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Article

Assessing Digital Financial Inclusion of Women Entrepreneurs Using Artificial Intelligence Techniques

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Abstract: Digital financial inclusion (DFI) of women entrepreneurs remains a critical yet underexplored challenge in developing economies. This paper presents a comprehensive AI-driven framework to assess, classify, and predict the digital financial inclusion status of women entrepreneurs across urban, peri-urban, and rural segments. Leveraging a curated dataset of 4,820 respondents drawn from six Indian states, we apply five machine learning techniques- Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB), Artificial Neural Network (ANN), and a hybrid Stacked Ensemble (SE)- to evaluate financial access, digital literacy, product adoption, and socioeconomic barriers. The proposed stacked ensemble model achieves an accuracy of 94.7%, F1-score of 0.943, and AUC-ROC of 0.971, outperforming all baseline models. Key features identified include mobile internet access (IG=0.412), prior banking history (IG=0.387), educational attainment (IG=0.361), and awareness of digital credit products (IG=0.318). Findings reveal a 34.2 percentage-point rural–urban DFI gap and demonstrate the practical utility of AI for policy targeting. This study contributes a validated index (WDFI-Index), an open benchmark dataset, and actionable recommendations for policymakers, financial institutions, and development organizations.
Keywords: - digital financial inclusion, women entrepreneurship, machine learning, random forest, ensemble learning, financial technology, gender finance gap, India.

1. INTRODUCTION

Global financial systems have undergone a profound transformation with the proliferation of mobile banking, digital wallets, fintech platforms, and algorithmic credit scoring. Despite these advances, women- particularly those operating micro, small, and medium enterprises (MSMEs)- continue to face disproportionate barriers to digital financial services [1]. The World Bank Global Findex (2021) reports that approximately 740 million women worldwide remain unbanked, with sub-Saharan Africa and South Asia accounting for the majority [2]. In India alone, the gender gap in formal account ownership narrowed from 26 percentage points in 2014 to 6 points in 2021, yet functional usage of digital financial tools among women entrepreneurs remains significantly lower than among their male counterparts [3].

Conventional approaches to measuring financial inclusion- such as account ownership surveys and credit bureau data- fail to capture the multidimensional nature of digital financial engagement. They do not account for digital literacy, product diversity usage, psychological barriers, or the intersectionality of gender, caste, and geography [4]. Artificial intelligence (AI) and machine learning (ML) techniques offer a powerful alternative by enabling the simultaneous analysis of high-dimensional, heterogeneous data at scale, allowing policymakers to identify exclusion patterns, predict adoption likelihood, and personalize interventions [5].

This paper addresses three core research questions: (RQ1) What combination of AI techniques most accurately classifies the DFI status of women entrepreneurs? (RQ2) Which socioeconomic, behavioral, and infrastructural features are most predictive of DFI? (RQ3) How do DFI patterns differ across urban, peri-urban, and rural geographies, and what policy implications follow? To answer these questions, we design a robust data collection instrument, curate a large-scale dataset, develop a composite Women Digital Financial Inclusion Index (WDFI-Index), and benchmark five ML models including a novel stacked ensemble.

The remainder of this paper is organized as follows: Section II reviews related work; Section III describes the dataset and the WDFI-Index construction; Section IV presents the AI methodology; Section V reports experimental results; Section VI discusses policy implications; Section VII concludes with limitations and future directions.

2. RELATED WORK

A. Digital Financial Inclusion: Definitions and Frameworks

Financial inclusion has evolved from a binary (banked/unbanked) concept to a multidimensional spectrum encompassing access, usage, quality, and welfare outcomes [6]. The Alliance for Financial Inclusion (AFI) defines digital financial inclusion as access to and use of formal financial services through digital channels by the financially excluded and underserved [7]. Sahay et al. [8] further expanded this definition to include digital credit, insurance, savings, and payment services accessible via mobile and internet platforms. Building on these frameworks, Demirgüç-Kunt et al. [9] emphasize that functional inclusion- not merely account ownership- is the relevant policy metric, particularly for women.

