDBI and TransUnion CIBIL, 2022). The problem is not a lack of creditworthiness in any fundamental sense; it is rather a measurement problem. The financial activity of these enterprises — and of the gig workers, daily wage earners and informal-sector employees who support them — does not appear in the data points that conventional credit scoring systems are designed to read. As noted by the International Finance Corporation (IFC, 2017), the global MSME finance gap exceeds \$5 trillion, with emerging economies accounting for the largest share.

Traditional credit evaluation frameworks were built for borrowers with stable employment, formal credit histories and documented repayment records. They cannot capture the creditworthiness of a street vendor who processes dozens of UPI transactions daily, files GST returns consistently or pays utility bills on time. The World Bank (WB, 2017) has emphasised that alternative data can transform SME finance by enabling lenders to assess creditworthiness using non-traditional sources. Over the past decade, India has built one of the world's most sophisticated digital public infrastructure ecosystems — the India Stack. The Unified Payments Interface, GSTN, Aadhaar-based e-KYC, DigiLocker and the Account Aggregator framework together generate a real-time, consent-based stream of financial behavioural data that can serve as a far more representative proxy for creditworthiness than a static bureau score derived from historical formal credit. The Reserve Bank of India's Account Aggregator framework (RBI, 2021) provides the regulatory backbone for consent-based data sharing.

Problem Statement

The central problem this study addresses is the systematic exclusion of creditworthy borrowers from formal lending markets because the tools used to assess them were not designed for their circumstances. Specifically, existing models over-rely on credit bureau histories; static scorecards cannot process transaction-level behavioural signals; opaque algorithmic systems provide no borrower-level explanation for rejection, violating both borrower rights and regulatory expectations; and no published Indian prototype integrates fairness auditing with AI-based scoring. The consequences are felt disproportionately by MSMEs — which face prohibitive documentation requirements, seasonal cash flow variability and absence of audited accounts — and by individuals whose financial lives are increasingly digital but remain formally invisible. Experimental comparisons of classification algorithms for imbalanced credit scoring data (Brown and Mues, 2012) have shown that ensemble methods significantly outperform traditional approaches, yet such techniques remain underutilised in the Indian context.

Objectives of the Study

The study was designed to achieve five specific objectives:

- Design and develop an AI-based alternative credit scoring prototype using digital financial indicators from India's public infrastructure.
- Demonstrate the prototype's predictive performance through AUC, Brier score, precision and recall metrics.
- Implement SHAP-based explainability for transparent, borrower-level decision attribution.
- Assess fairness across income groups and GST compliance cohorts using Disparate Impact Ratios aligned with RBI FREE-AI norms.
- Simulate portfolio-level Expected Loss and demonstrate economic value relative to a random approval baseline.

Research Gaps Addressed

The gaps mentioned above all point to the five areas in which this research fills voids left by the current literature:

1. absence of dual-segment. There is limited coverage of loans made to both individuals and MSMEs from one architecture;
2. non-integration of India-specific digital data (UPI, GSTN) into published models;
3. no fairness governance dashboard within lending research in India;
4. no academic prototypes aligned with the Global AI Framework developed by Reserve Bank of India (RBI); and
5. no economic validation for AI credit scoring systems on a portfolio basis for borrowers in India.

Recent work by Frost *et al.* (2019) on BigTech and financial intermediation, as well as Gambacorta *et al.* (2019) on machine learning and non-traditional data, has highlighted the global potential of alternative credit scoring, but India-specific implementations remain scarce.

Significance of the Study

This prototype serves as a pilot pathway for both Banks, Non-Banking Financial Corporations (NBFCs) and Fintech lenders from which to provide compliant, inclusive, and economically efficient capital and credit to under-served borrowers. As such, the model demonstrates for regulators and policy makers how responsible deployment of artificial intelligence under the RBI FREE-AI Framework looks like in practice. Additionally, it provides researchers with a replicable, single-architecture solution for integrating prediction modelling, explainability, fairness auditing, and simulation of portfolios – a combination not previously documented in the Indian scholarly literature.

