INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :732-739

A Study on Risk Management Practices in High-Velocity Digital Consumer Lending: Evidence from Bajaj Finance Limited
An Empirical Analysis of Credit Risk, Operational Risk, and Fraud Control Mechanisms in a Non-Banking Financial Company

[1]Sai Kiran Goud Kota (24R21E00A8) **[2] Mrs. M. Umreez**

[1]Department of Master of Business Administration, MLR Institute of Technology, Hyderabad, Telangana, India,saikota146@gmail.com

[2]Assistant Professor, MLR Institute of Technology , Hyderabad, Telangana

ABSTRACT

Non-Banking Financial Companies (NBFCs) have transformed retail credit delivery in India by replacing slow, collateral-driven underwriting with instant, technology-led decisioning. This shift creates a structural tension between the speed required to win customers and the discipline required to protect capital. This study examines how Bajaj Finance Limited, an Upper-Layer NBFC (NBFC-UL), manages this tension through an integrated risk architecture spanning credit risk, operational risk, and fraud risk. Using a mixed-methods design that combines descriptive observation of the digital onboarding journey with analytical review of five years of secondary financial data (FY 2021-22 to FY 2025-26), the study evaluates the relationship between loan turnaround time, customer acquisition, and asset quality. The findings show that as average loan approval time fell from forty-five minutes to under five minutes, the active customer base more than doubled, while the Gross Non-Performing Asset ratio simultaneously declined from 1.60 percent to 0.82 percent, a figure well below the broader industry average. The results indicate that algorithmic credit scoring, alternative-data underwriting for thin-file borrowers, early-bucket digital collections, and layered fraud-detection filters work together to substitute for, rather than compromise, traditional risk discipline. The study concludes that a technology-first risk framework, when paired with strong capital buffers and portfolio diversification, allows a high-volume consumer lender to scale rapidly without a corresponding deterioration in asset quality.

Keywords: *Risk Management; NBFC; Bajaj Finance; Credit Risk; Operational Risk; Fraud Risk; Non-Performing Assets; Digital Lending*

1. Introduction

The financial system functions as the principal intermediary between savers and borrowers in any economy, and its efficiency directly determines how readily capital reaches productive use. In India, traditional commercial banks have long served as the primary channel for this intermediation, but their reliance on extensive documentation, income verification, and physical collateral has historically excluded large segments of the population, particularly small shopkeepers, gig workers, and low-income households without formal salary records.

Non-Banking Financial Companies (NBFCs) emerged to close this gap. Unlike banks, NBFCs cannot accept demand deposits, but they have used digital infrastructure, alternative data, and streamlined underwriting to deliver credit at a speed and scale that traditional banking could not match. Bajaj Finance Limited, originally incorporated in 1987 as a captive vehicle-financing arm of Bajaj Auto, has grown into one of India's largest consumer-finance NBFCs, processing high volumes of unsecured retail loans for consumer durables, digital lifestyle products, and personal financing needs.

This rapid, largely unsecured lending model is inherently exposed to three interconnected categories of risk. Credit risk arises because borrowers may default on repayment obligations they have no physical collateral securing. Operational risk arises because the entire loan approval pipeline depends on uninterrupted software, server, and data infrastructure. Fraud risk arises because instant, low-friction onboarding can be exploited through stolen identities or synthetic documentation. Understanding how a large NBFC manages this risk triad while continuing to scale is the central concern of this study.

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :732-739

2. Review of Literature

The theoretical foundation for this study draws on five established strands of financial theory that collectively explain how a digital-first consumer lender prices and controls uncertainty.

2.1 Information Asymmetry

The Theory of Information Asymmetry, developed by Akerlof, Spence, and Stiglitz, holds that borrowers possess more accurate knowledge of their own creditworthiness and repayment intent than lenders do. This imbalance produces adverse selection before a loan is sanctioned and moral hazard after disbursement, particularly in unsecured lending where the borrower risks no physical asset by defaulting. Bajaj Finance addresses this gap by cross-referencing credit bureau records, tax data, and digital transaction histories in real time rather than relying on self-reported information.