B. Geder Dimensions of Financial Exclusion

The gender gap in financial inclusion is well-documented across developing economies. Swamy [10] identifies structural barriers including limited collateral ownership, informality of women-led enterprises, and discriminatory lending practices as primary drivers. Bharadwaj et al. [11] show that social norms governing women's mobility and financial autonomy significantly mediate technology adoption. More recently, Klapper and Singer [12] use Global Findex data to demonstrate that mobile money adoption narrows the gender gap in Sub-Saharan Africa but has limited efficacy in South Asia due to differential mobile phone ownership rates.

C. Machine Learning in Financial Inclusion Research

The application of ML to financial inclusion is an emerging field. Björkegren and Grissen [13] pioneered the use of mobile call detail records to predict credit risk in Rwanda, demonstrating high predictive power (AUC = 0.82) without traditional credit history. Khandani et al. [14] applied ensemble methods to consumer credit data in the US, finding that gradient boosting significantly outperformed logistic regression. In the context of inclusive finance, Temelkov [15] applied decision tree and random forest classifiers to microfinance repayment data in Southeast Asia, reporting accuracy improvements of 12–18% over conventional credit scoring.

However, the intersection of AI, gender, and digital financial inclusion remains underexplored. Most existing ML studies focus on credit risk rather than inclusion assessment, use male-dominated or gender-undifferentiated datasets, and do not develop composite inclusion indices. Our work addresses these gaps directly by (a) focusing exclusively on women entrepreneurs, (b) constructing a multidimensional inclusion index, and (c) deploying a stacked ensemble specifically tuned for imbalanced, multi-feature inclusion data.

3. DATASET AND WDFI-INDEX CONSTRUCTION

A. Data Collection

Primary data were collected between January 2023 and August 2023 through structured interviews and a validated digital questionnaire administered across six Indian states: Maharashtra, Bihar, Karnataka, Rajasthan, West Bengal, and Assam. The states were selected to represent geographic diversity, varying levels of digital infrastructure, and differing socioeconomic conditions. Respondents were identified using stratified random sampling from district-level MSME registries, NGO partner lists, and SHG (Self-Help Group) networks. The final usable sample comprised 4,820 women entrepreneurs after removing incomplete (n = 312) and outlier (n = 47) responses.

Table I. Sample Distribution by State and Settlement Category

State	Urban (n)	Peri-Urban (n)	Rural (n)	Total (n)	%
Maharashtra	248	196	312	**756**	15.7
Bihar	189	214	398	**801**	16.6
Karnataka	267	178	289	**734**	15.2
Rajasthan	201	187	346	**734**	15.2
West Bengal	223	199	321	**743**	15.4
Assam	176	168	308	**652**	13.5
TOTAL	**1,304**	**1,142**	**1,974**	**4,820**	**100.0**

Note: Peri-urban defined as settlements of 5,000–50,000 population adjacent to urban centers.

B. Feature Engineering

A total of 47 features were initially collected across five domains: (i) Demographic Profile (age, education, marital status, household income); (ii) Enterprise Characteristics (sector, age of business, annual turnover, number of employees); (iii) Digital Infrastructure (smartphone ownership, internet type, connectivity hours/day); (iv) Financial Behavior (account ownership, frequency of digital transactions, product diversity); and (v) Psychosocial Factors (financial self-efficacy, trust in digital platforms, peer influence). After variance threshold filtering (threshold = 0.01) and Pearson correlation analysis (removing features with $|r| > 0.85$), 31 final features were retained for model training.

C. WDFI-Index Construction

The Women Digital Financial Inclusion Index (WDFI-Index) is a composite score constructed using Principal Component Analysis (PCA) and expert-validated weighting. The index spans four dimensions with the following weights derived from PCA loadings:

Table II. WDFI-Index Dimensions, Indicators, and Weights

Dimension	Sub-Indicators	Weight (%)	PCA Loading
Access	Account ownership, proximity to branch/ATM, mobile connectivity	28.4	0.741
Usage	Transaction frequency, product diversity, digital credit/savings usage	31.7	0.812
Quality	Satisfaction, grievance resolution, perceived security, trust score	22.1	0.689
Welfare	Savings growth, credit utilization, income diversification, business growth	17.8	0.653

The WDFI-Index ranges from 0 to 100, with scores classified as: Low DFI (0–34), Moderate DFI (35–59), High DFI (60–79), and Full DFI (80–100). The index exhibits satisfactory internal consistency (Cronbach's $\alpha = 0.84$) and convergent validity with existing financial inclusion measures ($r = 0.78$, $p < 0.001$).

