# A study of borrower financial stress and its implications for retail credit risk- An integration of artificial intelligence in behavioral finance

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**Abstract**

Indian banking system has a unique blend of participants Banks and non-banking financial corporations (NBFCs). Banks base their lending primarily based on deposits while NBFCs are non -deposit based institutions. The NBFCs play an important role in the financial eco-system of an economy by providing last-mile credit intermediation, absorbing, and diversifying risks by catering to those segments of the society which remains unbanked, underserved, and underdeveloped. The lending of both banks and NBFCs expanded their credit portfolios under the Viksit Bharat initiative in recent years, resulting in borrowers having easier access to loans than ever before. Retail lending has witnessed significant growth in India in recent years. As a result, borrowers often take multiple loans to meet their financial needs. However, the increased availability of credit has adversely affected people's financial well-being, especially after the pandemic. This research paper examines the relationship between borrowers' financial stress, its impact on repayment behaviour, and credit risk in the retail segment.

The aim of the study is to analyse the crucial financial and behavioural factors that contribute to defaults among retail borrowers and to examine their influence on repayment capacity. Variables such as EMI burden, income stability, unexpected expenses, and overall debt obligations have been considered as key indicators for this study. In addition, behavioral and psychological factors such as financial anxiety and perceived repayment pressure have been analysed to understand their role in influencing borrowers' credit behaviour. With the increase in adaption of artificial intelligence (AI) the current pilot study explores the impact of AI in process of data collection, monitoring, credit assessment of barrowers and also the repayment ability is being modelled.

The findings reveal that there is no significant difference in the level of financial stress between borrowers of Non-Banking Financial Companies and retail banks, indicating that stress is driven more by individual financial circumstances than by the source of borrowing. The study concludes that financial stress indicators are critical tools for evaluating borrower credit risk for both Non-Banking Financial Companies and retail banks. It enhances the risk assessment process and provides lenders with early warning signals of default. It also highlights that lenders should place greater emphasis on financial factors such as income stability, debt levels, and exposure to unexpected expenses while assessing borrower risk.

**Keywords:**

Borrower Financial Stress, Retail Credit Risk, Behavioural finance, Retail banks, NBFCs

## I. Introduction

Rerail lending has witnessed significant growth influenced by factors such as increase in financial inclusion, rise in digital lending platforms and rising demand and consumption in this space. Retail lending products such as home loans and consumer durable loans have become easily accessible to everyone. This expansion of digital lending has contributed to economic growth in the country and improved the access to credit borrowers, but it has also created a lot of concern regarding repayment capacity of the borrowers and the credit growth sustainability.

Financial stress can arise due to multiple factors such as increase in the EMI amount, instability of income among various age groups, and highly relying on credit card which will eventually lead to vicious cycle of debt. When borrowers go through financial difficulty, their ability to repay the credit or loan is affected, this increases the default probability of the borrower.

## II. Literature Review

Rinku and Sharma (2026) studied the impact of high interest emergency loans given by the NBFCs and conclude that it creates high debt-trap, psychological stress and default in loans for the borrowers. The study shows that rising interest rates and shorter repayment periods surge financial strain, which increases stress and the likelihood of default by borrowers. It also underscores the importance of responsible lending and the need to address the blocking of formal credit sources in rural India that compels farmers to opt for informal credit facilities which inevitably result in distress sale of agriculture produce at sub-optimal prices.

Altaf and Shah (2025) applied a PLS-SEM method, showed that credit score literacy has a significant effect on financial behavior and borrowing decisions of the people in India. According to the study, psychological characteristics and financial literacy are found to have a combined influence on the borrowing behavior, but the influence of credit score literacy is found to be significant in the case of borrower behavior without considering the psychological characteristics. It also emphasizes the need for financial consciousness and behavioral characteristics to further improve responsible borrowing and credit risk assessment mechanisms.

Jha et al. (2025) investigated how loan burden affects the livelihoods of micro enterprises in suburban regions. Furthermore, the research underscores that there is a need to be more stringent in protecting borrowers, as well as more supportive of institutions, in order to further reduce financial stress among small business owners. It highlights the importance of developing better regulatory systems, access to credit and better borrower protection policies to encourage sustainable growth and less financial vulnerability.

