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A Study on Loan Default Prediction at Bajaj Finance Limited

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***Abstract-** Loan default remains one of the more persistent challenges facing non-banking financial companies, and Bajaj Finance Limited, as one of India's largest NBFCs, is no exception. This article examines the factors that shape borrowers' likelihood of default and the analytical approach through which such risk can be anticipated. Drawing on a structured survey of 101 respondents together with an underlying logistic regression framework, the study looks at how income level, EMI burden, existing liabilities, credit score, repayment history and exposure to unexpected expenses relate to repayment outcomes. It also outlines a probability-based classification scheme that sorts borrowers into low-, medium- and high-risk categories, a tool intended to support faster and more consistent credit decisions. The survey results show that respondents are drawn predominantly from younger, lower- and middle-income segments, that a substantial share have experienced delayed EMI payments at some point, and that poor financial planning, existing debt obligations and unexpected expenses are widely seen as significant contributors to repayment difficulty. Credit score and repayment history, meanwhile, are broadly recognised as central to loan approval and to predicting future behaviour. The article concludes that combining sound credit assessment with continuous account monitoring and predictive analytics allows lenders such as Bajaj Finance to identify risk earlier and manage it more effectively, supporting growth without compromising portfolio quality.*

***Keywords-** Loan Default, Credit Risk, Bajaj Finance, NBFC, Logistic Regression, Risk Classification, Repayment Behaviour*

I. INTRODUCTION

Financial intermediation channels savings toward borrowers and is one of the more consequential mechanisms by which an economy grows, yet for a long time this channel ran narrowly through banks that favoured applicants with steady employment and an established repayment record. Stricter documentation and lending norms left a considerable share of the population without easy access to credit. Over the past two decades, lighter-touch regulation, improving technology and rising demand for credit have reshaped this landscape, and non-banking financial companies have emerged as a significant complement to traditional banks — faster to approve loans, more adaptable in their documentation requirements, and more willing to serve customers that conventional lenders often overlook.

Bajaj Finance Limited is among the more prominent examples of this shift. A loan default occurs whenever a borrower is unable to meet a repayment obligation, and such events carry consequences well beyond the individual loan — they weigh on profitability, cash flow and, at scale, on institutional stability. Identifying the warning signs of default before repayment actually breaks down is therefore central to how a lender like Bajaj Finance manages credit risk, and it is this question — what predicts default, and how that prediction can be operationalised — that this study sets out to examine.

II. INDUSTRY PROFILE

The financial services sector in India spans banks, insurance companies, investment firms and non-banking financial companies, together forming the infrastructure through which savings are mobilised and credit is extended. NBFCs occupy a distinctive place within this system: unable to accept demand deposits as banks do, they have nonetheless built a reputation for quick loan approval and simpler documentation, making them a natural channel for borrowers who might not qualify easily at a conventional bank.

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Demand for consumer loans, personal loans and digital credit has grown rapidly in India in recent years, and this growth has been accompanied by a corresponding rise in default risk. In a lending environment shaped increasingly by digital channels and intense competition, data-driven decision-making has become central to how credit risk is managed. For lenders, a clear understanding of default is valuable chiefly because it helps reduce bad debts, sharpen loan-approval decisions, protect profitability, and safeguard company assets more broadly.

III. PROFILE OF BAJAJ FINANCE LIMITED

Bajaj Finance began operations in 1987 as Bajaj Auto Finance Limited, originally set up to fund two- and three-wheeler purchases. Over the following decades the company broadened its focus well beyond vehicle finance, and today, as Bajaj Finance Limited, it ranks among India's leading non-banking lenders. Operating under the umbrella of the Bajaj Group and its financial-services arm, Bajaj Finserv, the company now offers a wide array of products, including consumer loans, personal loans, business loans, home loans, EMI financing and insurance-related services, delivered through a mix of branch offices, digital platforms, mobile applications and partner stores across urban, semi-urban and rural India.

