From Carts to Credits: Behavioral Approaches in Indian FinTech Lending

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***Abstract*—The trending expansion of FinTech-driven digital lending platforms in India has significantly enhanced access to credit, particularly for new-to-credit and under banked customers. Despite this progress, accurate assessment of credit risk continues to remain a big challenge, as traditional bureau-based credit scoring models often fail to capture behavioural and transactional nuances of borrowers. In this context, FinTech firms are increasingly exploring alternative data sources to strengthen their risk assessment frameworks.**

The present study attempts to analyze the relevance of e-commerce behavioural data as an alternative input for credit risk modelling in Indian FinTech lending platforms. Behavioural indicators such as order frequency, return-to-origin (RTO) rates, payment mode preference, refund behaviour, and transaction consistency are examined to identify their association with loan repayment outcomes. A data driven analytical approach, supported by exploratory data analysis and behavioural segmentation, is adopted to evaluate the predictive significance of these variables.

The findings shows that selected e-commerce behavioural signals exhibit a meaningful relationship with credit performance and can effectively complement traditional financial indicators during underwriting. The study further outlines key business and product-level implications, including improved on boarding risk filters, dynamic credit limit allocation, and reduction in early- stage defaults. By reviewing the practical application of alternative data, this research offers actionable insights for FinTech lenders seeking to balance financial inclusion with sustainable portfolio performance in the Indian digital lending ecosystem.

***Index Terms*—FinTech Lending, Credit Risk Modeling, E-Commerce Behaviour, Alternative Data, Data Analytics.**

I. INTRODUCTION

1. General Context and Significance of Digital Lending

Over the past decade, the Indian financial services sector has experienced a fundamental shift with the emergence of FinTech- enabled digital lending platforms. These platforms leverage technology to simplify loan application processes, reduce turnaround time, and improve customer accessibility. Digital lending has played a particularly important role in extending credit to individuals and small businesses that were previously underserved by traditional banking institutions.

While digital lending has enhanced credit penetration, it has simultaneously intensified concerns related to credit risk and loan defaults. The rapid on boarding of borrowers, especially those with limited credit histories, has increased exposure to repayment uncertainty. As a result, effective credit risk assessment has become a critical priority for FinTech lenders operating in a highly competitive and regulated environment.

2. Statement of the Problem and Research Gap

Conventional credit risk assessment methods primarily depend upon credit bureau scores, income documentation, and historical banking transactions. Although these approaches are effective for borrowers with established financial records, they provide limited insights into the creditworthiness of new-to-credit customers. This limitation is particularly evident in the Indian market, where a significant proportion of the population remains credit-invisible.

In contrast, e-commerce platforms generate extensive behavioural data reflecting customer purchasing

habits, payment discipline, Delivery success, and transaction consistency. Such behavioural indicators can indirectly signal reliability, intent, and financial responsibility.

Despite their potential value, these data points remain under utilized in formal credit risk modelling, especially within the Indian FinTech context.

Existing literature offers limited empirical evidence on the integration of e-commerce behavioural data into credit risk assessment frameworks. This gap restricts the ability of FinTech lenders to leverage alternative data sources for more accurate and inclusive underwriting decisions. The present study seeks to address this gap by examining the applicability of e-commerce behavioural metrics in credit risk modelling for Indian digital lending platforms.

II. OBJECTIVES OF STUDY

1. To observe e-commerce behavioural variables relevant to credit risk modelling.
2. To analyze the relationship between consumers behavioural patterns and loan default outcomes.
3. To explore the effectiveness of alternative data in complementing traditional credit evaluation methods.
4. To understand practical insights for FinTech product and risk management strategies.

Scope of the Study

The study focuses on non-traditional behavioral data generated through e-commerce activities.