Komatineni (2025) examined the application of automated data processing approaches. The author identifies the need of using multiple data types and behavioural cues, in addition to algorithmic risk classification, to enhance credit decisions. It also highlights the use of data-driven credit scoring frameworks as a means to enhance risk management, especially in complex and changing lending environments.

KS (2025) explored the journey of credit risk management in India's financial landscape, emphasizing the shift from reactive to proactive risk management systems. The study highlights the key role of strengthening regulation, better risk governance and dynamic risk assessment mechanisms as solutions. It also highlights the importance of ongoing updating of credit risk indicators to strengthen financial stability and resilience to cope with systemic and macroeconomic shocks.

Radhika and Resmi (2025) discussed borrower perceptions of the credit risk management practices in urban cooperative banks and note that appropriate credit risk assessment, transparency and monitoring processes influence their behavior. This study indicates that borrowers consider structured evaluation of their credit and fair treatment to be necessary to maintain financial discipline and minimize default risk. It also underscores the need to fortify credit risk management practices to boost borrower confidence and strengthen the cooperative banking institutions' stability and performance.

Singh and Mohanty (2025) examined how credit-risk assessment systems in Indian commercial lending have performed and conclude that algorithmic and machine learning–based systems are much more effective than traditional systems in predicting default rates and in lowering non-performing asset (NPA) rates. The study emphasizes the improvements in the efficiency and consistency of credit evaluation through automation, especially when it comes to retail and MSME lending. It does, however, also highlight key areas of concern, including algorithmic bias and the lack of reliability in evaluating the creditworthiness of borrowers without bank accounts or with thin files, where responsible governance of AI and hybrid credit scoring are all the more necessary.

Tilwani (2025) compared the stress in loan repayment faced by banks and NBFCs in terms of GNPA and NNPA, suggesting that asset quality indicators are important proxies for measuring stress in loans and their ability to be repaid.

Raje (2024), discussed the increasing importance of psychological and behavioural characteristics, in addition to conventional financial data, in default risk for collateral lending in the country. The study indicates that personality-based characteristics could be used to augment the credit evaluation systems and be a useful element in understanding the reliability of a borrower as well as the nature of their decision-making process, especially when financial information is sparse. This is consistent with recent studies demonstrating the predictive power of behavioural and psychological characteristics of loans, including in credit scoring models, and their role in default risk assessment.

Goel and Rastogi (2023) reviewed previous studies and observed that the behavioural and psychological characteristics of borrowers are vital non-financial factors affecting credit risk and borrower default behaviour. Based on the study, a conceptual framework is suggested to present how these attributes can be incorporated into credit evaluation using behavioural credit scoring concepts which would help the lenders to evaluate the reliability of the borrower beyond financial parameters. The authors also call attention to the lack of studies that used to incorporate such psychological constructs, especially in emerging markets, and their potential in the credit assessment of borrowers with few financial records.

In the context of Indian microfinance institutions, Sangwan et al. (2021) discussed the determinants of credit risks on the borrower level and the effect of repayment interventions on loan delinquency. The study concluded that the perception of repayment interventions and group homogeneity have a significant effect on the moral hazard and consequently the level of delinquencies, and that the socio-economic characteristics have a significant role in the repayment behavior. The study emphasizes the importance of studying the relationship among borrower perception, moral hazard and credit risk factors for better credit risk management in unsecured microfinance lending.

Ahuja (2019) analysed macro-economic stress testing model for evaluating the default payments in the finance and services sector in the country. There is a growing need to integrate the macro-economic variables with the performance of loan portfolio. The research paper emphasizes the need to include stress scenarios for economic downturn, interest rate movements and sectoral shocks. It emphasizes the importance of adopting a system-based risk assessment for the financial sector to enhance financial stability and resilience.

Pandey, Bandyopadhyay and Guiette (2019) examined the contributions of various credit sources to farmers' distress in India and conclude that the informal credit sources are important in heightening the farmers' financial vulnerability with high rates of interest and biased lending practices. The study points out that the absence of institutional credit and constraints in the agricultural sector push farmers to rely on unregistered intermediaries, which leads to the cycle of debt and increase in distress. It also stresses the importance of the nature and source of credit as a key determinant of borrower wellbeing, apart from the quantum of credit.

Field et al. (2012) have found strong empirical evidence, based on the results of a randomized control trial, that higher repayment flexibility has a negative impact on borrowers' financial stress in microfinance environments. Those borrowers who had more flexible repayment schedules (monthly rather than weekly) were significantly less worried and had higher investments and incomes.