The company's stated vision is to become the most trusted and preferred provider of financial services in the country by delivering customer-focused solutions that help people meet their financial goals with confidence, supported by a mission built around easy and quick access to finance, strong customer service, the use of technology in decision-making, and sustainable growth. Its quality policy places emphasis on customer satisfaction, service quality, transparency, innovation and risk management.

Bajaj Finance's principal competitors include HDFC Bank, ICICI Bank, Muthoot Finance, Shriram Finance and Tata Capital, all of which compete aggressively on loan pricing, speed of approval and digital convenience. A SWOT assessment points to a strong brand, a large customer base, fast approvals and a well-developed digital platform as key strengths, offset by a heavy dependence on loan repayments, exposure to customer default and sensitivity to broader economic slowdown. Growth in digital lending, rising demand for personal credit and expansion into rural markets stand out as the clearer opportunities ahead, while rising competition, loan defaults, regulatory change and economic instability remain the principal threats. Looking forward, the company appears to be placing growing emphasis on AI-based credit analysis and improved default prediction as tools for managing risk as its lending book continues to expand.

IV. THEORETICAL FRAMEWORK FOR LOAN DEFAULT PREDICTION

At the centre of default prediction lies a straightforward but consequential question: how likely is a given borrower to fail to repay? Lenders such as Bajaj Finance address this question by examining spending habits, transaction histories and past repayment patterns rather than relying on guesswork, using these signals to inform who is approved, on what terms, and how closely an account should be monitored after disbursement. As digital lending has expanded access to credit, the accuracy of these predictions has become more consequential, since a wider and more varied pool of borrowers also means a wider range of underlying risk.

Several theoretical strands inform how default risk is understood. Foundational finance theory treats risk and return as inherently linked — the possibility of greater reward typically comes bundled with the possibility of greater loss — which is one reason lenders price loans to riskier borrowers at higher interest rates, effectively compensating for the added uncertainty of non-repayment. The Capital Asset Pricing Model, developed originally for equity markets, extends this logic by relating expected return to the level of risk assumed, an idea whose reasoning carries over into how lenders think about pricing credit. Modern Portfolio Theory, in turn, underpins the practice of diversifying a loan book across borrower types and product categories, on the premise that a well-diversified mix of exposures reduces overall risk more effectively than concentration in any single segment. The Efficient Market Hypothesis, though developed for securities markets, offers a related insight for lending: that available information tends to be reflected quickly in how loans are priced and structured. Behavioural factors round out the picture — borrowing decisions are often shaped as much by social influence, habit or confidence as by careful calculation, and repayment discipline can weaken when emotion or group behaviour override financial logic.

Risk itself, in a lending context, refers to the uncertainty over whether a borrower will be able to repay, and can usefully be separated into two broad categories. Systematic risk arises from factors external to any individual borrower — economic slowdown, inflation, interest-rate movements, regulatory change or global financial stress — and affects the entire lending system in ways that cannot be diversified away. Unsystematic risk, by contrast, is specific to a borrower or narrow market segment, arising from circumstances such as job loss, poor money management, business failure or personal crisis, and can be reduced through careful credit evaluation, diversification, and ongoing monitoring through credit-rating and account-tracking systems.

V. REVIEW OF LITERATURE

Research on credit risk and default prediction spans a wide range of statistical and machine-learning approaches, each with its own strengths and limitations. Early classification work by Cover and Hart (1967) and Hand and Henley (1997) established the k-nearest neighbours method as effective for smaller datasets, though computationally demanding once applied at scale. Decision-tree approaches such as ID3 and CART, introduced by Quinlan (1986) and Breiman et al. (1984), offered a more interpretable alternative but were found prone to overfitting, tailoring themselves too closely to training data at the expense of generalisability. Breiman (2001) and Liaw and Wiener (2002) showed that Random Forest, an ensemble of decision trees, addressed much of this overfitting problem while improving predictive accuracy, and ensemble methods more broadly have since become valued for their robustness.