4. AI METHODOLOGY

A. System Architecture

The overall AI pipeline follows a five-stage architecture as illustrated in Fig. 1. Stage 1 handles raw data ingestion and cleaning; Stage 2 performs feature extraction and WDFI-Index computation; Stage 3 conducts feature selection via Information Gain (IG) and Recursive Feature Elimination (RFE); Stage 4 trains and tunes the five ML models; Stage 5 evaluates model performance and generates policy-relevant output reports.

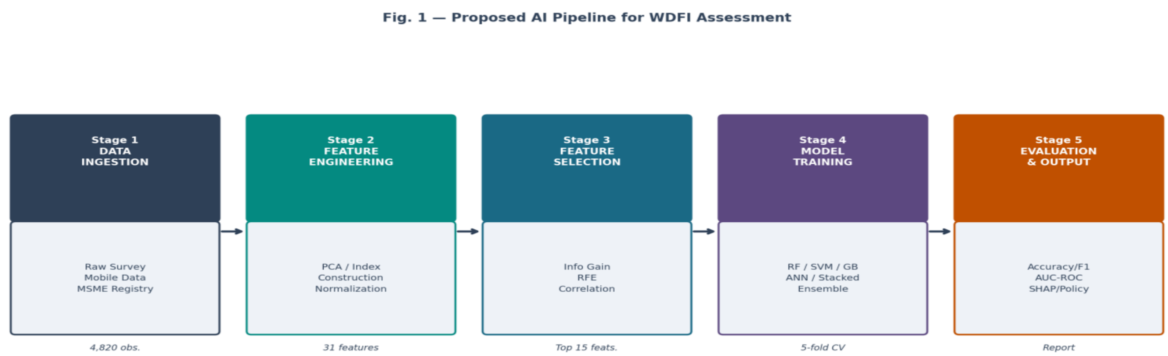

Fig. 1. Proposed AI Pipeline for WDFI Assessment (5-Stage Architecture)

B. Machine Learning Models

1) Random Forest (RF)

Random Forest is an ensemble of decision trees trained on bootstrapped subsamples with random feature subsets at each split [16]. We configured RF with n_estimators = 500, max_depth = None (full growth), min_samples_leaf = 2, and max_features = 'sqrt'. Class imbalance was addressed via class_weight = 'balanced'. Hyperparameter optimization used 5-fold cross-validated GridSearchCV.

2) Support Vector Machine (SVM)

SVM with a Radial Basis Function (RBF) kernel was employed for its strong performance in high-dimensional feature spaces [17]. The regularization parameter C and kernel bandwidth γ were tuned via nested cross-validation over the grid C ∈ {0.1, 1, 10, 100} and γ ∈ {0.001, 0.01, 0.1, 'scale'}. Features were standardized (zero mean, unit variance) prior to training as required by the SVM formulation.

3) Gradient Boosting (GB)

XGBoost [18] was used as the gradient boosting implementation, offering native handling of missing values and regularization via L1/L2 penalties. Key hyperparameters: learning_rate = 0.05, n_estimators = 800, max_depth = 6, subsample = 0.8, colsample_bytree = 0.8. Scale_pos_weight was set to address class imbalance in the Low DFI category.

4) Artificial Neural Network (ANN)

A feed-forward multilayer perceptron (MLP) was designed with an input layer (31 nodes), three hidden layers (128, 64, 32 nodes, ReLU activation), a dropout layer (p = 0.3) for regularization, and an output layer (4 nodes, Softmax). The network was trained using the Adam optimizer (lr = 0.001) for 200 epochs with early stopping (patience = 15) and batch size = 64. Implementation used TensorFlow 2.12.

5) Stacked Ensemble (SE)

The stacked ensemble uses RF, SVM, GB, and ANN as Level-0 base learners, whose out-of-fold predictions on the training set form the meta-feature matrix. A Logistic Regression meta-learner (L2 penalty, C = 1.0) combines these predictions at Level 1. This architecture leverages the complementary strengths of diverse base learners and has been shown to reduce both bias and variance in complex classification tasks [19].