Sahu, Madheswaran and Rajasekhar (2004) underscored the need for credit constraints, under-financing and the lack of bargaining power forcing borrowers into mutually coupled credit-output markets, further increasing financial vulnerability. It also highlights the importance of weak institutional support and weak implementation of pricing policies in exacerbating financial distress and the indebtedness trap in rural economies.

## III. Objectives of the study:

- To determine the association among borrower financial stress and retail risk of credit among the Indian loan customers
- To examine how different factors like burden of EMI, instability of income among individuals, unsecured loans and informal borrowing that are affecting repayment behavior.
- To understand how different factors of behavioral and psychological stress such as financial anxiety and the pressure of repayment increasing the chances of default.
- To study how the stress faced by the borrower is causing financial stress based on the lender i.e. (Retail banks vs NBFC).
- To investigate the impact of implementing financial stress indicators on improving credit risk assessment and enabling early warning mechanisms.
- Integrate AI in data capturing, monitoring and propose prediction models of financial stress.

## IV. Hypothesis of the study:

**$H_{01}$:** Borrower financial stress and retail credit risk are interrelated.

**$H_{02}$:** Factors such as EMI burden, income instability, unsecured loans, and informal borrowing significantly affect repayment behaviour.

**$H_{03}$:** Psychological financial stress significantly influences the probability of default.

**$H_{04}$:** There is a significant difference in borrower financial stress between customers of retail banks and NBFCs.

**$H_{05}$:** Including borrower financial stress indicators significantly improves credit risk assessment and early detection.

## V. Method:

### 5.1 Design

The study is exploratory in nature. A descriptive approach has been used to know the borrowers' characteristics, financial behavior and stress levels whereas the analytical approach in the study is used to examine the relationship between various variable factors using the statistical tool SPSS. A structured questionnaire has been developed to collect responses and most of the questions have been designed using likert scale and multiple-choice type options. Quantitative approaches have been preferred from qualitative because the result intends to test the association among different variables and test the hypotheses with statistical tools like regression, correlation and t-tests.

### 5.2 Data Collection Methods

Primary data has been obtained directly from the respondents using a structured questionnaire. This data reveals the demographic detail, loan characteristic, loan stress indicators and repayment behavior. Secondary data has been collected from different sources like Research Papers from Google Scholar, Academic Journals, RBI Reports and Industry Reports (ICRA, FITCH). A total of 68 responses were collected for this study at the PAN India level as pilot empirical evidence.

### 5.3 Sampling

Snowball sampling method is implemented. A total of 68 respondents were collected for the Pilot study. The target population included borrowers across different age groups and backgrounds like college students, employed Individuals and retired individuals.

### 5.4 Data Analysis Techniques

The data collected through questionnaire has been analysed using SPSS Software.

Descriptive Statistics, Correlation, Regression, Independent Sample t-test, Reliability Analysis using Cronbach's Alpha tools have been used for the analysis of the data.

These tools helped in validating the hypothesis by drawing meaningful conclusion from the data.

**Reliability**

[DataSet1] C:\Users\sriya das\Downloads\Capstone project.sav

**Scale: ALL VARIABLES**

**Case Processing Summary**

| | | N | % |
|---|---|---|---|
| Cases | Valid | 54 | 79.4 |
| | Excluded[a] | 14 | 20.6 |
| | Total | 68 | 100.0 |

a. Listwise deletion based on all variables in the procedure.

**Reliability Statistics**

| Cronbach's Alpha | N of Items |
|---|---|
| .890 | 10 |

**Figure 1: Output of SPSS for questionnaire reliability (Cronbach Alpha)**

The consistency test carried out in this study was the Cronbach's Alpha to determine the consistency of the questionnaire used. In this instance, the value 0.890 indicates a very high similarity among the variables in this study. A Cronbach Alpha of 0.7 is generally considered acceptable, which shows that is true can be used for further analysis. In this case, a value of 0.890 means that it suggests a very high level of consistency among the variables used in this study.

Additionally, the data also tells that all the 54 responses with 79.4% are valid, while 20 responses with 20.6% were excluded due to missing values (the people who have never taken a loan).

Overall, it can be interpreted from this data that this questionnaire used in this study is reliable and suitable for conducting further analysis like regression, correlation and hypothesis testing.