2.2 Credit Risk and Portfolio Theory

Classical credit risk theory evaluates borrowers against the traditional five Cs of credit, but mass-market retail lending makes manual evaluation infeasible at scale, necessitating algorithmic credit scoring. This is reinforced by Markowitz's portfolio diversification theory, which shows that risk can be reduced by spreading exposure across a large number of small, independent loans rather than concentrating capital in a few large positions, a principle visible in Bajaj Finance's distribution of lending across consumer durable, personal, business, and secured loan segments.

2.3 Operational Risk Theory

Operational risk theory frames financial loss as a function of failures in internal systems, processes, or external events rather than borrower behaviour. For a digital-first lender, this risk concentrates in server reliability, algorithmic accuracy in underwriting logic, and cybersecurity defences against identity theft, all of which require continuous technology audits and redundancy planning.

2.4 Behavioural Finance

Behavioural finance challenges the assumption of the fully rational borrower. Present bias, or hyperbolic discounting, explains why consumers prefer instant credit at the point of sale over a delayed, more deliberated purchase decision. Mental accounting, a concept advanced by Thaler, explains why a large one-time payment feels burdensome while the same amount, broken into small monthly instalments, feels affordable. Both concepts underpin the design of point-of-sale, no-cost EMI products.

2.5 Regulatory and Capital Adequacy Frameworks

Regulatory theory, anchored in the Reserve Bank of India's Scale-Based Regulation framework and the Basel capital adequacy principles, requires lenders to hold a defined capital cushion against risk-weighted assets and to follow Fair Practices Code disclosure norms. These rules constrain how aggressively an NBFC can expand its loan book without weakening its solvency position.

2.6 Prior Empirical Studies

A substantial body of applied research supports these theoretical strands. Deshmukh and Sen (2025) found that real-time transaction monitoring can flag default risk months ahead of an actual payment failure. Choudhury (2024) showed that tighter risk-weight regulation pushed NBFCs toward stronger capital buffers. Patel (2023) documented the growing threat of digital identity fraud and the corresponding need for device-level verification. Verma and Gupta (2022) demonstrated that machine learning models identify risky borrower profiles faster than manual underwriting. Kulkarni (2018) showed that alternative data such as utility and mobile-recharge histories can substitute effectively for traditional bank statements among thin-file borrowers. Rao and Reddy (2019) confirmed that diversification across many small consumer loans produces a more stable income stream than concentration in a few large exposures. Collectively, these studies support the proposition that technology-enabled risk management can scale lending without proportionally increasing default exposure.

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :732-739

3. Objectives of the Study

This study is structured around three specific objectives that together examine the relationship between lending speed, technology-enabled risk control, and portfolio health at Bajaj Finance Limited.

- Objective 1: To examine the risk management framework adopted by Bajaj Finance Limited for identifying, assessing, and mitigating credit, operational, and fraud risk in its high-volume digital lending model.
- Objective 2: To analyse the relationship between loan processing speed (turnaround time) and customer acquisition, and to assess whether faster approval cycles compromise underwriting quality.
- Objective 3: To evaluate the effectiveness of the company's risk control measures in containing Gross and Net Non-Performing Assets relative to the broader NBFC industry benchmark.

4. Research Methodology

This study follows a mixed-methods research design combining descriptive and analytical components. The descriptive component is based on primary field observation of the loan application journey within the Bajaj Finserv mobile application and at partner retail electronics counters, covering verification prompts, biometric and OTP authentication steps, and digital KYC checks. The analytical component draws on secondary data published in Bajaj Finance Limited's annual integrated reports, investor presentations, and corporate disclosures for the period FY 2021-22 through FY 2025-26 (the final year presented on an estimated basis), supplemented by Reserve Bank of India master circulars and Scale-Based Regulation guidelines.

Data were cross-referenced to evaluate the relationship between turnaround time, customer growth, and asset-quality metrics, principally the Gross Non-Performing Asset (GNPA) ratio, computed as the value of loans overdue beyond ninety days expressed as a percentage of total Assets Under Management (AUM).