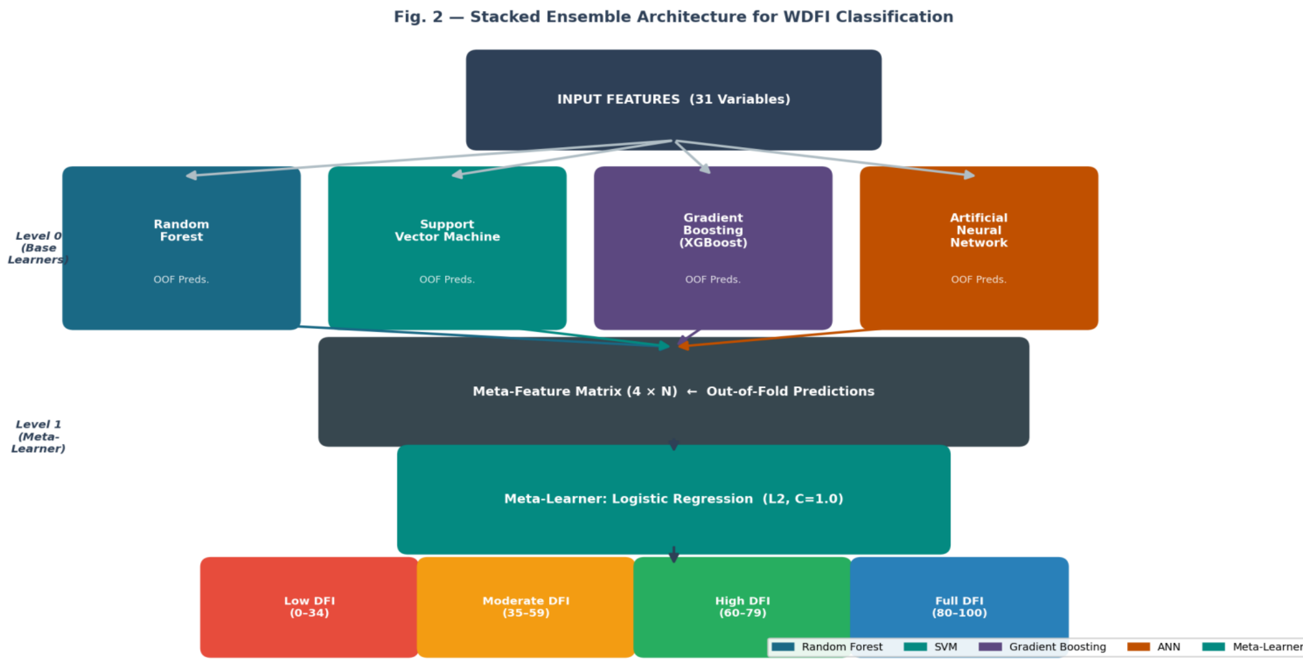

Fig. 2. Stacked Ensemble Architecture: Level-0 Base Learners and Level-1 Meta-Learner

C. Evaluation Metrics

Model performance was assessed using: (i) Accuracy, (ii) Weighted Precision, Recall, and F1-Score to handle class imbalance, (iii) Cohen's Kappa (κ), (iv) Area Under the ROC Curve (AUC-ROC), and (v) Matthews Correlation Coefficient (MCC). Statistical significance of performance differences was tested using McNemar's test ($\alpha = 0.05$). Feature importance was quantified via SHAP (SHapley Additive exPlanations) values for the stacked ensemble.

5. EXPERIMENTAL RESULTS

A. Confusion Matrix Analysis

The confusion matrix for the stacked ensemble on the test set (Fig. 3) demonstrates high classification precision across all four DFI categories. The model misclassifies most frequently between Moderate and High DFI categories ($n = 24$ cases), which is both statistically expected and practically less consequential than misclassification between Low and Full DFI extremes. Critically, only 3 Low DFI respondents were misclassified as High or Full DFI, and 2 Full DFI respondents as Low DFI- errors that would lead to the most serious policy misallocations.