REVIEW OF LITERATURE

Evolution of Credit Scoring

In the 1950s and 1960s, the U.S. developed credit scoring, which used statistical analysis to calculate borrowers' risk of default based on demographic information and past payment behaviour. The FICO score was created in 1989 and became the international standard for credit assessment (Hand and Henley, 1997). However, these scoring systems suffered from three main problems: they did not include borrowers with no traditional credit history, they could not adapt as financial households changed, and they were inaccurate for borrowers whose financial stories were outside of the model's estimated distribution (Thomas *et al.*, 2002).

Machine Learning in Credit Risk

Machine learning has gained significant traction in academia to improve credit scoring since the mid-2000s. Khandani *et al.* (2010) showed that machine learning-based credit risk models had consistently outperformed logistic regression-based models. A comprehensive study by Lessmann *et al.* (2015) measuring the performance of classification algorithms used for credit scoring found that ensemble methods such as Gradient Boosting consistently delivered superior discrimination with well-calibrated probability outputs. Gradient Boosting models can model nonlinear interactions between features and resist overfitting through sequential modelling of trees (Deswal and Pal, 2025). Brown and Mues (2012) experimentally demonstrated that classification algorithms tailored for imbalanced datasets yield substantial improvements in credit scoring accuracy, particularly for rare default events.

Alternative Data in Credit Assessment

Non-Traditional data, or Alternative Data, consists of financial information that is not captured by the world's credit-bureau systems, has become a very large focus in the field of financial inclusion. Berg *et al.* (2020) showed that by using digital footprint data to create a credit score can greatly enhance the ability to assess a borrower's likelihood of defaulting on a loan above and beyond the traditional credit bureau score. Jagtiani and Lemieux (2019) focused on alternative data being a tool for fintech lenders to grant loans to thin-file borrowers while minimising the risk in the lenders' overall credit portfolios. Bazarbash (2019) highlighted the opportunities that both mobile transaction data and e-commerce purchase patterns present to lending institutions when evaluating borrowers' creditworthiness in emerging market settings. In the case of India, the UPI transaction history and GSTN compliance records that are available are under-utilised in credit assessments, even though both sets of data have proven to be useful indicators of financial stability and reliability and in establishing discipline in a business owner.

The World Bank (2017) has documented that alternative data can transform SME finance by enabling lenders to assess creditworthiness using non-traditional sources such as utility payments, rental history, and digital transaction trails. Similarly, the IFC (2017) highlighted that the global MSME finance gap represents both a challenge and an opportunity for fintech innovation. Frost *et al.* (2019) found that BigTech firms' entry into financial services, leveraging their vast datasets, could reshape credit markets, particularly in emerging economies. Gambacorta *et al.* (2019) demonstrated that machine learning models incorporating alternative data achieve superior predictive performance compared to traditional models, especially for thin-file borrowers.

Explainable AI in Lending

Lundberg and Lee (2017) introduced SHAP (SHapley Additive exPlanations). As a theoretically sound modelling technique that lets us break down how much each variable (or feature) contributes to the overall prediction made by a machine learning model. Being able to produce both global feature importances and local (borrower level) modelling explanations makes SHAP ideally suited for use in the lending space where there are both regulatory and ethical requirements for transparent decision-making. And so, the RBI FREE-AI framework requires all AI-based lending decisions that are made to include an understandable level (explanation) of how the model arrived at its conclusion; therefore, using SHAP to provide attributions based on the lending decision is necessary to comply with the guidelines that the RBI has set out.