Limitations

Data Privacy and Regulatory Constraints (The "Legal" Limit)

- The DPDP Act (2023/2025): With India’s new Digital Personal Data Protection rules, many behavioral data points (like granular browsing history or social circles) may now require explicit, purpose-linked consent. This limits a lender's ability to "scrape" data without friction.
- Storage and Deletion: Regulations now mandate that data cannot be stored indefinitely, which limits the ability to perform long-term longitudinal studies on borrower behavior over several years.

2. Algorithmic and Proxy Bias (The "Fairness" Limit)

- Socio-Economic Proxies: E-commerce data can inadvertently act as a proxy for sensitive attributes. For example, owning an iPhone or living in a specific pin code might correlate with high credit scores, potentially discriminating against rural or low-income users who may be creditworthy but lack "premium" digital footprints.
- Gender Disparity: Studies in India have shown that women often have different digital spending patterns or may use shared family accounts, which can lead to lower approval odds if the model isn't "gender-neutralized."

3. Data Integrity and "Noise" (The "Technical" Limit)

- Intent vs. Reality: A high rate of "cart abandonment" might be interpreted by an AI as financial indecisiveness, whereas in the Indian context, it is often just a method of price comparison or "window shopping."
- Account Sharing: In many Indian households, one e-commerce account (e.g., Amazon/Flipkart) is used by multiple family members. This "muddies" the behavioral profile, making it difficult to isolate the credit risk of the actual loan applicant.

4. Selection Bias (The "Sample" Limit)

- Digital Divide: The study is limited to "digitally active" Indians. It does not account for the vast population that transacts primarily in cash or through offline local markets, meaning the findings cannot be generalized to the entire Indian population.
- Survival Bias: Risk models are often trained only on "accepted" applicants (those who got the loan). We rarely know if the people we rejected based on their "cart behavior" would have actually been good repayers.

5. Volatility of Behavioral Signals (The "Time" Limit)

- Short-term Patterns: Shopping habits can change overnight due to sales (like the "Big Billion Days"), life events, or economic shifts (like inflation). Unlike a steady salary slip, e-commerce data is highly volatile and may not

always predict long-term (1–3 year) loan repayment reliability.

III. REVIEW OF LITERATURE

Credit risk modelling has been a central area of research within financial studies, traditionally focusing on demographic attributes, financial ratios, and historical credit behaviour. Bureau-based credit scoring systems have proven effective in predicting defaults for borrowers with established credit histories. However, several studies highlight their limitations in emerging markets, where formal credit penetration remains uneven.

Recent research focuses on the growing importance of alternative data sources in improving credit risk prediction accuracy.

Digital footprints, including online transaction behaviour and payment patterns, have been identified as useful proxies for assessing borrower reliability. Studies conducted in global FinTech markets suggest that behavioural consistency and transaction discipline are positively correlated with repayment performance.

E-commerce behavioural data, in particular, has gained attention as a potential indicator of consumer intent and stability. Variables such as purchase frequency, payment completion, and return behaviour have been linked to financial responsibility and decision-making tendencies. However, Indian-focused empirical research integrating e-commerce behavioural indicators into FinTech credit risk models remains limited.

The existing literature therefore indicates a clear research gap, particularly in the Indian context, regarding the systematic use of e-commerce behavioural data for credit risk assessment. This study contributes to the literature by addressing this gap through a data-driven examination of alternative behavioural indicators relevant to digital lending platforms.

IV. RESEARCH METHODOLOGY

The study adopts a descriptive and analytical research design using a quantitative approach. The analysis is based on anonym iced and aggregated customer-level behavioural data derived from e-commerce transactions various with loan repayment outcomes.
Variables considered include order frequency, average order value, return-to-origin (RTO) percentage, payment mode preference (COD versus prepaid), refund frequency, and transaction consistency. Credit performance is measured using repayment status and repayment delay indicators.
Data analysis techniques Include exploratory data analysis, behavioural segmentation, and correlation analysis. Analytical tools such as
Python (Pandas and Num Pie) and SQL are utilized to process and interpret the dataset.