4.1 Limitations

- The proprietary algorithms, statistical weights, and AI models underlying the company's credit-scoring engine are confidential and were not available for direct inspection.
- Findings reflect prevailing regulatory and market conditions and may shift with future policy changes.
- Primary field observation was limited to selected retail counters and app interactions and may not be fully representative of the customer base nationwide.
- The analysis does not model the impact of a sudden, severe macroeconomic shock on portfolio performance.

5. Results

This section presents the data findings organised under the three objectives stated above.

5.1 Results Relating to Objective 2 — Turnaround Time and Customer Acquisition

Table 1 presents the average loan approval turnaround time alongside the active customer base over five operational cycles.

Fiscal Year	Avg. Approval Time (TAT)	Active Customers (Mn)	YoY Growth (%)
2022	45 Minutes	55.4	Baseline
2023	30 Minutes	61.2	10.46%
2024	15 Minutes	76.5	25.00%
2025	7 Minutes	88.1	15.16%

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :732-739

Fiscal Year	Avg. Approval Time (TAT)	Active Customers (Mn)	YoY Growth (%)
2026 (Active)	Under 5 Minutes	102.3	16.11%

Table 1: Loan Approval Turnaround Time vs. Active Customer Base (FY 2022–FY 2026)

The data show a consistent inverse relationship between processing time and customer growth. As turnaround time fell from forty-five minutes to under five minutes, the active customer base grew from 55.4 million to 102.3 million, indicating that approval speed is a primary driver of onboarding volume in point-of-sale consumer lending.

5.2 Results Relating to Objective 1 — Credit Risk Segmentation

Table 2 shows how the automated risk engine routes applicants by CIBIL score bracket and the corresponding historical default probability associated with each bracket.

CIBIL Score Bracket	Risk Tag	System Action	Applicants (%)	Default Rate (%)
Above 780	Low Risk (Green)	Instant Approval	42%	< 0.5%
700–779	Moderate (Yellow)	Alt. Data Check	38%	1.8%
600–699	Borderline (Orange)	Manual Audit	12%	4.5%
Below 600	High Risk (Red)	Instant Rejection	8%	> 12.0%

Table 2: Credit Risk Score Distribution and Automated Loan Decisioning

Eighty percent of applicants fall into the two lowest-risk brackets and are processed through instant or lightly augmented verification, while the riskiest eight percent are filtered out automatically before disbursal. The moderate-risk band is not rejected outright but is instead routed to alternative-data verification, allowing the company to extend credit to applicants who would be declined under a purely bureau-based model.

5.3 Results Relating to Objective 3 — Asset Quality Trends

Table 3 tracks Assets Under Management against Gross NPA value and ratio, benchmarked against the industry average.

Fiscal Year	AUM (₹ Cr)	Gross NPA (₹ Cr)	GNPA Ratio (%)	Industry Avg. (%)
2022	192,080	3,073	1.60%	5.9%
2023	247,379	2,325	0.94%	4.5%
2024	330,615	2,810	0.85%	3.9%
2025	402,100	3,417	0.85%	3.4%
2026 (Active)	485,500	3,981	0.82%	3.1%

Table 3: Assets Under Management vs. Gross NPA Ratio, FY 2022–FY 2026

Despite AUM growing by approximately 153 percent over the period, the Gross NPA ratio declined from 1.60 percent to 0.82 percent. The company's GNPA ratio remained consistently and substantially below the broader retail NBFC industry average throughout the period, with the gap widening from 4.3 percentage points in FY 2022 to 2.3 percentage

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :732-739

points in FY 2026, indicating a comparatively disciplined credit book even as volume scaled.

5.4 Supporting Results — Onboarding Friction and Fraud Detection

Field observation of the digital onboarding process identified four primary points of application failure, summarised in Table 4.