Fairness, Bias and Regulatory Framework

According to Mehrabi *et al.* (2021), the primary sources of discrimination in lending algorithms are: (1) data-level bias; (2) proxy variable correlation with protected characteristics; and (3) practices for setting thresholds. The Disparate Impact Ratio (DIR), which compares acceptance rates across demographic or risk stratified groups, is the primary measurement of lending fairness in regulations worldwide. The RBI FREE AI framework's (RBI, 2025) five governing principles: Fairness; Robustness; Explainability; Ethics; and Effectiveness, are a comprehensive standard for responsible AI in the Indian financial sector. These five governing principles will be combined with the Digital Lending Directions (RBI, 2022) and the Digital Personal Data Act (GOI, 2023) to provide a complete governance framework.

SYSTEM DESIGN AND METHODOLOGY

Research Design

The research applied to this study used an applied methodology based around prototypes and systematic evaluations. Synthetic datasets provided a means to control the testing of the prototype model without the data governance complications of live borrower records while maintaining the statistical characteristics that exist in the real Indian borrower population, calibrated against the published data of NABARD (2023), SIDBI-CIBIL MSME Pulse (SIDBI and TransUnion CIBIL, 2022), and RBI Financial Inclusion Statistics-Tables 2022-2023 (RBI, 2023). The research comprised of five sequential phases: dataset

Table 1: Combined feature engineering - Individual and MSME borrower datasets.

Feature	Type	Credit Relevance	Individual	MSME
Monthly Income / Sales (Rs.)	Continuous	Revenue adequacy	Yes	Yes
Income / Sales Volatility (0-1)	Normalised	Earnings stability	Yes	Yes
UPI Transaction Count	Integer	Digital activity level	Yes	-
UPI Inflow/Outflow Ratio	Ratio	Cash flow balance	Yes	-
Expense-to-Income Ratio	Normalised	Financial stress indicator	Yes	-
Savings Rate (0-1)	Normalised	Financial buffer	Yes	-
EMI Bounce Count (6 months)	Integer	Repayment reliability	Yes	-
Utility Bill Payment Score	Normalised	Payment discipline proxy	Yes	-
GST Filing Delay (Days)	Integer	Tax compliance behaviour	-	Yes
GST Growth Rate	Ratio	Revenue trajectory	-	Yes
Working Capital Cycle (Days)	Integer	Liquidity management	-	Yes
Vendor Payment Delay (Days)	Integer	Supplier payment discipline	-	Yes
Average Bank Balance (Rs.)	Continuous	Liquidity buffer	-	Yes
Digital Sales Ratio (0-1)	Normalised	Formalisation level	-	Yes
Business Age (Years)	Integer	Operational maturity	-	Yes

Table 2: Model performance metrics — Individual and MSME Gradient Boosting classifiers.

Metric	Individual Model	MSME Model	LR Baseline (Individual)	LR Baseline (MSME)
AUC Score	0.765	0.784	0.769	0.784
Brier Score	0.195	0.184	—	—
Precision	0.626	0.614	—	—
Recall	0.709	0.729	—	—
True Negatives (TN)	389	—	—	—
True Positives (TP)	304	—	—	—
False Positives (FP)	182	—	—	—
False Negatives (FN)	125	—	—	—

construction, model development and calibration, integration of explainability, evaluation of fairness and simulation of portfolios.

Dataset Construction

Two synthetic datasets of 5000 records each were developed for individual and MSME borrowers, respectively. See Table 1 for feature engineering for each of these populations.

Model Development and Calibration

To develop our Gradient Boosting Classifier models for each borrower segment, we used the scikit-learn toolkit, comparing performance with Logistic Regression baselines. We performed an 80/20 stratified train-test split to conduct out-of-sample validation. AUCs were specifically targeted between 0.76 and 0.79 to realistically represent model performance when considering classes that are overlapping and synthetic in nature, rather than over-inflated >0.95 AUCs due to having perfectly separable datasets. Isotonic Regression was used to calibrate probability outputs, relating the empirical rates of default to the probability of default derived from our classifiers. Brier scores of< 0.20 confirmed the quality of calibration for both models. A three-tiered probability of default (PD) approval hierarchy was used to determine whether to approve, conditionally review or reject an application based on an applicant's PD, where applicants with a PD < 20% would be approved, applicants with a PD value between 20% and 40% would be conditionally reviewed and applicants with a PD > 40% would be rejected. The Risk Score was calculated as (1-PD) x 100.

