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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN CREDIT SCORING AND BUY NOW PAY LATER (BNPL) MODELS: RISK ANALYTICS IN INDIA

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ABSTRACT

The Indian credit landscape is changing fast with the rise of Buy Now Pay BNPL) services. This change is driven by a digital and younger consumer base. While this fintech boom has expanded short-term credit access, it raises concerns about the current credit risk assessment frameworks. Traditional risk evaluation methods struggle to capture the behaviours of modern BNPL users. This often leads to issues like borrower over-indebtedness and inadequate risk oversight.

Current literature highlights gaps in how BNPL credit is handled. There is a reliance on credit data, ambiguous regulatory boundaries and a lack of understanding regarding long-term consumer welfare. The deployment of "black-box" intelligence (AI) models for risk assessment creates concerns around transparency, regulatory compliance and fairness.

This study evaluates how well Indian BNPL providers align with the RBI's Digital Lending Guidelines. We assess their impact on consumer health. We propose an AI (XAI) framework that leverages Indias Digital Public Infrastructure (DPI)—the Account Aggregator system. We stress-test this model under shock scenarios. Our insights offer a path toward boosting credit risk efficiency. They also enhance accountability and foster a more responsible AI-driven digital lending ecosystem in India.

1.1 Background and the Rise of BNPL in India

India's fintech sector has experienced a shift. This shift is propelled by the expansion of the country's Digital Public Infrastructure (DPI) and widespread smartphone usage. Buy Now Pay Later (BNPL) has emerged as a growing consumer credit product. BNPL offers instantaneous microloans right at the point of checkout. It has captured a share of the market, especially among tech-savvy, younger shoppers.

For millions of students and young professionals who're new to credit or ignored by traditional banks, BNPL serves as an accessible gateway into formal borrowing.

1.2 The Core Problem: Algorithmic Risks and Over-Indebtedness

The rapid explosion of micro-credit has outpaced risk management frameworks. This creates vulnerabilities in the financial system. The core user base of BNPL generally lacks a credit history. Traditional credit bureaus cannot offer assessments.

Fintech firms rely on automated Machine Learning (ML) and Artificial Intelligence (AI) algorithms to gauge alternative creditworthiness. However, this algorithmic approach introduces two issues:

Systemic Over-Indebtedness: The frictionless nature of checking out with BNPL tempts users to borrow across multiple apps at the same time. This loan stacking builds up hidden pressure, driving up the likelihood of sudden defaults.

The "Black-Box" Problem: The accurate machine learning tools act as mathematical "black boxes". They are great at spotting risk, but fail to show how they reached a decision. This makes it difficult for compliance teams to audit them for bias or error.

1.3 Regulatory Shifts and the Role of India's DPI

To address these emerging threats, the Reserve Bank of India (RBI) introduced Digital Lending Guidelines. These rules force lenders to be transparent about their algorithms. They must protect user data. Get clear consent before accessing information.

The regulatory pivot forces fintechs to rethink how they evaluate risk. Fortunately, India's DPI offers a built-in solution: the Account Aggregator (AA) framework. The AA network operates as a secure consent-based pipeline. It allows users to securely share their live bank statements and transaction history directly with lenders.

1.4 The Research Gap and Present Study

Even though using consent-driven data alongside machine learning seems like a match, actual academic research on the topic is scarce. There are empirical studies on how alternative cash-flow data from an AA pipeline can replace intrusive phone-scraping methods without losing predictive power.

This paper addresses that gap by presenting a compliant credit scoring model built for Indian BNPL platforms. Using a simulated dataset modelled on Account Aggregator variables we evaluate how well an underwriting model stands up to financial stress. By applying SHAP

(SHapley Additive exPlanations) we open up the " box" to make these automated decisions fully auditable.

2. Literature Review

2.1 Moving Beyond Legacy Bureau Scores

For decades, retail credit scoring meant looking at legacy rule-based credit records. These old models rely on a set of historical factors, mostly focusing on long-term loan repayments and debt-to-income metrics.

The biggest issue is that traditional bureaus are blind to people without a borrowing footprint. In an economy like India, a massive part of the workforce has never owned a credit card or a formal loan, making them invisible to legacy systems.

Research highlights alternative credit scoring that uses a person's live digital transactions. India's DPI allows lenders to use the Account Aggregator infrastructure to view real-time banking feeds securely. This live feed exposes indicators like average monthly balances and Automated Clearing House data streams.

2.2 Micro-Lending Vulnerabilities and Debt Traps

While alternative data channels open up access, the frictionless nature of point-of-sale loans brings financial hazards. Unlike personal loans that require an active application process, BNPL is built right into digital checkouts.