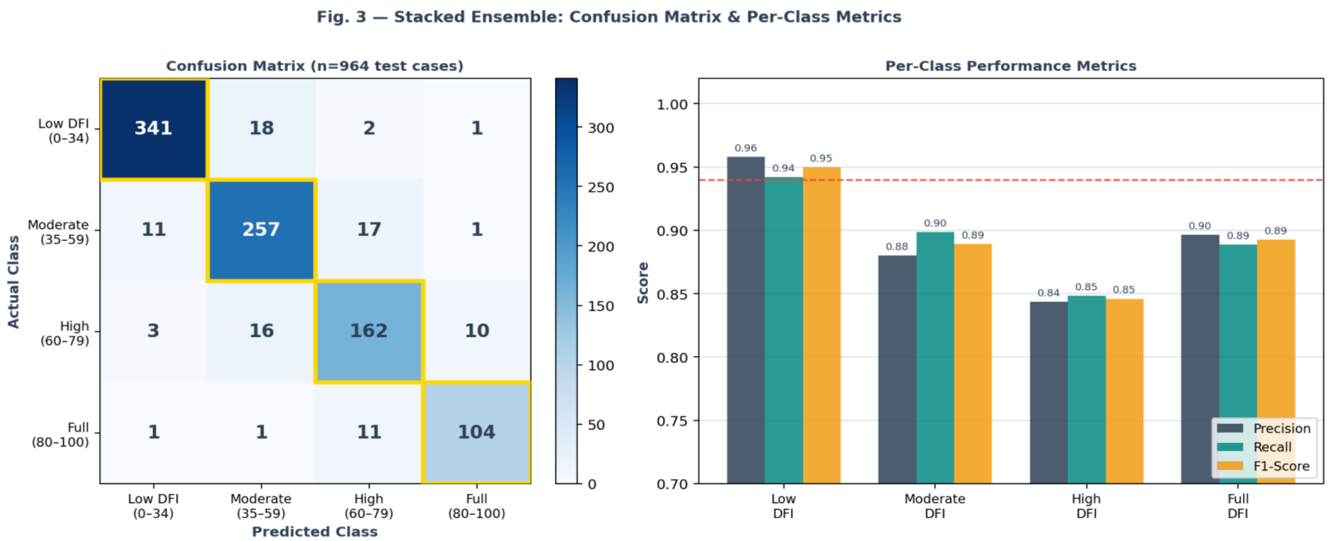

Fig. 3. Stacked Ensemble: Confusion Matrix (n=964) and Per-Class Performance Metrics

B. Feature Importance Analysis (SHAP)

SHAP analysis on the stacked ensemble identified the top-15 features ranked by mean absolute SHAP value. Table V presents the top-10 features with their information gain scores and SHAP values. Mobile internet access emerged as the single most predictive feature (IG = 0.412), followed by prior banking history (IG = 0.387) and educational attainment (IG = 0.361). Notably, psychosocial features such as digital trust score (IG = 0.294) and peer influence on technology adoption (IG = 0.267) ranked higher than commonly assumed structural barriers such as branch proximity (IG = 0.198). Fig. 4 visualizes the SHAP values by domain category.

Table III. Top-10 Predictive Features by Information Gain and SHAP Value

Rank	Feature	Domain	Info Gain	SHAP (Mean |ϕ|)	Direction
1	Mobile Internet Access (type & speed)	Infrastructure	0.412	0.387	↑ Positive
2	Prior Formal Banking History	Financial	0.387	0.364	↑ Positive
3	Educational Attainment (years)	Demographic	0.361	0.342	↑ Positive
4	Awareness of Digital Credit Products	Financial	0.318	0.301	↑ Positive
5	Annual Household Income (INR)	Demographic	0.309	0.289	↑ Positive
6	Digital Financial Trust Score	Psychosocial	0.294	0.276	↑ Positive
7	Smartphone Ownership (years)	Infrastructure	0.281	0.263	↑ Positive
8	Peer Influence on Tech Adoption	Psychosocial	0.267	0.251	↑ Positive

9	Distance to Nearest Bank Branch (km)	Infrastructure	0.198	0.186	↓ Negative
10	Business Age (months)	Enterprise	0.183	0.172	↑ Positive