Explainability and Fairness Architecture

SHAP-proxy feature attribution was provided on a borrower level via waterfall charts and panel-style plain-language explanations to present the numerical attribution in a format that could be easily understood. Fairness was evaluated using the Disparate Impact Ratio (DIR) with respect to income levels at an individual model level (i.e., individual models per income level) and Government Small business Trust (GST) compliance groups for the MSME model. The DIR was reviewed with respect to the average default rates per group to determine if differences could be justified by risk or if they were a result of systemic discrimination. The expected portfolio loss was also estimated using EL = PD x LGD x EAD, where LGD was conservatively estimated at 45% and compared.

RESULTS — SYSTEM WALKTHROUGH AND OUTPUTS

Global Model Performance

Both models underwent testing using separate (held-out) test data sets that contained 1,000 records each, with the results of the entire evaluation process summarised in Table 2.

The AUC score for the single model is equal to 0.765, while the Logistic regression model is 0.769. The close AUC between the two models reflects the intentional development of overlapping synthetic classes, which forces the models to work more diligently to obtain performance metrics congruent with actual credit data. The Brier score of 0.195 for both models indicates that their predictive probabilities are appropriately calibrated, allowing for accurate computation of expected losses. While the MSME model's AUC score (0.784) outperformed the single model slightly, its Brier score was also superior (0.184), again confirming that this model's predictive probabilities were appropriately calibrated.

The analysis of the feature importance scores (Table 3) shows that the most significant predictor of MSMEs is Sales Volatility (0.246), followed by GST Filing Delay (0.190) and Vendor Payment Delay (0.145), which reinforces that tax compliance and payment discipline are the two most critical credit risk indicators when lending to Indian SMBs.

Decision Engine — Three Borrower Scenarios

Three representative loan applicant profiles were tested across a full spectrum of credit risk to evaluate both the

Table 3: Top feature importance rankings — MSME and individual models.

Feature (MSME Model)	Importance Score	Feature (Individual Model)	Importance Score
Sales Volatility	0.246	Utility Bill Payment Score	0.246
GST Filing Delay	0.190	Savings Rate	0.203
Vendor Payment Delay	0.145	Expense-to-Income Ratio	0.159
GST Growth Rate	0.091	UPI Inflow/Outflow Ratio	0.147
Business Age	0.086	Income Volatility	0.091
Working Capital Cycle	0.065	EMI Bounce Count	0.087

Box 1: Profile A.

Borrower Profile	LOAN APPROVED
Safe Borrower (Low Risk) Monthly Income: Rs. 75,000 | Income Volatility: 0.15 UPI Count: 60 | UPI Inflow/Outflow: 1.40 Expense-to-Income: 0.38 | Savings Rate: 0.32 EMI Bounces: 0 | Utility Bill Score: 0.71 **Risk Score: 86/100** Default Probability: **PD: 13.5%** Model Confidence: **82% Confidence**	**Key Decision Factors:** ▪ No EMI bounces on record — perfect repayment discipline ▪ Utility Bill Score 0.71 vs. population average 0.23 (3x above average) ▪ Strong savings rate (0.32 vs. population average 0.29) ▪ Active digital payment usage: 60 UPI transactions ▪ Income well above population average (Rs. 75,000 vs. Rs. 58,338)

discriminative capability of the decision engine as well as to provide explanatory outputs.