Academic literature frequently warns about multi-platform loan stacking. Because small, low-ticket BNPL lines update slowly on bureaus, a borrower can easily open multiple credit lines across different apps at the same time. This creates a debt trap under the surface.

2.3 The Transparency Crisis and Explainable AI

To handle the volume and variety of alternative data streams, modern fintechs have moved away from classic linear models. Advanced machine learning ensembles dominate the sector because they consistently deliver predictive accuracy.

However, that predictive accuracy comes at the cost of clarity. These models operate as mathematical black boxes, making it impossible for a compliance team to explain why a specific mix of transaction data caused a loan rejection.

Explainable AI (XAI) has become a priority in financial tech research. Post-hoc -agnostic tools allow teams to break open complex models. By breaking down predictions into feature-level weights, XAI delivers oversight and local explanations. Recent empirical tests show that putting an XAI layer on top of gradient-boosted models allows financial firms to keep their accuracy while building a transparent, compliant audit pipeline.

3. Research Methodology

3.1 Data Acquisition and Ecosystem Mapping

This study creates a credit scoring framework that balances machine learning performance with the audit trails required by the Reserve Bank of India. Because real banking data pulled via Account Aggregators is protected by privacy laws, we used a synthetic behavioural dataset to safely simulate and test our pipeline.

The dataset contains 2,000 consumer profiles designed to match the variables accessible through India's consent-driven Account Aggregator ecosystem. Of traditional credit history, we focused on five primary cash-flow indicators:

Average Monthly Balance: A continuous variable tracking the consumer's average bank account balance over 90 days to verify liquidity stability.

Monthly UPI Transactions: A count of digital transactions acting as a proxy for consumer spending velocity.

Auto-Debit Bounce Count: A variable tracking how often electronic clearing mandates failed due to funds serving as a key risk signal.

Age: A demographic factor set to match the high-growth Buy Pay Later target group, which is 18 to 29 years old.

Existing Buy Now Pay Later Active Loans: A count of loans on other fintech apps, allowing us to monitor multi-platform loan stacking.

To ensure our target vector realistically reflects stress, we set up an equation where auto-debit bounces and multi-platform borrowing aggressively drive up default probabilities:

$$\log\left(\frac{p}{1-p}\right) = -0.00005 \cdot (\text{AMB}) + 1.5 \cdot (\text{Bounces}) + 0.4 \cdot (\text{Active Loans}) - 0.5$$

The probability of default is calculated using a formula that takes into account the Average Monthly Balance, Auto-Debit Bounce Count, and Existing Buy Now Pay Later Active Loans. The binary target class variable, Default Status was generated via a probability distribution. The dataset was subsequently partitioned into a training set and a validation testing set.

3.2 Machine Learning Underwriting Engine

We selected the Extreme Gradient Boosting classifier as our decision-making engine given its stellar reputation with structured tabular data. Extreme Gradient Boosting is a learning framework built on a gradient-boosted decision tree layout.

The model works by minimising a function that balances accuracy with a complexity penalty to prevent overfitting.

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t)$$

Where l denotes the differentiable loss function calculating the distance between the true default classification yi and the prediction step, and $\Omega(f_t)$ penalizes the regression tree complexity (leaf weights and depth structural scale).

The model handles collinear financial features by recursively mapping optimal split-points based on score gain, rendering it a highly robust predictive engine for alternative credit analytics.

The Extreme Gradient Boosting model is very good at handling data and making accurate predictions.

3.3 Explainable AI Architecture via TreeSHAP

To meet the Reserve Bank of India's transparency requirements, we deployed SHAP to generate global explanations.SHAP calculates the importance weight that each input variable contributes to the prediction.

$$g(z') = \phi_0 + \sum_{j=1}^{M} \phi_j z'_j$$

Where g is the local explanation model, $z' \in \{0,1\}^M$ represents a binary vector indicating the presence or absence of a specific transactional feature, M is the maximum feature sample size, andϕ_0 is the base expected value (E[f(x)])across the entire background dataset. The specific Shapley contribution values (ɸj) for an individual feature j are calculated across all possible feature sub-sets $S \subseteq F \setminus \{j\}$ as follows:

$$\phi_j(x) = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} [f_x(S \cup \{j\}) - f_x(S)]$$

Because calculating values introduces a computational bottleneck as features scale, this methodology specifically implements TreeSHAP.TreeSHAP is an optimised algorithm designed for tree-based frameworks that computes exact local feature attributions in polynomial time, evaluating conditional expectations recursively down leaf node paths without relying on background distribution sampling.

