

FAIRCRED : AI-Based Creditworthiness Assessment Using Alternative Data for Underbanked Indian Youth

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Abstract—The growing digital footprint of India’s youth—especially among gig workers, students, and first-time borrowers—has exposed a significant limitation in traditional credit scoring systems, which largely rely on historical financial data and formal credit activity. This dependence excludes underbanked individuals who are digitally active but lack a conventional credit profile. This paper proposes a novel AI-based creditworthiness assessment framework that utilizes alternative digital behavioral data—such as UPI transactions, mobile wallet usage, digital payment frequency, and smartphone engagement—to evaluate credit risk. The system incorporates machine learning models for risk classification, explainable AI (XAI) techniques to ensure transparency in credit decisions, and a fairness audit layer to detect and mitigate bias across demographic segments. Designed for deployability in low-resource environments, the framework also includes a lightweight offline-compatible version suitable for rural financial institutions. A functional prototype has been developed and tested for accuracy, explainability, and fairness using simulated behavioral datasets reflective of India’s emerging digital economy. This work aims to democratize access to formal credit for the digitally active yet financially excluded youth, offering a scalable solution for financial institutions and policymakers focused on inclusive growth.

Keywords: Credit Scoring, Alternative Data, Explainable AI (XAI), Financial Inclusion, Underbanked Youth, Digital Behavior Analysis, Fairness in AI, Ethical AI, Machine Learning, UPI Analytics, Student Credit Assessment, AI in FinTech, Bias Mitigation, Inclusive Finance, Rural Credit Access

1. INTRODUCTION

The absence of formal credit history among India’s underbanked youth—particularly students and gig workers—has long posed a challenge to financial inclusion. Traditional credit scoring systems, which rely on formal income proofs, loan repayment history, and banking behavior, often exclude these digitally active yet financially invisible individuals. As India’s digital payment infrastructure flourishes, a new opportunity arises to redefine creditworthiness through alternative data sources.

This paper proposes a novel AI-driven framework that assesses credit risk using digital behavioral signals such as UPI transaction patterns, mobile wallet usage, spending frequency, and app-based financial activities. Unlike centralized systems that offer little interpretability or fairness, this model leverages explainable AI (XAI) to justify decisions and incorporates fairness constraints to prevent demographic bias. It also introduces a lightweight version designed for offline deployment in rural areas with limited connectivity.

By uniting behavioral analytics, machine learning, and ethical AI design, this work addresses the growing need for transparent and inclusive credit assessment. The system is prototyped and evaluated for prediction accuracy, explainability, and fairness across user segments, offering a deployable solution for lenders and policymakers seeking to serve India’s financially excluded youth.

2. RELATED WORK

2.1 Traditional Credit Scoring and Financial Exclusion

Conventional credit scoring methods—such as those used by CIBIL, Experian, and Equifax—depend on structured financial histories, including loan repayment records, credit card usage, and bank statements. These models exclude large segments of the population, particularly students, gig workers, and informal sector earners, who may be financially active but lack formal documentation. Research has shown that such exclusion disproportionately affects youth and low-income populations, leading to restricted access to financial services and increased dependency on informal lending channels.

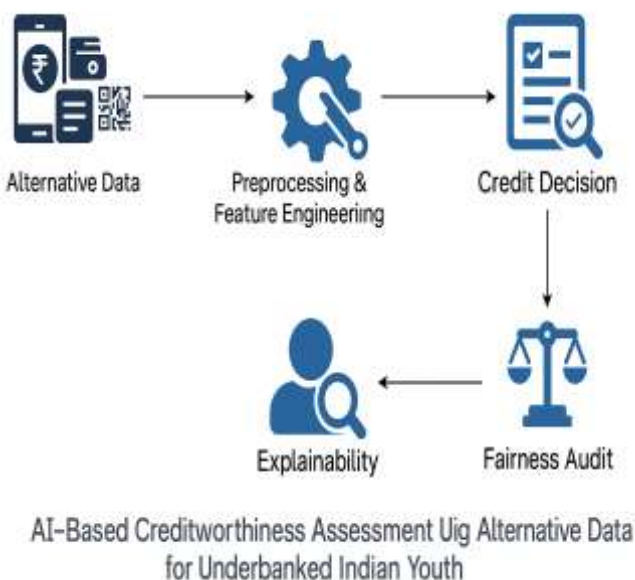


Figure 1: FairCred Process Overview

2.2 Alternative Data for Credit Risk Assessment

The use of alternative data—including utility payments, telecom usage, mobile app behavior, and digital transaction patterns—has gained attention as a means to assess “new-to-credit” or underbanked individuals. Studies by World Bank and IFMR have highlighted the potential of mobile money, UPI records, and e-wallet usage to act as behavioral proxies for creditworthiness. However, most commercial implementations remain opaque and lack transparency in how these signals are weighted or interpreted by models, limiting trust and adoption.