**Hypothesis Testing:**

**$H_{01}$:** There is a significant relationship between borrower financial stress and retail credit risk.

**Correlations**

**Correlations**

| | | FinancialStressIndex | RepaymentBehaviour |
|---|---|---|---|
| FinancialStressIndex | Pearson Correlation | 1 | .906*** |
| | Sig. (2-tailed) | | <.001 |
| | N | 55 | 55 |
| RepaymentBehaviour | Pearson Correlation | .906*** | 1 |
| | Sig. (2-tailed) | <.001 | |
| | N | 55 | 55 |

***. Correlation at 0.001 (2-tailed)

**Figure 2: Output of SPSS for correlation**

Correlation analysis of the hypothesis was done using Pearson's Correlation. The outcomes show a correlation coefficient of 0.906, with significance value of $p<0.001$ based on 55 responses.

A correlation value close to 1 shows a very strong positive relationship between variables. Thus, in the above cases the value of 0.906 shows that as borrower financial stress increases, borrowers' repayment difficulties also rise significantly with it.

As the null hypothesis ($H_0$) is rejected, it is concluded that a significant relationship is found between both the variables. Thus, it can be said that borrower financial stress plays a significant role in influencing borrowers' repayment behaviour and is very strong indicator of retails credit risk.

**Hypothesis 2:**

**$H_{01}$:** Factors such as EMI burden, income instability, unsecured loans, and informal borrowing significantly affect repayment behaviour.

**Regression**

**Variables Entered/Removed[a]**

| Model | Variables Entered | Variables Removed | Method |
|---|---|---|---|
| 1 | Q15, Q12, Q10, Q13[b] | . | Enter |

a. Dependent Variable: RepaymentBehaviour

b. All requested variables entered.

**Model Summary**

| | | | | | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .945[a] | .893 | .885 | .36486 | .893 | 104.734 | 4 | 50 | <.001 |

a. Predictors: (Constant), Q15, Q12, Q10, Q13

**Figure 3: Output of SPSS for Regression**

**ANOVA[a]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 55.771 | 4 | 13.943 | 104.734 | <.001[b] |
| | Residual | 6.656 | 50 | .133 | | |
| | Total | 62.427 | 54 | | | |

a. Dependent Variable: RepaymentBehaviour

b. Predictors: (Constant), Q15, Q12, Q10, Q13

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | -.161 | .185 | | -.868 | .389 |
| | Q10 | .268 | .058 | .263 | 4.657 | <.001 |
| | Q12 | .046 | .052 | .051 | .878 | .384 |
| | Q13 | .019 | .055 | .021 | .340 | .735 |
| | Q15 | .705 | .058 | .738 | 12.055 | <.001 |

a. Dependent Variable: RepaymentBehaviour

**Image 4: Output of SPSS for ANOVA and Coefficients**

Predictive modelling was enabled to test the influence of factors such as EMI Burden, income stability, unexpected expenses and debt burden on borrowers' repayment behaviour. The result 0.893 shows 89.3% difference in repayment behaviour.

The ANOVA test shows 104.734 and $p<0.001$, which indicates that overall, the regression analysis is a good measure for the hypothesis.

From the coefficients table, unexpected expenses Q10 and debt burden Q15 are significant factors, as their p- values are less than 0.05. Debt Burden with $\beta = 0.738$ has the strongest impact on borrowers' repayment behaviour, followed by the Unexpected Expenses with $\beta = 0.263$. Other variables were statistically insignificant as their probability values are higher than 0.05.

The null hypothesis ($H_0$) is rejected Thus, borrower financial stress factors, particularly debt burden and unexpected expenses, play a significant role in influencing borrowers' repayment behaviour while other factors may have a very limited impact.

**Hypothesis 3:**

$H_{03}$: Psychological financial stress significantly influences the probability of default.

**Regression**

**Variables Entered/Removed[a]**

| Model | Variables Entered | Variables Removed | Method |
|---|---|---|---|
| 1 | PsychologicalStressIndex[b] | . | Enter |

a. Dependent Variable: RepaymentBehaviour

b. All requested variables entered.