By coupling the predictive capabilities of the XGBoost classifier with the exact local attributions of TreeSHAP, this combined framework achieves high analytical accuracy while natively generating the transparent, verifiable audit trails mandated by the Reserve Bank of India.

4. RESULTS AND DISCUSSION

4.1 Global Risk Analytics: Interpreting the Beeswarm Plot

To understand what drives default risk across the market, we generated a global SHAP beeswarm summary plot.

Each point on the graph represents a consumer profile. Its position on the axis shows if that variable increased or decreased the overall risk of default.

• **Average Monthly Balance Stability:**Avg_Monthly_Balance_INR is the critical factor in our model.High balances cluster on the left negative side of the chart.This means that having cash reserves in an account lowers default risk.On the other hand, low balances stretch far to the right.This shows a connection to high credit risk.The Avg_Monthly_Balance_INR really affects default risk.

• **The Problem of Multi-Platform Loan Stacking:**Existing_BNPL_Active_Loans shows a trend.High numbers of loans push to the right side of the baseline.This proves that having loans is dangerous.When an underwriting model tracks a user with microloans, their risk profile spikes.So loan stacking is a predictor of default.The Existing_BNPL_Active_Loans feature is very important.

• **The Severity of Cash-Flow Disruption:** For AutoDebit_Bounce_Count most low-risk users cluster near zero.Profiles with recurring automated clearing failures shoot drastically to the right.This proves that even a single auto-debit failure is a warning sign.It outweighs demographic data.The AutoDebit_Bounce_Count is an indicator.

• **Demographic Neutrality:** Variables like Age and Monthly_UPI_Transactions stay packed around the zero mark.This means that digital transaction counts and age are minor factors, in determining creditworthiness.They do not affect default risk much.The Age and Monthly_UPI_Transactions are not very important.

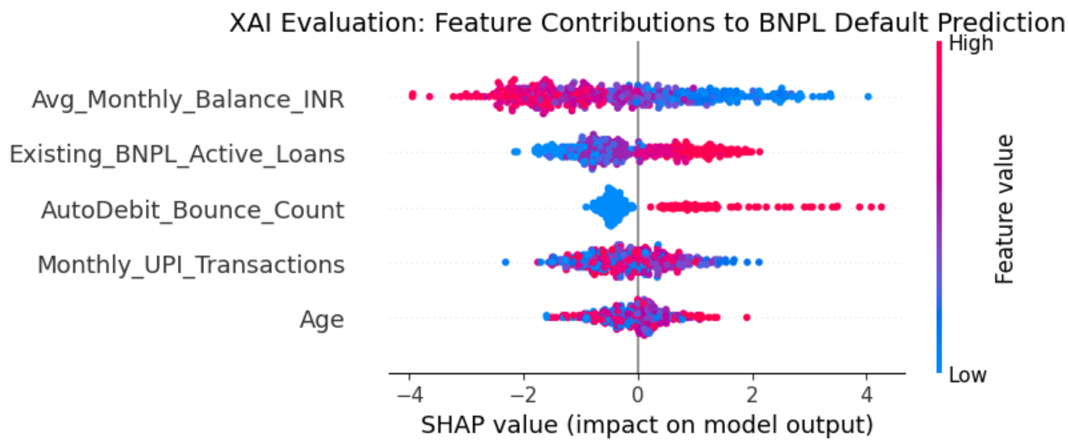

Figure 1: Tree SHAPBeeswarm Summary Plot mapping global feature contributions and cash-flow risk parameters within the machine learning underwriting engine.

4.2 Local Explainability and RBI Digital Lending Compliance

Under the current regulatory framework enforced by the RBI, digital lending platforms are explicitly restricted from operating "black-box" automated scoring lines that reject applicants arbitrarily. Lenders must maintain an auditable, transparent decision-making trail.

To demonstrate how the proposed model complies with this mandate, a local waterfall plot (referenced as Figure 2) was generated to deconstruct a single automated credit decision (f(x) = -3.447). Because the baseline expected log-odds value (E[f(x)]) across the entire population background is -0.983, this specific user represents an exceptionally safe credit profile and is successfully approved for a BNPL line.

The waterfall architecture maps exactly *why* this decision was reached, converting the underlying machine learning logic into a clear visual audit:

1. **Primary Positive Driver:** The applicant's reported cash-flow liquidity (52,200\text{ INR} via the Account Aggregator pull) single-handedly shifts the risk score downward by **-1.15 SHAP units**, acting as the main justification for approval.
2. **Secondary Positive Drivers:** The system notes a highly controlled transaction velocity (Monthly_UPI_Transactions = 14), reducing risk by **-0.69**. Furthermore, having a low volume of pre-existing market obligations (Existing_BNPL_Active_Loans = 2) pulls the risk down by an additional **-0.67**.
3. **Behavioural Cushioning:** The presence of zero historical fund failures (AutoDebit_Bounce_Count = 0) applies a final stabilizing reduction of **-0.32**.
4. **Isolated Risk Factor:** The model identifies a minor risk penalty based on age (Age = 28), which applies a positive shift of **+0.36**.