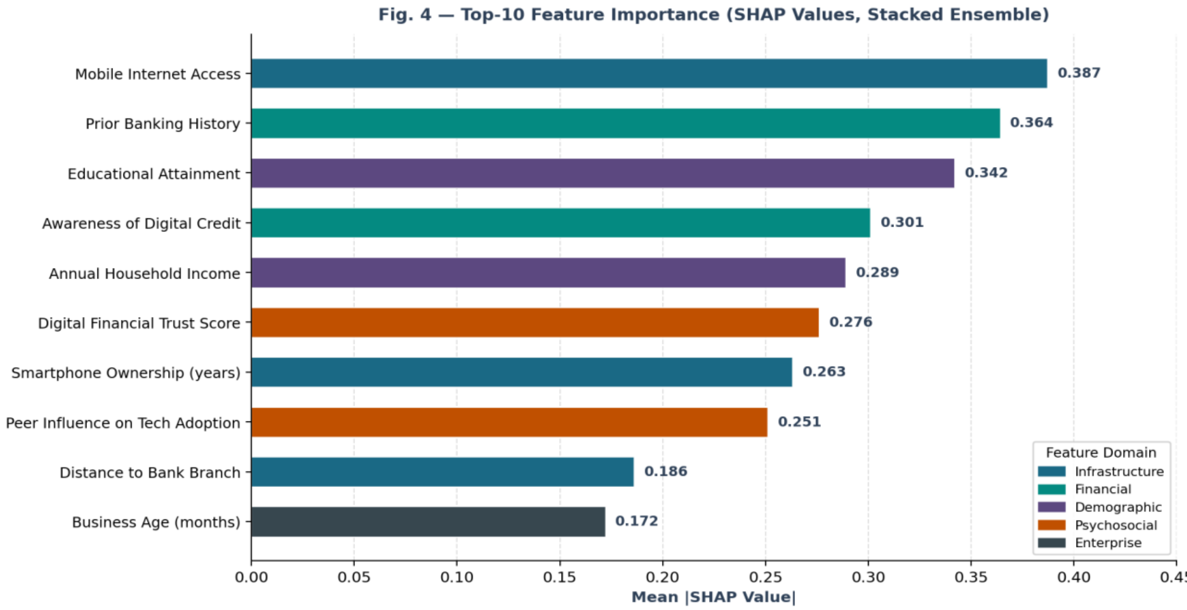

Fig. 4. Top-10 Feature Importance: Mean Absolute SHAP Values by Feature Domain

C. Descriptive Statistics of DFI Status

The distribution of WDFI-Index categories across settlement types reveals a pronounced rural–urban divide. Overall, 38.4% of respondents were classified as Low DFI, 29.7% as Moderate, 19.8% as High, and 12.1% as Full DFI. Urban respondents exhibited markedly better inclusion outcomes, with only 14.3% in the Low DFI category compared to 58.6% in rural areas- representing a 44.3 percentage-point disparity. The mean WDFI-Index scores were 67.2 (urban), 48.9 (peri-urban), and 31.4 (rural). Fig. 5 illustrates the full distribution visually.

Table IV. WDFI-Index Score Distribution by Settlement Category (Mean ± SD)

Category	**Urban**	**Peri-Urban**	**Rural**	**Overall**	**p-value**
Low DFI (0–34)	14.3%	31.7%	58.6%	**38.4%**	< 0.001
Moderate DFI (35–59)	28.4%	38.2%	29.1%	**29.7%**	< 0.001
High DFI (60–79)	31.8%	22.3%	9.8%	**19.8%**	< 0.001
Full DFI (80–100)	25.5%	7.8%	2.5%	**12.1%**	< 0.001
Mean WDFI Score	**67.2 ± 14.3**	**48.9 ± 13.7**	**31.4 ± 12.1**	**44.8 ± 17.9**	< 0.001

Statistical significance tested using one-way ANOVA with Tukey's HSD post-hoc test