Profile A: Safe Borrower — Loan Approved

The Profile A is presented in Box 1. The analysis of SHAP (SHapley Additive exPlanations) showed that all eight features negatively influenced the probability of default (risk-reducing). The Utility Bill Payment Score (SHAP value -0.862) was by far the dominant protection factor, followed by the Expense-to-Income Ratio (-0.210) and Income Volatility (-0.140). The profile reflects a borrower who would qualify for either traditional or alternative scoring systems, confirming that the AI model does not over-restrict approvals to obviously creditworthy applicants.

Profile B: Moderate Borrower — Loan Rejected (Borderline Zone)

The Profile B is presented in Box 2. The SHAP analysis indicated the Savings Rate (+0.248) was the dominant amplifier of risk, with Expense-to-Income Ratio (+0.125) and UPI Inflow/Outflow Ratio (+0.104) being additional contributors. Importantly, the Utility Bill Payment Score (-0.574) represented the only risk-free element, providing only one point of a successful positive signal; however strong, it is insufficient to overcome a composite adverse risk profile.

Box 2: Profile B.

Borrower Profile	LOAN REJECTED
Moderate Borrower (Medium Risk) Monthly Income: Rs. 42,000 | Income Volatility: 0.42 UPI Count: 28 | UPI Inflow/Outflow: 1.05 Expense-to-Income: 0.62 | Savings Rate: 0.14 EMI Bounces: 1 | Utility Bill Score: 0.55 **Risk Score: 45/100** Default Probability: **PD: 55.0%** Model Confidence: **97% Confidence**	**Key Decision Factors:** ▪ Savings Rate 0.14 is primary risk amplifier (SHAP +0.248) ▪ Expense-to-Income Ratio 0.62 vs. population average 0.53 (above average) ▪ Income below average: Rs. 42,000 vs. Rs. 58,338 population mean ▪ Insufficient UPI activity: 28 vs. population average 45.21 ▪ One EMI bounce recorded - repayment reliability concern

Box 3: Profile C.

Borrower Profile	LOAN REJECTED
High-Risk Borrower Monthly Income: Rs. 28,000 | Income Volatility: 0.78 UPI Count: 8 | UPI Inflow/Outflow: 0.72 Expense-to-Income: 0.88 | Savings Rate: 0.04 EMI Bounces: 4 | Utility Bill Score: 0.22 **Risk Score: 14/100** Default Probability: **PD: 86.4%** Model Confidence: **82% Confidence**	**Key Decision Factors:** ▪ Expense-to-Income Ratio 0.88 is dominant risk amplifier (SHAP +0.489) ▪ Savings Rate 0.04 - critically below population average 0.29 (SHAP +0.411) ▪ 4 EMI bounces in 6 months - severe repayment distress signal ▪ Income volatility 0.78 vs. population average 0.37 - highly unstable earnings ▪ UPI outflows exceed inflows (ratio 0.72) - negative net cash position ▪ Utility Bill Score 0.22 below population average 0.23 - poor payment history

Thus, the preserved explanatory trail allowed the borrower to identify ways to improve their financial situation, primarily via savings increases and decreasing discretionary expenses.

Profile C: Risky Borrower — Loan Rejected (High Risk)

The Profile C is presented in Box 3. Of the seven modelled features, all reflected positive (risk-increasing) SHAP values. Expense-to-Income Ratio (+0.489) and Savings Rate (+0.411) were the most significant amplifying features of risk, with Income Volatility (+0.279), EMI Bounce Count (+0.272), and UPI Inflow/Outflow Ratio (+0.252) contributing significantly. In fact, there is not one metric that could be considered positive versus the average for the population: Monthly Income (Rs. 28,000 vs. Rs. 58,338), Income Volatility (0.78 vs. 0.37), and EMI Bounces (4 vs. 0.84). Thus, there is clear evidence of the ability of the model to identify borrowers in severe financial distress.

Portfolio Simulation Results

Portfolio-level Expected Loss was examined at a Probability of Default approval level of 35% and Loss Given Default value of 45% for both borrower categories. The results of the

Table 4: Portfolio simulation results - Expected loss compared to random approval baseline. (*Source*: Authors' own construction).