DATA ANALYSIS & INTERPRETATION

Spending Categories vs. Default Rates

Sr No	Spending Category	Avg. Monthly Spend (INR)	Default Rate (%)	Interpretation
1	Electronics/Gadgets	12,500	4.20%	High-value, planned purchases often correlate with stable income.
2	Groceries/Essentials	8,000	2.10%	Consistency in "Essential" spending is the strongest predictor of stability.
3	Luxury/Fashion	15,000	9.50%	High discretionary spending without savings can signal "lifestyle creep" and higher risk.
4	Utility Bill Payments	4,000	1.80%	Timely digital bill payments are highly correlated with loan discipline.

2. How much does adding e-commerce data improve the accuracy of a traditional credit model?

Model Performance Metrics

Model Version	Gini Coefficient	KS Statistic	Accuracy (AUC)
Traditional (CIBIL-only)	0.42	32.5	0.71
Behavioral (E-commerce only)	0.38	28.1	0.68
Integrated (CIBIL + E-commerce.)	0.58	44.2	0.84

Interpretation- The Gini Coefficient increases significantly (from 0.42 to 0.58) when e-commerce data is integrated. This suggests that while e-commerce data isn't a replacement for traditional scores, it serves as a powerful booster, particularly for "thin-file" customers who have no prior credit history.

3. Do "fringe" digital behaviors (like Cash on Delivery or Cart Abandonment) correlate with financial impulsivity?

Variable	Coefficient (β)	P-Value	Risk Impact
High Cart Abandonment	+0.24	0.012	High (Sign of indecision/impulsivity)
Primary Use of UPI	-0.15	0.005	Low (Sign of digital literacy)
Frequent COD Usage	+0.41	0.001	High (Sign of lack of digital trust/liquidity)
Late Night Shopping	+0.08	0.15	Negligible (Not statistically significant)

Interpretation-
COD Usage: Interestingly, in the Indian context, heavy reliance on Cash-on-Delivery (COD) despite having a digital-first bank account often correlates with higher default risk. This may indicate a "cash-crunch" or lack of digital financial integration.
Cart Abandonment: A high abandonment rate may suggest "window shopping" without financial means, which the model interprets as a slight risk increase.

V. RESULTS & FINDINGS OF THE STUDY

1. Significant Predictive Lift for "Thin-File" Borrowers
The primary finding of this study is that integrating e-commerce behavioral data significantly improves the predictive accuracy of credit models, particularly for the New-to-Credit (NTC) segment.
2. Consistency Over Volume: The "Grocery Effect"
Data analysis revealed that the nature of spending is a more reliable predictor than the volume of spending.
3. Digital Trust as a Proxy for Creditworthiness
A strong correlation was found between a borrower's "digital maturity" and their likelihood of repayment.
4. Behavioral Stability and Geo location

VI CONCLUSION

The integration of e-commerce behavioral data into credit risk modeling represents a paradigm shift in the Indian FinTech landscape. This study has demonstrated that "digital footprints" the trail of transactions, preferences, and habits left by consumers on e-commerce platforms are not merely indicators of consumption but are robust proxies for financial character and repayment reliability.
As India continues its trajectory toward a $5 trillion economy, the move from "Carts to Credits" will be instrumental. By turning everyday shopping data into a tool for financial empowerment, the FinTech industry is not just changing how loans are approved it is redefining the very meaning of creditworthiness in the digital age.

VII. SUGGESTIONS

1. Transforming digital shopping trails into financial trust, Indian FinTechs can bridge the credit gap for millions of 'thin-file' consumers.
2. Integrating e-commerce behavioral signals significantly improves credit risk accuracy, proving that how a consumer spends is as predictive as what they earn.
3. The future of Indian lending lies in the 'Carts to Credits' shift, where alternative data turns digital consumption into a powerful tool for financial inclusion.

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