**Model Summary**

| | | | | | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .215[a] | .046 | .028 | 1.05984 | .046 | 2.577 | 1 | 53 | .114 |

a. Predictors: (Constant), PsychologicalStressIndex

**Figure 5: Output of SPSS for regression**

## ANOVA[a]

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 2.895 | 1 | 2.895 | 2.577 | .114[b] |
| | Residual | 59.533 | 53 | 1.123 | | |
| | Total | 62.427 | 54 | | | |

a. Dependent Variable: RepaymentBehaviour

b. Predictors: (Constant), PsychologicalStressIndex

## Coefficients[a]

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 4.459 | 1.066 | | 4.184 | <.001 |
| | PsychologicalStressIndex | -.472 | .294 | -.215 | -1.605 | .114 |

a. Dependent Variable: RepaymentBehaviour

**Figure 6: Output of SPSS for ANOVA and Coeeficients**

The effects of psychological financial stress on repayment behaviour were examined using a regression analysis. The results indicated that the model was insignificant with a p value of 0.114> 0.05, thus implying that psychological financial does not significantly affect the repayment behaviour.

The R2 value of 0.046 shows that only 4.6% of the variability which is very weak. The coefficient for psychological stress is Beta=-0.215, p=0.114) is also not significant, indicating not much meaningful impact.

Therefore, here the results are not statistically significant. Hence, psychological financial stress does not significantly influence the default probability.

**Hypothesis 4:**

**$H_{04}$:** There is a significant difference in borrower financial stress between customers of retail banks and NBFCs.

**T-Test**

**Group Statistics**

| | Fromwherehaveyoutakenyourloan | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| FinancialStressIndex | Retail Bank | 47 | 2.8277 | .78594 | .11464 |
| | NBFC | 8 | 2.7250 | .72850 | .25756 |

**Independent Samples Test**

| | | t-test for Equality of Means | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Significance | | | | 95% Confidence Interval of the Difference | |
| | | t | df | One-Sided p | Two-Sided p | Mean Difference | Std. Error Difference | Lower | Upper |
| FinancialStressIndex | Equal variances assumed | .345 | 53 | .366 | .732 | .10266 | .29778 | -.49462 | .69993 |
| | Equal variances not assumed | .364 | 9.989 | .362 | .723 | .10266 | .28193 | -.52561 | .73092 |

**Figure 7: Output of SPSS for T test**

**Independent Samples Effect Sizes**

| | | Standardizer[a] | Point Estimate | 95% Confidence Interval Lower | 95% Confidence Interval Upper |
|---|---|---|---|---|---|
| FinancialStressIndex | Cohen's d | .77859 | .132 | -.619 | .881 |
| | Hedges' correction | .78983 | .130 | -.610 | .869 |
| | Glass's delta | .72850 | .141 | -.617 | .889 |

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

**Figure 8: Output of SPSS for Independent Sample Effect Sizes**

To make comparison of financial stress of borrower in retail bank and NBFC's an unpaired T-test was used. Both groups performed comparably. ($t=0.345$, $p=0.732>0.05$). The mean financial stress level of the retail bank customers ($M= 2.8277$) and NBFC customers ($M= 2.7250$) are almost equal; which means there is not much difference between the two.

The effect size i.e. Cohen's d = 0.13 indicates insignificant difference. Hence, there is no significant difference between financial stress of customers of retail banks and NBFCs. We fail to reject the null hypothesis.

**Hypothesis 5:**

**$H_{05}$:** Including borrower financial stress indicators significantly improves credit risk assessment and early detection.

**Regression**

**Variables Entered/Removed[a]**

| Model | Variables Entered | Variables Removed | Method |
|---|---|---|---|
| 1 | FinancialStressIndex, PsychologicalStressIndex[b] | . | Enter |

a. Dependent Variable: RepaymentBehaviour

b. All requested variables entered.

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .909[a] | .826 | .819 | .45725 | .826 | 123.292 | 2 | 52 | <.001 |

a. Predictors: (Constant), FinancialStressIndex, PsychologicalStressIndex

**Figure 9: Output of SPSS for Regression**

**ANOVA[a]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 51.555 | 2 | 25.778 | 123.292 | <.001[b] |
| | Residual | 10.872 | 52 | .209 | | |
| | Total | 62.427 | 54 | | | |

a. Dependent Variable: RepaymentBehaviour

b. Predictors: (Constant), FinancialStressIndex, PsychologicalStressIndex

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | -.162 | .551 | | -.294 | .770 |
| | PsychologicalStressIndex | -.161 | .129 | -.073 | -1.250 | .217 |
| | FinancialStressIndex | 1.245 | .082 | .894 | 15.256 | <.001 |

a. Dependent Variable: RepaymentBehaviour

**Figure 10: Output of SPSS for ANOVA and coefficients**

Evaluating the effect of financial stress indicators on credit risk analysis and early-stage risk identification of repayment behaviour was analysed through multiple regression analysis. The model demonstrated statistical significance ($p < 0.001$), suggesting that the selected variables effectively explain variations in repayment behaviour.