Metric	Individual Portfolio	MSME Portfolio
Approval Threshold (PD)	35%	35%
Loss Given Default (LGD)	45%	45%
Approved Loans (Count)	2,142	2,515
Total Portfolio Exposure	Rs. 623.3 million	Rs. 1,720.7 million
Expected Loss (EL)	Rs. 57.55 million	Rs. 158.73 million
AI-Based EL Rate	9.23%	9.22%
Random Baseline EL Rate	19.12%	17.85%
Expected Loss Reduction vs. Baseline	51.7%	48.3%

Table 5: Individual model fairness assessment by income group (DIR acceptable range: 0.80-1.25).

Income Group	Approval Rate	Default Rate	DIR Value	Fairness Status
Low Income (< Rs. 25,000)	41.9%	40.9%	1.000 (Reference)	PASS
Lower-Mid (Rs. 25,000 - 50,000)	41.0%	44.8%	0.979	PASS
Upper-Mid (Rs. 50,000 - 100,000)	43.0%	42.3%	1.025	PASS
High Income (> Rs. 100,000)	49.3%	40.5%	1.175	PASS

analysis for both segments are displayed in Table 4 in relation to the random approval baseline, allowing for the economic value of Artificial Intelligence based credit selection to be calculated.

The independent model approved 2142 loans with a total exposure value of Rs. 623.3 million (approx. US $ 12.8 million), resulting in an Expected Loss of Rs. 57.55 million (approx. US $ 1.16 million) and an Expected Loss Rate of 9.23%. In comparison to a random approval baseline that delivered an Expected Loss Rate of 19.12% for the same loans, the AI strategy delivered to lenders a lower Expected Loss Rate of 51.7%. The MSME model approved 2515 loans with total exposure of Rs. 1,720.7 million (approx. US $ 34.4 million) and an Expected Loss of Rs. 158.73 million (approx. US $ 3.2 million) at 9.22% ELR, compared to its random approval baseline of 17.85%, reflecting a 48.3% reduction. The similar Expected Loss Rates of each model (approximately 9.22%) demonstrate consistent risk calibration and will therefore benefit lenders who are managing multi-segment portfolios.

Fairness and Governance Dashboard Results

The Disparate Impact Ratio was calculated between income categories for the independent model and between GST compliance categories for the MSME model. Table 5 reveals the fairness of the independent model results.

DIRs produced for the four income categories were all within the acceptable RBI FREE-AI range of 0.80-1.25, demonstrating a PASS. The higher approval rate of the upper-income borrowers at 49.3% corresponds with their lower default rate of 40.5%, confirming that the relative differential is risk-based and not discriminatory. Table 6 reveals similar results for all four income categories.

As the MSME model demonstrated a need for the REVIEW NEEDED assessment process because of the Extremely Low and Low Decile DIR values found on both the moderate (0.260) and poor (0.054) compliance classes within the MSME Model population. However, this outcome is contextually appropriate and analytically important: the Moderate and Poor groups carry default rates of 50.1% and 71.4%, respectively, meaning that their dramatically lower approval rates are entirely risk-justified. This case demonstrates a crucial methodological distinction: low DIR values arising from genuine risk differentiation must be distinguished from structural discrimination, which requires reading DIR values alongside group-level default rates — a feature explicitly built into this governance dashboard.

ANALYSIS AND DISCUSSION

Predictive Performance and Calibration

The AUC scores of 0.765 and 0.784 for the individual and MSME models, respectively, represent genuinely meaningful discriminatory performance. Their interpretation requires context: these figures were deliberately produced on overlapping synthetic classes that prevent either model from achieving easy separation, reflecting the real-world conditions under which credit scoring models must operate. The two Gradient Boosting Models had almost identical AUC values as the logistic regression baseline models at a sample size very close to 10,000 — this indicates that the construction of these individual datasets was intentional — all models are doing significant amounts of work producing valid classifications for hard classification problems. MSMEs' AUC (0.784) and Brier score (0.184) suggest that operational features will produce marginally better risk signals than the single behavioural features since GST filing habit and how a company pays its vendors are commitments that many companies can provide, and not a statistical proxy.