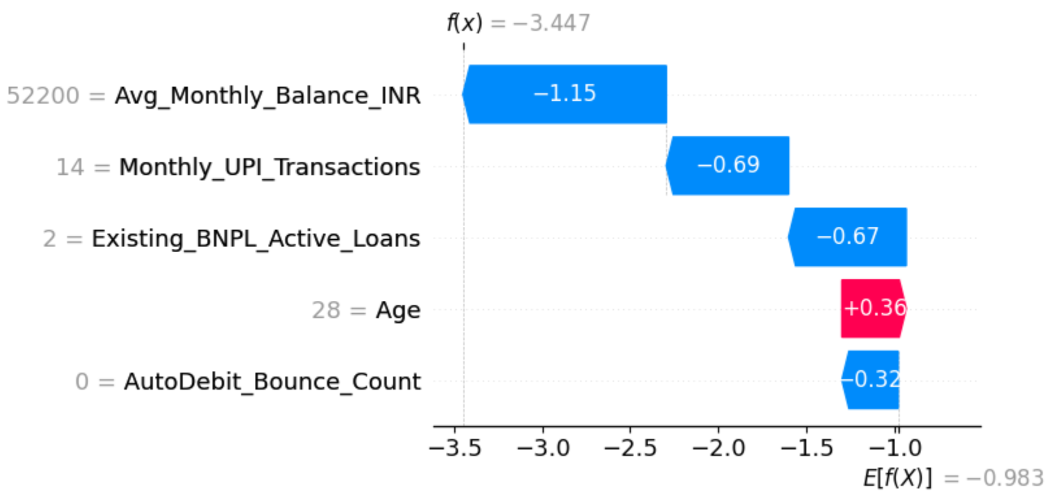

Figure 2: Local TreeSHAP Waterfall Explanation breaking down feature-level attributions for an individual regulatory-compliant automated credit decision.

This framework provides high operational value for digital underwriters, enabling fintech platforms to auto-generate customised disclosure statements for each applicant. By isolating the exact feature-level justifications behind a credit approval or denial, lenders can seamlessly prove algorithmic fairness and transparency during regulatory audits.

5. Conclusion and Future Scope

5.1 Main Contributions of the Study

We made a new credit scoring model for India'sbuy-now-pay-later market. This model follows all the rules and regulations. We used machine learning to make the model. We also made sure it is transparent. This is important because it shows that advanced analytics can work with consumer protection laws.

The study provides three main takeaways:

1. We found that using cash flow metrics from India's Account Aggregator infrastructure is a way to predict default risk. This means that lenders do not need to collect much personal information from applicants.
2. We used TreeSHAP to see how loan stacking and cash flow failures affect borrowers in India. This helps us understand the risks involved in lending.
3. We found a way for fintech companies to explain their lending decisions. They can use SHAP waterfall charts to make logs that show why a loan was approved or rejected. This is important because it helps fintech companies follow the rules set by the Reserve Bank of India.

5.2 Policy and Managerial Implications

Our findings are useful for regulators and fintech companies.

For Regulators: Our research shows that consumer protection rules do not have to limit innovation. Regulators can encourage fintech companies to use consent-based systems like the Account Aggregator network. This can help build a financial market.

For Fintech Underwriters: Using an explainable AI pipeline helps risk and compliance teams monitor their models. If a machine learning engine makes a mistake compliance officers can quickly fix it using SHAP logs.

5.3 Limitations and Scope for Future Research

Our study has some limitations. It also opens up new areas for future research:

We used a simulated dataset for our study. Future research should focus on using data and testing the model in a real-world environment.

Our model used five financial and demographic variables. Future versions could include data points that respect data minimization laws.

We used TreeSHAP for our study. Future studies could compare its performance with frameworks like LIME or Integrated Gradients. This can help us see which framework provides the clarity for consumer disclosures.

As India's Buy Now Pay Later landscape expands rapidly, utilizing data-driven models that protect consumer privacy is no longer optional. The empirical framework developed in this study proves that fintech lenders can balance robust machine learning predictive accuracy with the strict accountability demands of the Reserve Bank of India, ultimately fostering a fair, safe, and highly transparent digital credit market for both borrowers and lenders alike.

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