Other studies examined simpler, more transparent models. Domingos and Pazzani (1997) and Baesens et al. (2003) found Naïve Bayes classifiers efficient though constrained by their assumption of feature independence, while Thomas et al. (2002) and Hosmer and Lemeshow (2000) highlighted logistic regression as particularly well suited to credit-risk work owing to its interpretability, even though it struggles to capture more complex, nonlinear relationships in borrower behaviour. Neural networks, examined by West (2000) and Malhotra and Malhotra (2003), delivered higher predictive accuracy but at the cost of interpretability, a trade-off echoed in later work on Support Vector Machines by Baesens et al. (2003) and Huang et al. (2007), which showed strong classification performance contingent on careful parameter tuning.

More recent research has increasingly turned to comparative and hybrid approaches. Lessmann et al. (2015) benchmarked machine-learning methods against traditional statistical models and found the former generally superior in prediction accuracy, while Guyon and Elisseeff (2003) demonstrated that careful feature selection both simplifies models and improves their performance. The Basel Committee (2004) and Khandani et al. (2010) argued for integrating machine-learning techniques with established risk-management frameworks to strengthen institutional stability, and Tsai and Wu (2008) showed that hybrid models combining multiple algorithms can meaningfully improve accuracy, albeit at the cost of added complexity. Russell and Norvig (2010) and Khandani et al. (2010) further explored how artificial intelligence enhances predictive performance in financial risk management even as it complicates transparency, a concern echoed by Chen and Guestrin (2016) and Ke et al. (2017) in their work on gradient-boosting methods such as XGBoost and LightGBM.

Several studies address concerns specific to explainability and emerging lending contexts. Ribeiro et al. (2016) and Lundberg and Lee (2017) introduced explainable-AI techniques such as LIME and SHAP, aimed at making complex model predictions more transparent and usable in financial decision-making. Chen et al. (2012) and Fan et al. (2014) examined the role of big data in improving prediction accuracy, while Malekipirbazari and Aksakalli (2015) emphasised the value of early default prediction in identifying high-risk borrowers before losses accumulate. Goodfellow et al. (2016) and Sirignano et al. (2018) explored deep-learning approaches to time-series financial data, finding improved accuracy alongside considerable computational cost. Closer to the Indian context, Arner, Barberis and Buckley

(2016) discussed how fintech innovation has reshaped credit-risk management, and the RBI (2021) together with Kumar and Mishra (2022) documented how digital lending platforms in India increasingly draw on alternative data such as transaction history and behavioural signals, even as this raises fresh concerns around data privacy and credit risk.

VI. RESEARCH GAP

Much of the existing literature centres on banks or on international lending contexts rather than on Indian NBFCs specifically, leaving relatively little direct, head-to-head comparison of how machine-learning methods perform against traditional statistical models within firms like Bajaj Finance. A large share of prior research also predates the pandemic and may not fully capture how borrower behaviour has shifted since. Real-time data analysis, behavioural indicators drawn from digital engagement, and prediction tools built specifically for India's fast-growing digital-lending environment remain comparatively underexplored, and this study aims to speak to that gap by examining borrower-level risk factors directly within the Bajaj Finance context.

VII. STATEMENT OF THE PROBLEM

When borrowers fail to repay, the effects extend beyond the individual loan to profits, cash flow and day-to-day operations at the lending institution. Bajaj Finance serves a broad and varied customer base across multiple loan products, making it important to understand which borrower characteristics are most closely associated with default, and how those characteristics can be combined into a workable predictive framework.

VIII. OBJECTIVES OF THE STUDY

- To identify the key factors influencing loan default.
- To analyse the relationship between borrowers' income and loan repayment behaviour.
- To examine the impact of EMI burden and existing debts on loan default risk.
- To evaluate the significance of credit score and repayment history in predicting loan default.
- To assess the effect of financial emergencies and unexpected expenses on EMI repayment.

IX. SCOPE OF THE STUDY

The study is confined to an examination of borrower-level financial and behavioural variables associated with loan default at Bajaj Finance Limited, drawing on both a structured borrower survey and secondary data on company performance. It aims to support more informed credit decisions by identifying the characteristics most closely linked to default risk and by illustrating how these characteristics can feed into a predictive scoring framework.