The calibration results are noteworthy. Since Brier scores less than .20 indicate that model predicted probability outputs are closely aligned with empirical default rates, this serves not only as an intellectual exercise but is fundamental for providing valid expected loss simulation outputs. If PD values are incorrectly calibrated, projected portfolio EL's are not representative of actual EL experience. The probability calibration graphs show model-predicted probability outputs across the full probability continuum from 0-1 closely adhere to ideal calibration lines, confirming that Isotonic Regression corrected model-predicted probability outputs from these classifiers.

Implications for Financial Inclusion

Fairness results have significant implications for the financial inclusion strategy of India. In terms of the individual model, the low-income borrower's approval rate (41.9%) was only 7.4 percentage points lower than the high-income borrower's approval rate (49.3%) – representing a relatively small gap that indicates true risk differentiation rather than structural

Table 6: MSME model fairness assessment by GST compliance group.

GST Compliance Group	Approval Rate	Default Rate	DIR Value	Assessment
Excellent (0-15 days delay)	100%	7.5%	1.000 (Reference)	PASS
Good (16-45 days delay)	91.5%	20.8%	0.915	PASS
Moderate (46-90 days delay)	26.0%	50.1%	0.260	REVIEW
Poor (> 90 days delay)	5.4%	71.4%	0.054	REVIEW

exclusion. All four income groups' DIR values were contained within the acceptable RBI FREE-AI ranges; therefore, a properly constructed alternative credit scoring will pursue inclusion while also ensuring sound risk management practices. The approval rate of 41.9% within the lowest income segment — exactly the group which has been systematically excluded from access to credit via traditional bureau-based systems — demonstrates meaningful financial inclusion.

For MSMEs, the facts that GST filing behaviour and sales volatility are the two best predictors of credit risk present a practically actionable finding; therefore, compliance with GST's filing and stable revenue are forms of "reputational collateral" which allow businesses to demonstrate creditworthiness without having to provide audited financial statements or tangible assets. Supporting this finding is the existing policy goal of integration of GSTN data into the lending process - a goal that the Account Aggregator framework (RBI, 2021) has been developed to support.

Explainability and Regulatory Compliance

The RBI endorsed the “FREE-AI” framework of the SHAP attribution system, which meets the explainability requirement both globally and locally by providing lenders and auditors visibility into the data signals that generated the overall model through global feature importance rankings. In turn, borrowers receive the local SHAP waterfall plot presented as panels in plain language, which help them to understand why their application may have been denied, as well as by how much each feature in their financial profile has contributed to this outcome. By delivering such transparency, borrowers are empowered to appeal the decision, and also obtain a fair and equitable recourse; therefore, they can develop a plan of action on how they can improve their credit profile (i.e., by increasing their savings or decreasing discretionary spending).

The alignment with the regulations includes a thorough review of various components to ensure compliance. Indices of fairness in the design of the system are assessed through the Data Integrity Rating-based governance dashboard (DIR), and contextualized default rates. Indices of robustness have been evaluated by way of out-of-sample validation and the calibre of probabilistic outputs, and the three-tier decision threshold establishes a conditional review zone for borderline decisions. Indices of Explanation and Ethics (as they relate to the assessability of the system) have been established through the use of SHAP attribution and decision panels according to plain language. In addition, an explicit Fairness Audit examines instances of proxy discrimination at the design level and the evaluation of the system's output in terms of assessability, which is supported via portfolio simulation analyses which demonstrate the contingent economic value of the loans written through the system.

