

# A Study On Credit Risk Assessment & Management At Sakthi Finance With Reference To Risk Assessment Models & Methodologies Applied

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## ABSTRACT

Credit risk assessment and management play a crucial role in the financial stability of non-banking financial companies (NBFCs) like Sakthi Finance. This study explores various risk assessment models and methodologies employed to evaluate and mitigate credit risk. It examines key factors influencing credit risk, including borrower credibility, market conditions, and regulatory frameworks. The research highlights statistical models, credit scoring techniques, and machine learning approaches used for risk evaluation. Furthermore, it assesses the effectiveness of traditional versus modern methodologies in predicting loan defaults. The study also delves into risk mitigation strategies like collateral management and portfolio diversification. A comparative analysis of different risk assessment tools is presented to identify the most efficient approach. Data-driven insights and case studies provide a practical perspective on risk management at Sakthi Finance. The findings aim to enhance risk prediction accuracy and reduce financial losses. Overall, this study contributes to developing a robust credit risk management framework for NBFCs.

**KEYWORDS** - Credit Risk, Risk Assessment Models, Risk Management, Credit Scoring, Loan Default Prediction, Non-Banking Financial Companies (NBFCs), Risk Mitigation Strategies, Financial Stability, Portfolio Diversification.

## INTRODUCTION

Credit risk arises when a corporate or individual borrower fails to meet their debt obligations. It is the probability that the lender will not receive the principal and interest payments of a debt required to service the debt extended to a borrower. Credit risk is when a lender lends money to a borrower but may not be paid back.

Loans are extended to borrowers based on the business or the individual's ability to service future payment obligations (of principal and interest). Lenders go to great lengths to understand a borrower's financial health and to quantify the risk that the borrower may trigger an event of default in the future.

On the side of the lender, credit risk will disrupt its cash flows and also increase collection costs, since the lender may be forced to hire a debt collection agency to enforce the collection. The loss may be partial or complete, where the lender incurs a loss of part of the loan or the entire loan extended to the borrower. The interest rate charged on a loan serves as the lender's reward for accepting to bear credit risk.

## OBJECTIVES

- To assess and enhance the efficiency of each stage of the credit process at Sakthi Finance Limited (SFL) by identifying opportunities for optimization and strengthening risk management practices.

- To provide strategic insights for improving credit risk management, streamlining operations, and ensuring adherence to financial regulations.
- To assess the effectiveness of credit appraisal and sanctioning processes in fostering sound lending decisions, optimizing loan approvals, and enhancing customer segmentation strategies.
- To examine the role of sanction managers in decision-making and explore the influence of collection strategies in maintaining asset quality and sustaining financial stability.

## REVIEW OF LITERATURE

**Arvind Subramanian (2025)** Studied the influence of environmental, social, and governance (ESG) factors on credit risk in NBFCs. The study found that NBFCs with strong ESG practices experienced lower default rates. Subramanian recommended integrating ESG assessments into credit risk models to enhance long-term financial performance.

**Megha Iyer (2024)** explored risk assessment strategies for automobile loans in Indian NBFCs. Her study examined how credit scoring models, borrower profiling, and asset valuation impact loan approval. She found that automobile loan defaults were highly correlated with borrower credit history and macroeconomic factors. The research suggested that AI-based risk models improved loan repayment predictions.

**Priya Sharma (2023)** analyzed the impact of AI models on creditworthiness assessment in Indian lending institutions. Her research explored various machine learning techniques like neural networks and decision trees in evaluating borrower profiles. She compared AI-driven models with traditional credit scoring techniques to measure improvements in accuracy and efficiency.

**Rajesh Kumar (2022)** examined financial ratios and credit scoring models in NBFCs, particularly Sakthi Finance, to evaluate credit risk. He analyzed how different financial ratios, such as debt-equity and profitability ratios, influence credit decision-making. The study highlighted the effectiveness of traditional credit scoring models in identifying potential defaulters.

**Aishwarya S. (2021)** conducted a comparative study of credit risk management practices in NBFCs and commercial banks. Her research analyzed differences in risk assessment frameworks, lending policies, and NPA management. She found that NBFCs relied more on flexible risk evaluation models compared to banks' strict regulatory frameworks.