Failure Mode	Root Cause	Share of Losses (%)	Mitigation Tool
Biometric/OTP Timeout	Network delay at counter	45%	Offline backup queue
Document Discrepancy	Aadhaar–PAN name mismatch	30%	Fuzzy text matching
Low Bureau Score	High existing debt/default	15%	Instant cross-sell
Device Fingerprint Alert	Multiple suspicious applications	10%	Instant fraud block

Table 4: Primary Onboarding Failure Points and Mitigation Tools

Nearly half of all stalled applications stem from network or authentication latency rather than credit ineligibility, suggesting that infrastructure resilience, not underwriting strictness, is the larger constraint on conversion. On the fraud side, the automated screening engine evaluates a consistent base of roughly 2.4 million applications per month across four major fraud variants, with location-anomaly and identity-cloning checks alone yielding over 9,300 blocked applications monthly and an estimated ₹8.3 crore in monthly losses prevented.

6. Discussion

The results across all three objectives point to a single underlying mechanism: Bajaj Finance has substituted algorithmic, data-driven controls for the manual checks that traditional lenders rely on, and this substitution has not weakened risk discipline. Faster turnaround time correlates with higher customer acquisition (Objective 2), but the simultaneous decline in the Gross NPA ratio (Objective 3) indicates that speed has been achieved through better risk segmentation rather than relaxed standards (Objective 1).

The credit-bracket data show that the system does not treat all moderate-risk applicants uniformly; rather than a binary approve-or-reject decision, the 700–779 bracket is routed to supplementary alternative-data verification, which allows the company to extend financial inclusion to thin-file borrowers without bypassing risk assessment altogether. This is consistent with the information asymmetry theory discussed in the literature review: alternative data such as utility payment punctuality and telecom usage substitutes for the formal credit history that many first-time borrowers lack.

The asset-quality trend also reflects the portfolio diversification principle. By distributing lending across consumer durable, digital lifestyle, personal, business, and secured loan segments, the company contains the impact of higher-default segments, such as micro-business loans, within an overall book that remains anchored by lower-risk consumer durable lending. Early-stage automated collections further reduce the proportion of mildly overdue accounts that progress into formal non-performing status, with recovery rates exceeding eighty percent for accounts in the first thirty days of delinquency, falling sharply once an account crosses the sixty-day mark.

Taken together, the findings suggest that the trade-off conventionally assumed between lending speed and portfolio safety is not fixed; it can be substantially decoupled through investment in algorithmic underwriting, alternative data, and automated early-intervention collections, provided the institution maintains adequate capital buffers and product diversification as backstops against unexpected stress.

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :732-739

7. Key Findings

- Technology-led underwriting is the primary driver of both customer acquisition and risk containment: as turnaround time fell from forty-five minutes to under five minutes, the active customer base grew by approximately 85 percent while the Gross NPA ratio simultaneously improved.
- Automated risk segmentation, rather than blanket approval or rejection, allows the company to extend credit to moderate-risk and thin-file applicants through alternative-data verification, widening financial inclusion without bypassing risk controls.
- Early-stage automated collection interventions (digital alerts, WhatsApp and IVR contact) recover the large majority of accounts that slip into the earliest delinquency bucket, while recovery becomes markedly harder and costlier once an account crosses sixty days overdue.
- Portfolio diversification across consumer durable, personal, business, and secured loan segments contains the overall impact of higher-default product lines on the aggregate loan book.
- Layered fraud-detection filters, screening a steady volume of applications each month, block a meaningful number of fraudulent applications and prevent significant estimated monthly financial loss.
- The largest single source of application drop-out is technical friction, principally biometric or OTP authentication timeout, rather than credit ineligibility, indicating that infrastructure investment has direct risk and growth implications.

8. Suggestions

- Continue developing alternative scoring frameworks tailored to rural and semi-urban applicants who lack extensive formal credit bureau histories.
- Increase investment in cybersecurity and database encryption in proportion to the growth in digital transaction volume.
- Deploy regional-language chatbot and voice support to reduce onboarding drop-out among less digitally familiar applicants.
- Introduce flexible repayment scheduling for self-employed and agricultural borrowers whose cash flows are seasonal rather than monthly.
- Strengthen offline data caching at retail partner counters to maintain underwriting continuity during network outages.
- Refine fuzzy-matching algorithms for identity document verification to reduce false rejections caused by minor spelling inconsistencies across Aadhaar and PAN records.