Portfolio Economics

The portfolio simulation results demonstrate a compelling financial justification for alternative scoring mechanisms. The individual model has shown to produce a 51.7% reduction in Expected Loss when compared to the Random Approval baseline, while the MSME model has shown to produce a 48.3% reduction. These results indicate that using predictive evaluation significantly decreases the lender's probability-weighted cost of default. Simply put, if an individual lender had a portfolio of Rs. 623.3 million, they would expect to incur a loss of Rs. 57.55 million using this system versus Rs. 119.1 million when using the Random Approval method. Also, EL rates are nearly identical for both scoring models (approximately 9.22%), indicating that the system provides consistent risk calibration across borrower segments, which is especially essential for any lending organization that lends to multiple segments.

Limitations

There are limitations that must be acknowledged. This prototype was trained using synthetic data, and the performance might be different on verified live data, although the distributions used for this analysis were calibrated against published data (NABARD, 2023; RBI, 2023). In the industry, an LGD of 45% is a reasonable assumption; however, it is anticipated that individual lenders may have a slightly different recovery rate based on specific products being offered. This system was designed without the ability to adapt to the impact of changing borrower behaviour over time, the impact of seasonal income on agriculture and festivals, as well as the entire demographic diversity of borrowers in India. Although the AUC value of .80 was used in the analysis, this value needs to be demonstrated as a robust value on real-world data.

CONCLUSION AND FUTURE SCOPE

Summary of Contributions

This research presents five key contributions to the existing literature about credit scoring with Artificial Intelligence (AI) technologies for India.

The first contribution is a published prototype in a single AI architecture developed for both Individual borrowers and MSMEs, addressing a known gap in AI credit models that exist specifically for MSMEs.

The second contribution of this study was the creation of a working predictive model that integrated India specific digital asset data, namely UPI transaction metrics and GSTN compliance, with an analysis of their impact on credit risk as indicators.

The implementation of the DIR-based fairness governance dashboard with contextualisation of default rate provides a more analytically sound illustration of fairness than a simple comparison of approval rates.

All design decisions are aligned with the RBI FREE-AI framework, Digital Lending Directions and DPDP Act, thereby providing the foundational requirements of a verifiable compliance framework.

Finally, the economic value of AI-based credit selection through portfolio simulation demonstrates the case for AI-based technologies in the business and provides a quantified business case to accompany the technical PDF prototype.

Future Research Directions

The immediate priorities for future research include testing the system against actual borrower data through the Account Aggregator framework within appropriate regulatory/ethical protocols. Time-series modelling to account for seasonality of cash flow dynamics will significantly improve the predictive power of models developed for seasonally dependent MSMEs throughout India, particularly for farmers and festival-dependent MSMEs. By expanding the assessment for discrimination to include gender, region and job type as categories under which to examine discrimination, the audit of Fairness will be a far more thorough assessment of discrimination. The addition of a stress test module that simulates Expected Loss on a portfolio in the event of macroeconomic shocks, such as rising interest rates, declining demand and increasing commodity prices, will add further value to this system as a risk management solution. Additional design modifications for "Buy Now Pay Later" (BNPL) products and micro loans, both of which have seen rapid growth in Indian digital lending, represent key opportunities for the applied extension of this research.

Final Reflection

This prototype illustrates how an AI-based alternative credit scoring framework can meet the objectives of lenders, borrowers, and regulators by creating an integrated construction that treats the three objectives of accuracy, transparency, fairness, and regulatory compliance as properties that can be accomplished together, rather than as trade-offs. The reduction of Expected Loss by 51.7%, combined with an approval rating of 41.9% for the lowest-income borrowers, demonstrates that alternative data, when used to create an accurate and equitable model, can provide increased access to credit and improved risk management. This combination is critical for creating access to formal credit for the 110 million Indians who do not currently have access to the formal lending system. This study contributes to the emerging literature on AI-driven financial inclusion in India.

ORCID iD

Ghanshyam Chand Yadav : 0009-0006-3695-4182

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

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