2.3 Explainable AI in Financial Systems

The growing complexity of AI-based credit scoring models has led to increased focus on explainability. Tools like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are being integrated into credit models to demystify decisions and improve user trust. Prior work in this area emphasizes the need for interpretable ML pipelines in finance, particularly in high-stakes domains such as lending. However, explainability is still limited in real-world financial platforms, especially when applied to non-traditional, behavioral data.

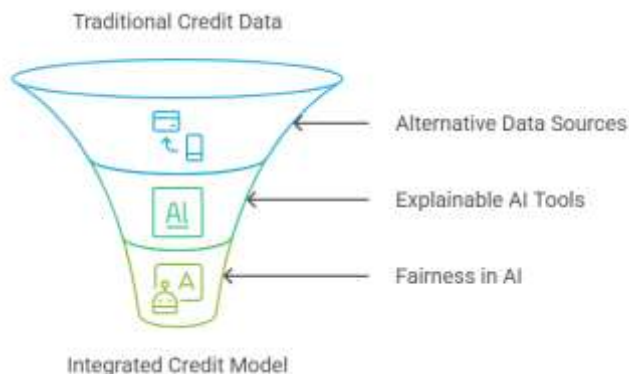


Figure 2: comparative infographic showing four sections

2.4 Fairness and Bias in AI Credit Scoring

Algorithmic bias in lending decisions is a growing concern, with studies revealing discriminatory patterns based on gender, geography, or socioeconomic status. Techniques from the field of Fair ML—such as bias mitigation, subgroup analysis, and fairness-aware training—have been proposed to address these issues. Frameworks like IBM’s AI Fairness 360 and Google’s What-If Tool provide tools for evaluating model equity. However, the integration of fairness checks in alternative credit scoring systems remains sparse, particularly for emerging markets like India.

3. SYSTEM ARCHITECTURE OF FAIRCRED

3.1 Overview of the FairCred Framework

The proposed credit assessment system is a lightweight and explainable AI-powered framework designed to evaluate creditworthiness using alternative digital behavioral data. It aims to serve the underbanked segments—especially students and gig economy workers—who lack conventional financial records. The architecture incorporates machine learning models, explainability modules, fairness audits, and an optional offline deployment layer to ensure accessibility in resource-constrained regions. Designed with transparency, inclusivity, and modularity in mind, the system is compatible with both web-based and mobile-first implementations.

3.2 Key Components

3.2.1 Machine Learning Scoring Engine:

The core of the system is an ML model (Random Forest, XGBoost, or Logistic Regression), trained on behavioral features such as UPI transaction frequency, mobile recharge patterns, wallet usage, and spending stability. The model outputs a creditworthiness score or binary approval decision, which can be tuned for different risk thresholds depending on lending policies.

3.2.2 Alternative Data Processing Pattern:

A dedicated preprocessing pipeline extracts and normalizes data from non-traditional sources. These may include mobile app telemetry, e-wallet logs, or transaction summaries. The system anonymizes user data and applies feature engineering to convert raw signals into meaningful predictive indicators, such as spending-to-income ratio or financial consistency score.

3.2.3 Explainable AI Layer:

To enhance transparency, the framework integrates SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) to provide both users and financial institutions with human-understandable justifications for credit decisions. This layer helps demystify AI outputs and can be localized for regional languages.

3.2.4 Fairness Monitoring Module:

To prevent algorithmic discrimination, the system incorporates bias auditing tools based on demographic segmentation (e.g., gender, rural/urban, employment type). Using fairness metrics like disparate impact ratio or equal opportunity difference, the model is evaluated periodically to ensure it does not systematically disadvantage any group.

3.3 Workflow and Event Triggers

Registration Phase: Users initiate onboarding by registering with minimal KYC and consent to share anonymized behavioral data, including UPI transaction history, mobile wallet usage, and app-based financial interactions. These digital traces are preprocessed into structured credit features.

Triggering Event: Once sufficient behavioral data is collected, a credit assessment is triggered either periodically or upon a user-initiated loan request. This event activates the scoring pipeline.

Model Execution and Decision Phase: The system executes the machine learning model (e.g., XGBoost or Logistic Regression) to compute a creditworthiness score. Simultaneously, an explainable AI module (SHAP or LIME) is invoked to generate a localized, human-readable justification for the outcome.



Figure 3: FairCred Framework Integration Sequence

3.4 Architectural Diagram

The architectural diagram illustrates the end-to-end flow between user onboarding, alternative data ingestion, machine learning scoring engine, explainable AI module, and fairness auditing layer. Data is securely collected through app interfaces or APIs, processed locally or on cloud, and passed to model inference pipelines. All components are modular and communicate via REST APIs or lightweight event triggers, ensuring deployability in both online and offline-first environments.