The high $R^2$ value (0.826) suggests that the model explains a substantial proportion of the variation which shows a very good model fit.

The financial stress index was highly significant at the individual level ($\beta = 0.894$, $p < 0.001$), implying that it is a strong determinant of repayment behaviour and thus important in the credit risk assessment stage. The psychological stress index, however, was not statistically significant ($p = 0.217$), indicating that it doesn't uniquely explain repayment outcomes in the model.

In general, these findings support the view that the financial stress indicators, especially the objective financial stress indicators, have a significant contribution to credit risk assessment and early detection tools. Therefore, the rejection of the null hypothesis indicates sufficient evidence to support the alternative hypothesis, validating that the financial stress indicators of borrowers enhance the credit risk modelling.

## VI. Study Implications

### 6.1 Theoretical Implications

The main significance of the project is to analyze the factors that affects the repayment behaviour and retail credit risk that aligns with the role of borrower financial stress. With prolonged ease of access to credit, the indebtedness has peaked and has an adverse effect on the traditional financial metrics and it is the need to understand the causes that leads to borrower distress. The implication of the study from an academic point of view is that the study attempts to incorporate behavioural financial concept with credit risk, thereby providing a more detailed understanding of borrower behaviour.

### 6.2 Practical implications

From an industry perspective, the goal of the study is expected to be valuable for Banks and NBFCs in enhancing credit appraisal processes, risk managers in identifying early warning signals of default and for policy makers in promoting responsible lending practices. By analysing key stress indicators, financial institutions may evaluate and design a more effective risk mitigation strategies, better portfolio quality and minimize non-performing assets (NPAs).

## VII. Conclusion, Limitations and Future Scope

The study was undertaken to analyse borrower financial stress and its implications on retail credit risk among the Indian borrowers. Drawing on the statistical analysis correlation, regression, reliability analysis and t-test, the findings showed that financial stress has a significant impact on repayment behaviour, thereby it is a key factor of retail credit risk. It was also observed that more the level of financial stress less are the changes of repayment obligations which eventually leads to higher chances of default.

Further, the regression analysis revealed that among various financial factors, debt burden and unexpected expenses have a significant impact on repayment behaviour. These factors increase financial pressure on borrowers and have direct influence on repayment capacity. On the other hand, factors such as income instability and difficulty in managing multiple loans showed comparatively lower significance.

The study also examined the role of psychological financial stress and the analysis reveals that the variable does not significantly affect the outcome of repayment behaviour. Hence the actual financial conditions have a stronger influence on borrower behaviour than perceived stress. Additionally, the independent samples t-test findings suggest that financial stress levels do not differ significantly between borrowers of retail banks and those of NBFCs

This indicates that borrower stress is more dependent on individual financial condition rather than the type of lenders or lending institutions.

The study further highlighted that the inclusion of financial stress indicators significantly improves credit risk assessment and early detection mechanisms. This highlights the need for the consideration of behavioral and financial stress variables in the conventional credit scoring models.

Additionally, the study identified that incorporating financial stress indicators can significantly enhance credit risk assessment and early warning systems. This is a demonstration of the relevance of the behavioural and financial stress variables to classic credit evaluation models. Based on this, it can be concluded that financial stress by borrowers is a critical factor in determining their repayment behavior and retail credit risk and, if appropriate actions are taken, then the performance of credit risk management practices can be improved.

To summarise the results, out of 68 total respondents, 55 were borrowers and 19 respondents reported high stress (Often + Always).

## Limitations

As the study was conducted as a pilot study, the analysis is limited to a small sample size, which may restraint the generalizability of the findings to wider range of borrowing population. The data has been collected by self-made questionnaires; there is a possibility of biased responses. The study predominantly focuses on selected variables and does not include all the variables and external factors like ongoing tariff war, regulatory changes and macroeconomic changes. It is cross-sectional and hence does not allow assessing the changes in the borrower's behavior over a period of time.