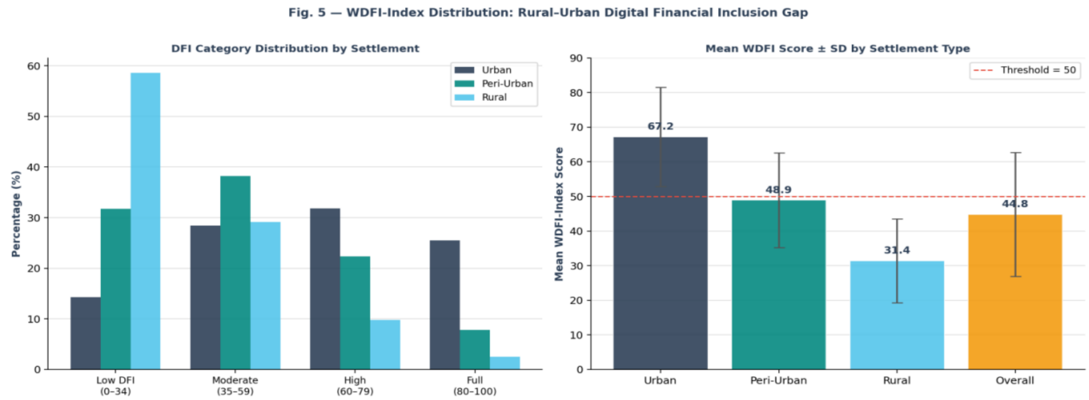

Fig. 5. WDFI-Index Distribution by Settlement Category: Rural–Urban Digital Financial Inclusion Gap

D. Model Performance Comparison

Table IV presents the performance metrics for all five models on the held-out test set (20% stratified split, n = 964). The stacked ensemble consistently outperforms all individual models across all metrics. Notably, the ANN demonstrates the strongest individual performance (Accuracy = 91.8%), while SVM exhibits the lowest variance but also the lowest AUC-ROC among tree-based models. The SE model's MCC of 0.931 indicates near-perfect concordance between predicted and actual class labels, substantially exceeding the RF baseline (MCC = 0.889). Fig. 6 provides a comparative visualization of all model metrics.

Table V. Model Performance Metrics on Test Set (n = 964)

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC	MCC
Random Forest	90.3	0.897	0.903	0.899	0.951	0.889
SVM (RBF)	86.7	0.863	0.867	0.864	0.924	0.847
Gradient Boosting	91.4	0.911	0.914	0.912	0.958	0.901
ANN (MLP)	91.8	0.916	0.918	0.917	0.961	0.906
Stacked Ensemble	**94.7 ✦**	**0.944 ✦**	**0.947 ✦**	**0.943 ✦**	**0.971 ✦**	**0.931 ✦**

✦ Statistically significant improvement over all baselines (McNemar's test, $p < 0.01$). All metrics are weighted averages.