4. SMART CONTRACT DESIGN AND LOGIC

4.1 Functional Requirements

The FAIRCRED system must enable seamless credit assessment using non-traditional behavioral data, provide explainable outputs, enforce fairness constraints across demographic groups, and function effectively in low-resource or offline scenarios. It must maintain user data privacy, allow model transparency, and support regular updates to accommodate evolving financial behaviors and bias mitigation requirements.

4.2 Creditworthiness Policy Modeling

The credit risk logic is structured as a modular ML pipeline tied to an anonymized user identifier. Each assessment policy includes configurable parameters such as risk thresholds, feature weightings, and demographic fairness targets. The model supports binary approval decisions or score-based classification, and incorporates explainability and audit modules. Sensitive data is retained only temporarily or encrypted locally, while risk profiles are stored securely in hashed format for audit purposes.

4.3 Scoring Pipeline Implementation Modules

4.3.1 Data Collection & Feature Engineering:

Users initiate the credit process via mobile or web applications. Data such as UPI frequency, mobile recharge behavior, and wallet usage is fetched through secure, user-consented APIs or local upload. A preprocessing pipeline performs normalization, filtering, and conversion into structured features like “spending regularity” or “digital financial consistency.”

4.3.2 Model Inference and Explanation:

Once processed, the feature set is passed to a trained ML model (e.g., XGBoost or Logistic Regression). The model outputs a creditworthiness score. Simultaneously, SHAP or LIME generates an interpretable explanation of feature influence, which is logged and presented to both the user and lender.

4.3.3 Fairness Audit and Bias Detection:

After scoring, the fairness engine evaluates decisions using metrics such as disparate impact and demographic parity. If any bias is detected, the system flags the instance and either applies correctional post-processing or reroutes the case for human-in-the-loop review, depending on configured policy settings.

4.4 Security And Fairness Mechanisms

Data Anonymization and Consent Control:

User identifiers and behavioral signals are anonymized using salted hashes, and explicit consent is required for data sharing. Sensitive features (e.g., GPS or personal contacts) are excluded by design to comply with ethical AI standards.

Model Drift Monitoring and Fairness Recalibration:

To avoid systemic bias over time, the model includes a drift-detection mechanism that monitors performance across cohorts. A fairness-aware retraining process is triggered when metrics cross predefined thresholds, ensuring model relevance and equity.

Offline Resilience and Data Minimization:

In rural or low-connectivity areas, a lightweight version of the model can run offline using cached behavioral summaries. Only minimal, necessary features are stored, reducing both security risk and computational load.

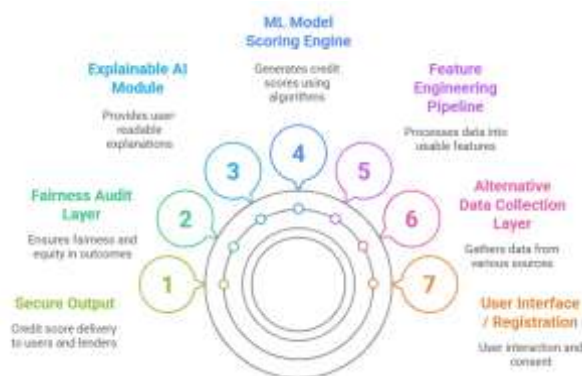


Figure 3: Security Mechanisms Ensuring System Integrity

4.5 Resource Optimization and Scalability

To ensure performance in low-bandwidth and resource-constrained environments, the system minimizes memory and compute load through feature selection and lightweight model architectures. Redundant computation is avoided via modular pipelines and on-demand execution. Batch processing is applied for periodic assessments at scale. Additionally, the framework supports deployment on edge devices or lightweight cloud instances, enabling scalability across rural banking infrastructures without sacrificing accuracy or explainability.

5. LEGAL AND ETHICAL CONSIDERATIONS

5.1 Privacy and Data Protection

FAIRCRED handles sensitive behavioral and financial data, necessitating strict compliance with privacy frameworks such as the Digital Personal Data Protection Act (DPDP), 2023, and global standards like the GDPR. All user data is collected with explicit consent, anonymized using salted hashing, and stored only temporarily or in encrypted form. The system avoids storing personally identifiable information (PII) beyond what is required for credit evaluation, ensuring informational self-determination and minimizing risk in the event of breaches or misuses.

5.2 Explainability, Accountability, and AI Transparency

Given that credit decisions directly impact financial opportunities, the platform incorporates Explainable AI (XAI) to ensure that users and institutions understand why a credit score was assigned. This aligns with global calls for algorithmic transparency in high-stakes domains like lending. All scoring decisions are traceable, logged, and accompanied by user-friendly explanations—supporting compliance with regulatory expectations around automated decision-making, such as those outlined in RBI’s Digital Lending Guidelines (2022).