X. RESEARCH METHODOLOGY

The study follows a descriptive, analytical and predictive research design, combining an examination of borrower characteristics with the development of a model capable of estimating default probability. Its quantitative and analytical nature reflects its reliance on measurable borrower variables — income, credit score, loan amount, existing liabilities and repayment record — analysed statistically to uncover their relationship with default outcomes.

Data were drawn from two sources. Secondary data, covering company financial statements from 2019 to 2023 together with published borrower-level information on age, income, employment status, credit score, loan amount, existing debt, tenure, repayment history and default status, were compiled from company reports, RBI publications, credit-risk datasets and academic sources. Primary data were gathered through a structured survey of 101 respondents, selected via convenience sampling to include a mix of borrowers with successful repayment records, delayed repayments, and partial or complete defaults, in order to support meaningful comparison between defaulting and non-defaulting profiles.

The dependent variable in the study is loan default status, a binary outcome in which a value of 1 denotes default and 0 denotes successful repayment. Eight independent variables were used to explain this outcome: income level, credit score, loan amount, employment status, existing liabilities, loan tenure, repayment history and borrower age — each selected for its established relationship with repayment capacity. Borrowers with stable, higher incomes and strong credit scores are generally associated with a lower probability of default, while higher loan amounts, longer tenures and heavier existing liabilities tend to push default probability upward.

To estimate this probability, the study applies logistic regression, a method well suited to binary classification problems of this kind. The model takes the form

$$P(Y = 1) = 1 / [1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)}]$$

where $P(Y = 1)$ is the estimated probability of default, β_0 is the constant term, β_1 through β_n are the regression coefficients, and X_1 through X_n are the independent variables described above. For instance, a borrower earning ₹30,000 a month with a loan amount of ₹5,00,000 and a credit score of 600 might generate a predicted default probability of around 0.75 — high enough that Bajaj Finance would likely decline the application or approve it only under stricter conditions.

Predicted probabilities are then translated into a three-tier risk classification: borrowers scoring between 0.00 and 0.30 are classed as low risk, reflecting stable income, sound credit history and consistent repayment behaviour; those between 0.31 and 0.60 fall into a medium-risk category requiring closer monitoring; and those above 0.60 are classed as high risk, typically marked by weak credit scores, irregular repayment history and heavy existing debt. This classification framework is intended to help the company sharpen lending decisions, reduce losses, monitor at-risk accounts more closely, and maintain overall portfolio quality. Descriptive statistics, correlation analysis, logistic regression, risk classification and graphical presentation together make up the principal analytical tools used in the study, and all borrower data were handled confidentially and used strictly for academic purposes.

XI. LIMITATIONS OF THE STUDY

- The findings are based on a convenience sample of 101 respondents and secondary data drawn from a five-year window, and may not fully generalise across Bajaj Finance's entire customer base or lending history.
- Self-reported survey responses may be influenced by personal perception and recall rather than verified financial records.
- The predictive framework outlined here relies on logistic regression; more complex machine-learning methods might yield different accuracy trade-offs.

XII. DATA ANALYSIS AND INTERPRETATION

The following tables summarise responses collected from the 101-respondent borrower survey.

Table 1: Age Distribution of Respondents

Response	No. of Respondents	Percentage (%)
Below 25 years	20	19.8
25–30 years	39	38.6
30–40 years	17	16.8
40–50 years	19	18.8
Above 50 years	6	5.9

Respondents in the 25–30 age bracket make up the largest single group, and together with those under 25 they account for close to three-fifths of the sample, indicating that borrowing activity is concentrated among individuals in the earlier stages of their careers. Very few respondents are above 50, suggesting that older customers rely less on credit, whether through accumulated savings or more conservative financial habits.

Table 2: Occupational Profile of Respondents

Response	No. of Respondents	Percentage (%)
Student	35	34.7
Salaried Employee	23	22.8
Business	18	17.8
Self-Employed	18	17.8
Others	8	7.9

Students form the largest occupational category, pointing to a growing reliance on consumer and educational credit among younger borrowers, while salaried employees, whose income tends to be steadier, make up the next largest share. Business owners and the self-employed, whose earnings are more likely to fluctuate, together account for over a third of the sample.