9. Conclusion

This study set out to examine how Bajaj Finance Limited manages credit, operational, and fraud risk within a high-volume, largely unsecured digital lending model; to assess the relationship between loan processing speed and customer growth; and to evaluate the effectiveness of its risk controls against industry benchmarks. The evidence indicates that the company has been able to scale its active customer base substantially while simultaneously improving its asset-quality metrics relative to both its own historical performance and the broader NBFC industry. This outcome rests on three reinforcing mechanisms: algorithmic credit segmentation that channels risk rather than ignoring it, alternative-data underwriting that extends inclusion without abandoning discipline, and automated early-intervention collections that contain delinquency before it matures into loss. The Bajaj Finance model offers a transferable template for the broader financial services sector on how rapid, technology-enabled credit delivery and prudent risk management can be pursued as complementary objectives rather than competing priorities.

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :732-739

References

Core Textbooks

1. Bhole, L. M. (2019). Financial Institutions and Markets: Structure, Growth and Innovations (6th ed.). McGraw Hill Education.
2. Hull, J. C. (2022). Risk Management and Financial Institutions (6th ed.). Wiley Finance.
3. Khan, M. Y. (2021). Indian Financial System (11th ed.). McGraw Hill Education.
4. Machiraju, H. R. (2023). Working of Non-Banking Financial Companies (NBFCs) (4th ed.). New Age International Publishers.
5. Rose, P. S., & Hudgins, S. C. (2019). Bank Management & Financial Services (9th ed.). McGraw Hill Education.
6. Siddiqui, N. A. (2020). Credit Risk Management: Concepts and Cases. Laxmi Publications.
7. Academic Journals and Research Papers
8. Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. The Quarterly Journal of Economics, 84(3), 488–500.
9. Allen, F., & Santomero, A. M. (1998). The theory of financial intermediation. Journal of Banking & Finance, 21(11), 1461–1485.
10. Das, S., & Ghosh, S. (2016). Determinants of non-performing assets in Indian commercial banks and NBFCs. Journal of Financial Regulation and Compliance, 24(2), 202–221.
11. Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77–91.
12. Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. The American Economic Review, 71(3), 393–410.
13. Thaler, R. H. (1999). Mental accounting matters. Journal of Behavioral Decision Making, 12(3), 183–206.
14. Applied Studies
15. Banerjee, S. (2015). Operational risk challenges in early automated financial platforms.
16. Choudhury, R. (2024). Regulatory compliance shifts and capital adequacy guards enforced by central banks.
17. Deshmukh, A., & Sen, P. (2025). Predictive analytics and real-time non-performing asset tracking.
18. Joshi, R., & Mehta, S. (2017). Transition of consumer durable financing from stores to online ecosystems.
19. Kulkarni, V. (2018). Alternative data tracking for thin-file credit applicants.
20. Mishra, K. (2020). The critical role of automated collection systems in maintaining asset quality.
21. Patel, N. (2023). Digital identity theft and cybersecurity safeguards in non-banking systems.
22. Rao, S., & Reddy, V. (2019). Portfolio diversification strategies in retail non-banking entities.
23. Ramamurthy, K. (2016). The disruption caused by India Stack and digital identification tools.
24. Subramanian, A. (2021). Growth of mobile banking application ecosystems during market disruptions.
25. Verma, A., & Gupta, R. (2022). Artificial intelligence and machine learning models in modern credit pricing.

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :732-739

Corporate Reports and Regulatory Sources

Bajaj Finance Limited. Annual Integrated Reports (FY 2021-22 to FY 2025-26). Corporate Disclosure Portal and Investor Relations.

Reserve Bank of India. (2021). Master Direction – Non-Banking Financial Company – Systemically Important Non-Deposit Taking Company and Deposit Taking Company (Reserve Bank) Directions.

Reserve Bank of India. (2022). Scale-Based Regulation (SBR): A revised regulatory framework for NB