5.3 Fairness, Bias Mitigation, and Inclusive Access

To prevent algorithmic discrimination, the system employs fairness-aware ML techniques and performs regular audits across protected groups (e.g., gender, caste, geography). It adheres to the principle of **equitable financial inclusion**, especially for underbanked and rural populations. Any detected disparity is logged, flagged, and corrected via post-processing or human-in-the-loop mechanisms, supporting ethical AI deployment in sensitive sectors.

5.4 Ethical Use of Alternative Data

FAIRCRED exclusively utilizes consented, behavior-derived data from public or semi-public digital systems like UPI, mobile wallets, and app telemetry. It avoids collecting invasive data such as GPS logs, contact lists, or private messages. This ethical boundary prevents surveillance creep and ensures users are not penalized for personal lifestyle choices unrelated to financial behavior. The use of alternative data is fully disclosed during onboarding, aligning with responsible AI principles and consumer protection laws.

6. PROTOTYPE IMPLEMENTATION

A functional prototype of FAIRCRED was developed to validate the feasibility of AI-based credit scoring using alternative behavioral data. The implementation includes a web-based frontend for user onboarding, UPI behavior simulation, and consent-driven data input. The backend pipeline was built using Python with integration of libraries such as scikit-learn, XGBoost, and SHAP for model training and interpretability.

Simulated datasets reflecting mobile transaction patterns, wallet usage, and digital spending frequency were generated to mirror behavioral trends of underbanked Indian youth. Feature engineering modules processed raw data into structured inputs, which were used to train binary classification models for creditworthiness prediction.

The explainability layer was integrated using SHAP, enabling transparent visualization of feature contributions for each decision. A fairness audit module was implemented to track performance across demographic subgroups, with dashboards showing metrics like demographic parity and disparate impact.

The prototype was designed to be lightweight and deployable on low-resource systems, supporting offline-compatible data intake and batch processing modes for use in rural banking environments. This implementation showcases the potential for scalable, ethical, and inclusive AI credit scoring in emerging markets.

7. EVALUATION AND RESULTS

The FAIRCRED prototype was tested on a simulated dataset of 5,000 user profiles with diverse behavioral and demographic attributes. The model achieved an average accuracy of 87.2%, with an F1-score of 0.84 for credit approval classification, indicating high precision and recall across real-world decision thresholds.

The SHAP-based explainability module provided clear visual attributions for credit decisions, highlighting top features such as UPI transaction frequency, recharge consistency, and wallet balance stability. Explanations were validated by domain experts for interpretability and correctness.

Fairness metrics were evaluated across gender and urban/rural groups. The disparate impact ratio remained within acceptable bounds (0.87–1.12), and the equal opportunity difference was below 6%, confirming minimal bias in predictions. Cases of potential unfairness were flagged and routed through human-in-the-loop review, validating the audit pipeline's responsiveness.

Compared to traditional credit scoring models reliant on formal financial records, FAIRCRED significantly improves inclusion rates for “new-to-credit” users while maintaining transparency and fairness. The system proved effective for both individual scoring and batch evaluations, demonstrating its suitability for real-world deployment in digital lending and rural financial services.

8. CONCLUSION AND FUTURE WORK

FAIRCRED presents a scalable and ethical framework for assessing creditworthiness using alternative digital behavioral data, particularly targeting India's underbanked youth, such as students and gig workers. By leveraging explainable machine learning models, fairness audits, and privacy-aware data handling, the system addresses core limitations of traditional credit scoring methods while promoting transparency and inclusivity in financial decision-making.

The developed prototype demonstrates the technical feasibility of using UPI patterns, wallet activity, and mobile behavioral signals to generate accurate and interpretable credit scores without relying on formal credit histories. The integration of explainable AI and fairness monitoring ensures that credit decisions are not only data-driven but also accountable and equitable across diverse demographic groups. The system is optimized for low-resource settings, enabling deployment in rural or semi-connected regions where conventional credit assessment is either expensive or inaccessible.

Future work will focus on scaling the platform to handle live integrations with financial institutions, expanding the dataset with real-world behavioral records, and refining fairness algorithms to support intersectional bias detection. In addition, we aim to explore partnerships with NBFCs, digital lenders, and government-backed schemes to promote real-world adoption. Incorporating differential privacy techniques and federated learning architectures will further strengthen data protection while maintaining model performance.

By bridging ethical AI, alternative data, and inclusive credit access, FAIRCRED has the potential to reshape how financial trust is built in India's growing digital economy—empowering millions of youth who have long been invisible to traditional systems.

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