Table 3: Monthly Income of Respondents

Response	No. of Respondents	Percentage (%)
Below ₹20,000	41	40.6
₹20,000–₹40,000	43	42.6
₹40,001–₹60,000	11	10.9
Above ₹60,000	6	5.9

More than four in five respondents earn below ₹40,000 a month, confirming that Bajaj Finance's customer base is drawn predominantly from lower- and middle-income segments — a group for whom unexpected financial strain is more likely to translate into repayment difficulty.

Table 4: Type of Loan Availed

Response	No. of Respondents	Percentage (%)
Personal Loan	34	33.7
Consumer Durable Loan	25	24.8
Business Loan	18	17.8
EMI Finance	10	9.9
Others	14	13.9

Personal loans are the most common product among respondents, followed by consumer durable financing, together pointing to individual and household needs as the dominant driver of borrowing, with business and EMI-based lending making up a smaller share of the portfolio.

Table 5: Approximate Loan Amount

Response	No. of Respondents	Percentage (%)
Below ₹50,000	48	47.5
₹50,000–₹1,00,000	33	32.7
₹1,00,000–₹5,00,000	19	18.8
Above ₹5,00,000	1	1.0

Close to half the respondents have borrowed less than ₹50,000, and loans above ₹5,00,000 are rare, suggesting that most customers favour smaller, more manageable amounts rather than large-ticket borrowing.

Table 6: Repayment Period of Loan

Response	No. of Respondents	Percentage (%)
Less than 1 year	37	36.6
1–3 years	44	43.6
3–5 years	19	18.8
Above 5 years	1	1.0

A repayment window of one to three years is the most common choice, balancing manageable EMI amounts against a reasonably short repayment horizon, while very few respondents opt for tenures beyond five years.

Table 7: Number of Active Loans Held

Response	No. of Respondents	Percentage (%)
One	56	55.4
Two	35	34.7
Three	10	9.9
More than Three	0	0.0

A majority of respondents are carrying only a single active loan at a time, which points to relatively contained debt exposure across the sample, though

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roughly a third are juggling two or more obligations simultaneously.

Table 8: Incidence of Delayed EMI Payments

Response	No. of Respondents	Percentage (%)
Yes	49	48.1
No	53	51.9

Just over half the respondents report having always paid on time, but the near-even split means that delayed payments are far from rare, pointing to meaningful repayment strain within a large part of the customer base.

Table 9: Perceived Effect of Low Income on Timely Repayment

Response	No. of Respondents	Percentage (%)
Strongly Disagree	26	25.5
Disagree	26	25.5
Neutral	26	25.5
Agree	16	15.7
Strongly Agree	8	7.8

Opinion on this item is unusually evenly split across three of the five categories, with roughly a quarter of respondents in each of the strongly-disagree, disagree and neutral bands; only around a quarter agree or strongly agree that low income directly compromises timely repayment, suggesting that income level alone is not seen as the dominant driver of delay.

Table 10: Perceived Effect of High EMI Burden on Default Risk

Response	No. of Respondents	Percentage (%)
To a Great Extent	36	35.3
Neutral	54	52.9
Not at All	10	9.8
Others	2	2.0

Just over a third of respondents clearly link a heavy EMI burden to higher default risk, though the largest group remains neutral, implying that the effect of EMI load is felt unevenly and likely depends on each borrower's broader financial position.

Table 11: Perceived Effect of Existing Debts on Repayment Capacity

Response	No. of Respondents	Percentage (%)
Always	27	26.5
Often	30	29.4
Sometimes	34	33.3
Rarely	6	5.9
Never	3	2.9
Others	2	2.0

The great majority of respondents acknowledge that existing debt obligations affect their repayment capacity at least some of the time, with over a quarter saying this happens always — underscoring how multiple concurrent liabilities can quickly compound repayment pressure.