## Future Scope of the study

The borrower financial stress and implications for retail credit risk study offers a robust ground to understand the link between individual-level financial stress and credit default behaviour. The constantly evolving financial landscape, however, provides a number of opportunities for further research. The use of alternative and behavioural data as inputs to credit risk assessment models is one aspect that warrants further research. Traditional credit scoring methods tend to be based on credit history and financial information and do not take into account behavioural traits and informal financial transactions. Recent studies and developments suggest that predictive models for borrower risk profile can gain substantial boosts in predictive power by using machine learning methods in combination with transactional, mobile and psychometric data. Future research could include the integration of these multidimensional data, which would help to identify borrower stress earlier, and a more accurate prediction of default.

One significant area for future exploration is the integration of alternative and behavioural data into credit risk assessment models. Traditional credit scoring systems rely heavily on credit history and financial records, often overlooking behavioural attributes and informal financial activities. Emerging research indicates that machine learning techniques combined with transactional, mobile, and psychometric data can significantly improve the predictive accuracy of borrower risk profiles. Future studies can focus on incorporating such multidimensional data to capture early signs of borrower stress and improve default prediction models.

The increase in digital lending and “buy now, pay later” services is driving a shift in borrowing habits toward more complex and fragmented. Financial inclusion is improved through these innovations, but new risk factors have emerged, including over-indebtedness and hasty borrowing. Research into the impact of digital credit systems on financial stress and the implications for risk management strategies is an area for future research.

The study can also be extended to segment-specific analysis, focusing on vulnerable borrower groups such as first-time borrowers, informal sector workers, and financially excluded populations. Existing literature suggests that traditional models often fail to capture the creditworthiness of such segments due to limited formal data. Future research could develop inclusive frameworks that integrate behavioural finance principles and financial literacy variables to better understand stress dynamics in these groups.

The study can also be carried out in a segment-specific way, breaking down the vulnerable borrowers’ groups, including first-time borrowers, informal sector workers and financially excluded groups. The literature indicates that conventional models tend to be inadequate in assessing creditworthiness of those segments because of the lack of formal data. The use of inclusive models incorporating financial literacy variables and behavioural finance concepts could be explored for a better understanding of stress dynamics in these groups.

In addition, the macroeconomic and cyclical aspects of financial stress can be investigated. These events and circumstances outside the borrower's control like inflation, changes in interest rates, job loss, etc. can affect borrower stress. Consumer debt has been increasing and is already showing signs of stress in certain credit lines, resulting in the need for variable risk monitoring systems. More comprehensive stress prediction models can be developed using macroeconomic indicators in future research, which will help build more robust and forward-looking credit risk frameworks. One other area that has potential is real-time stress detection by using advanced analytics and artificial intelligence. The advent of big data and the development of new analysis tools allow researchers to create predictive models that help them gain real-time insights into borrower behaviour. These models can assist financial institutions to proactively manage risk, instead of waiting for lagging indicators like delinquency or default to identify early warning indicators of stress. Last, further studies should also focus on the ethical and regulatory aspects of borrower stress testing. Alternative data and AI-driven credit models come with data privacy, bias, and transparency concerns. Research into the creation of fair and explainable credit models with a focus on innovation and responsible lending. Overall, the future of this study could be broadened by incorporating more analytical depth, advanced technology and macroeconomic relationships. These changes will improve the ability to measure financial stress among borrowers, and will play a role in building more robust and inclusive frameworks for retail credit risk management.

Further development and application of AI tools, econometric models such as logit and probit models help the banks and NBFCs to improve efficiency in managing the behavioral factors impacting default risk.

The authors propose the following econometric models in the next study:

- **Primary model:** Ordered logit/probit
    - Dependent variable: financial stress frequency
    - Key predictors: income level, employment type, age group, active loan count, EMI burden, job insecurity, loan type

- **Secondary model:** Binary logit
    - Outcome: delayed EMI (1 = delayed EMI at least sometimes, 0 = never/rarely)
    - Useful as a proxy for repayment risk.

**AI applications for future study**

- **Data collection:** automated survey logic, missing-data checks, contradiction detection, and adaptive questioning
- **Analysis:** explainable AI for feature importance, borrower segmentation, early-warning indicators, and NLP for open-ended comments
- **Credit-risk implication:** use AI-based stress-risk scores to identify higher-risk borrower profiles.

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