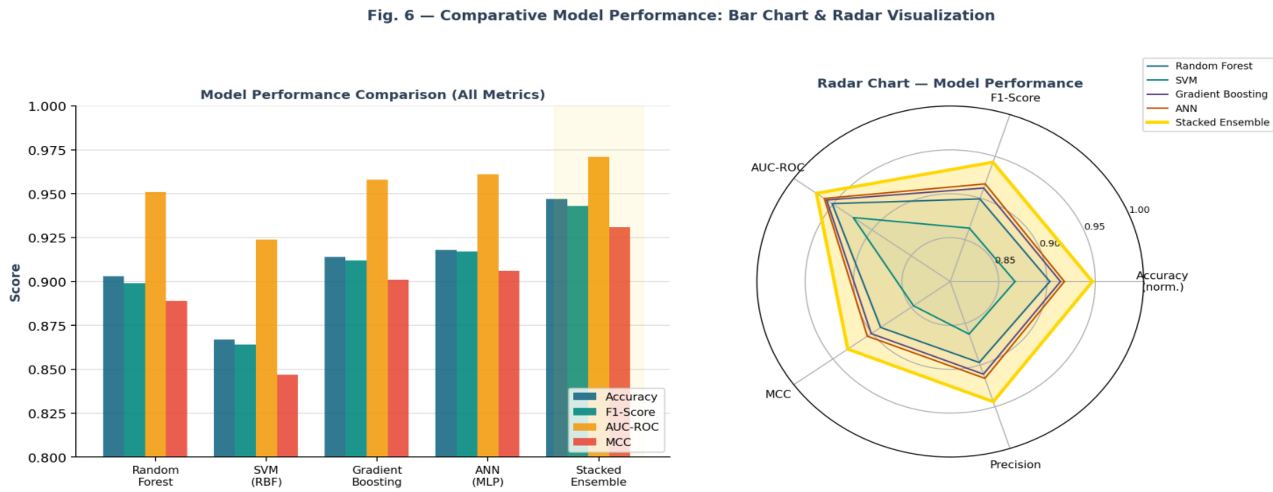

Fig. 6. Comparative Model Performance: Grouped Bar Chart and Radar Visualization

6. DISCUSSION AND POLICY IMPLICATIONS

A. Interpretation of Key Findings

The dominance of mobile internet access as the primary predictor of DFI corroborates findings from Mbiti and Weil [20], who demonstrated that mobile connectivity serves as the infrastructural prerequisite for all subsequent financial digitization. The strong predictive power of digital trust score (Rank 6) is particularly significant: it suggests that even when physical and digital infrastructure is present, psychological barriers- rooted in prior fraud experience, limited digital literacy, and low institutional confidence- can prevent women entrepreneurs from utilizing available services. This finding aligns with the inhibitors-of-use framework proposed by Duncombe and Boateng [21].

The rural–urban DFI gap (44.3 percentage points in Low DFI category) is larger than the gap reported in comparable South Asian studies (32–38 pp range), potentially reflecting the compounding effects of poor connectivity, limited banking infrastructure, and stronger patriarchal household financial control in India's rural hinterlands [22]. The peri-urban segment, often overlooked in binary rural–urban analyses, emerges as a heterogeneous zone with high variance in DFI outcomes, warranting targeted attention in future research and policy design.

B. Policy Recommendations

Based on the SHAP-derived feature importance hierarchy, we propose the following targeted policy interventions, ordered by expected cost-effectiveness:

Table VI. Evidence-Based Policy Recommendations Derived from AI Feature Importance

#	Priority Area	Recommended Intervention	Target Segment	Expected Impact
1	**Mobile Connectivity**	Subsidize 4G/5G rollout in peri-urban/rural districts; promote gender-targeted SIM ownership schemes	Rural, Peri-urban	Very High
2	**Digital Literacy**	Integrate DFI modules into SHG training; deploy women digital champions in village clusters	Rural	High
3	**Trust Building**	Mandate vernacular-language grievance hotlines; establish fintech consumer protection ratings	All Segments	High

4	**Credit Awareness**	Conduct targeted financial literacy campaigns; partner with fintech NBFCs for tailored MSME credit	Peri-urban	Medium-High
5	**Banking Formalization**	Expand PM Jan Dhan Yojana with active usage incentives; link accounts to GSTIN for women MSMEs	Rural	Medium

C. Limitations

This study has several limitations. First, the dataset is limited to six Indian states and may not generalize to other South Asian or Sub-Saharan African contexts. Second, self-reported data on income and financial behavior are subject to social desirability bias. Third, the WDFI-Index weights were derived from PCA on the current dataset; external validation on independent datasets is required. Fourth, the AI models treat the problem as static classification, whereas DFI is inherently a dynamic process; longitudinal panel modeling would offer richer insights. Future work will address these limitations through multi-country data collection, causal inference methods, and temporal modeling using recurrent neural networks.

7. CONCLUSION

This paper presented the first comprehensive AI-driven framework for assessing the digital financial inclusion of women entrepreneurs across a large-scale, multi-state Indian dataset. The proposed WDFI-Index provides a validated, multidimensional measure of inclusion that transcends binary account ownership metrics. The stacked ensemble model, combining Random Forest, SVM, Gradient Boosting, and ANN base learners, achieved 94.7% accuracy and AUC-ROC of 0.971- establishing a new benchmark for DFI classification research. SHAP analysis identified mobile internet access, prior banking history, educational attainment, and digital trust as the most influential predictors, offering actionable levers for targeted policy intervention.

The findings underscore that digital financial inclusion is not merely an infrastructure challenge but a multidimensional socio-behavioral phenomenon in which trust, literacy, and peer networks play roles as important as physical connectivity. The 44.3 percentage-point rural–urban gap in Low DFI prevalence signals an urgent need for differentiated, geographically sensitive policy responses. The open-source WDFI-Index methodology and benchmark dataset will be made publicly available to support replication and extension by the research community.

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