Table 12: Impact of Unexpected Expenses on EMI Delays

Response	No. of Respondents	Percentage (%)
High Impact	33	32.4
Medium Impact	49	48.1
Low Impact	19	18.6
No Impact	1	1.0

Nearly a third of respondents report that unplanned expenses have a strong effect on their ability to pay EMIs on time, and close to half report at least a moderate effect, making unexpected costs one of the more consistently disruptive factors identified in the survey.

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Table 13: Perceived Effect of Poor Financial Planning on Repayment Problems

Response	No. of Respondents	Percentage (%)
Strongly Agree	30	29.4
Agree	42	41.2
Neutral	19	18.6
Disagree	9	8.8
Strongly Disagree	0	0.0
Others	2	2.0

A clear majority of respondents agree or strongly agree that inadequate financial planning contributes to repayment problems, making this one of the more decisively endorsed items in the survey and pointing to budgeting discipline as a meaningful factor in default risk.

Table 14: Perceived Role of Credit Score in Loan Approval

Response	No. of Respondents	Percentage (%)
Strongly Agree	32	31.4
Agree	42	41.2
Neutral	22	21.6
Disagree	3	2.9
Strongly Disagree	1	1.0
Others	2	1.9

Most respondents recognise credit score as an important factor in loan approval decisions, with disagreement almost negligible — evidence that borrowers are broadly aware of how much their credit history weighs on lending outcomes.

Table 15: Perceived Predictive Value of Past Repayment Behaviour

Response	No. of Respondents	Percentage (%)
Yes	51	50.0
No	23	22.5
Maybe	28	27.5

Exactly half the respondents believe that past repayment behaviour is a reliable guide to future performance, while the rest are split between disagreement and uncertainty, broadly supporting the use of repayment history as one input among several in a prediction model rather than as a standalone indicator.

XIII. FINDINGS, SUGGESTIONS AND CONCLUSION

Findings

- Income level has a clear bearing on repayment behaviour, though the survey suggests it interacts with other factors rather than acting as the sole determinant of default.
- A heavier EMI burden and multiple concurrent loans are associated with a greater likelihood of default, consistent with the view that cumulative debt load compounds repayment risk.
- Credit score and repayment history are widely regarded by both the literature and survey respondents as strong indicators of future default risk.
- Financial emergencies and unexpected expenses were identified by a large share of respondents as a meaningful cause of delayed EMI payments.
- Default risk appears to be shaped by the interaction of several factors together — income, EMI burden, existing debt, credit score and exposure to financial shocks — rather than by any single variable in isolation.

Suggestions

- Bajaj Finance should continue to assess borrowers' income carefully at the point of loan approval, giving weight to income stability rather than income level alone.
- Borrowers carrying a high EMI burden or multiple active loans should be flagged for more regular monitoring after disbursement.
- Credit score and repayment history should remain central inputs to approval decisions, given how strongly both the literature and this survey support their predictive value.

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- Flexible repayment options, such as short-term restructuring, would help customers facing genuine financial emergencies without immediately classifying them as defaulters.
- Continued investment in predictive analytics — potentially extending beyond logistic regression into ensemble or explainable-AI methods — would help the company identify risk earlier and more precisely.

XIV. CONCLUSION

This study set out to understand what drives loan default at Bajaj Finance Limited and how that risk might be anticipated rather than simply managed after the fact. The evidence points to a familiar but important conclusion: default is rarely traceable to a single cause, but instead emerges from the interaction of income stability, existing debt, credit history and exposure to financial shocks. Borrowers with irregular income and heavier existing obligations are more likely to fall behind, while those in stable employment with disciplined repayment habits tend to manage their obligations more comfortably. A structured, data-driven approach to assessing these factors — of the kind outlined through the logistic regression framework and risk classification scheme presented here — offers lenders a more consistent basis for approval decisions than judgment alone, and allows early identification of accounts that may need closer attention. For Bajaj Finance, embedding this kind of predictive discipline into everyday lending decisions offers a practical path toward reducing bad debt while continuing to expand access to credit across its customer base.

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