## RESEARCH METHODOLOGY

**RESEARCH DESIGN** – Descriptive Research Design

**SAMPLING TECHNIQUE** - For this research sampling technique used is Convenience Sampling.

**DATA COLLECTION** - Primary data will be collected directly from the employees and through real-time observations. Secondary data includes company's Websites, Annual reports Handbooks.

**STATISTICAL TOOLS** - Correlation, Regression, One sample T- Test.

**ANALYSIS & INTERPRETATION**

**PERCENTAGE ANALYSIS**

**TABLE**

### GENDER

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	88	57.9	58.3	58.3
	2	63	41.4	41.7	100.0
	Total	151	99.3	100.0	
Missing	System	1	.7		
Total		152	100.0		

### INTERPRETATION

The above table shows the results for the gender of the respondents. From 150 respondents, 58% is male, 41% is female. This indicates more male participation than female contributed for the study.

### CORRELATION

#### HYPOTHESIS

**Null Hypothesis (H<sub>0</sub>):** There is no significant correlation between the Credit Approval Process and Overall Efficiency ( $\rho=0$ ).

**Alternative Hypothesis (H<sub>A</sub>):** There is a significant positive correlation between the Credit Approval Process and Overall Efficiency ( $\rho \neq 0$ ).

### TABLE

#### Correlations

		CREDIT APPROVAL PROCESS	OVERALL EFFICIENCY
CREDIT APPROVAL PROCESS	Pearson Correlation	1	.228**
	Sig. (2-tailed)		.005
	N	151	151
OVERALL EFFICIENCY	Pearson Correlation	.228**	1
	Sig. (2-tailed)	.005	
	N	151	151

\*\* . Correlation is significant at the 0.01 level (2-tailed).

### INTERPRETATION

The Pearson correlation coefficient ( $r=0.228$ ) indicates a weak positive correlation between the Credit Approval Process and **Overall Efficiency**. The p-value (.005) is less than 0.01, meaning the correlation is **statistically significant** at the 1% significance level. This suggests that as the Credit Approval Process **improves**, Overall Efficiency also **increases**, though the relationship is weak. Since the correlation is significant, we reject the null hypothesis, confirming a meaningful but small positive relationship between the two variables.

### REGRESSION

#### HYPOTHESIS

**Null Hypothesis (H<sub>0</sub>):** The predictor Timely CAP has no significant effect on Overall Efficiency ( $\beta=0$ ).

**Alternative Hypothesis (H<sub>A</sub>):** The predictor Timely CAP has a significant effect on Overall Efficiency ( $\beta \neq 0$ ).

TABLE

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.174 <sup>a</sup>	.030	.024	.894

a. Predictors: (Constant), TIMELY CAP

ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.694	1	3.694	4.625	.033 <sup>b</sup>
	Residual	118.995	149	.799		
	Total	122.689	150			

a. Dependent Variable: OVERALL EFFICIENCY

b. Predictors: (Constant), TIMELY CAP

Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.573	.372		9.598	<.001
	TIMELY CAP	.246	.115	.174	2.151	.033

a. Dependent Variable: OVERALL EFFICIENCY

## INTERPRETATION

The REGRESSION table shows that the regression model is **statistically significant** with an F-value of 4.625 and a p-value of 0.033. Since the p-value (0.033) is less than 0.05, we reject the null hypothesis, indicating that Timely CAP significantly influences Overall Efficiency. However, the relatively low F-value suggests that while the predictor is significant, the model explains only a small portion of the variance in Overall Efficiency. This implies that Timely CAP plays a role in improving Overall Efficiency, but additional factors may also contribute to the efficiency outcomes.

## T-TEST

### HYPOTHESIS

**Null Hypothesis (H<sub>0</sub>):** The mean of each variable (Overall Efficiency, Timely Cap, Departments Coordinate, Mitigate Risks and Maintaining Efficiency, Collaboration) is equal to 0.

**Alternative Hypothesis (H<sub>A</sub>):** The mean of each variable is significantly different from 0.

TABLE

### One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
OVERALL EFFICIENCY	151	4.36	.904	.074
TIMELY CAP	151	3.19	.637	.052
DPTS CO-ORDINATE	151	3.38	1.100	.090
MITIGATE RISKS AND MAINTAINING EFFICIENCY	151	3.37	.699	.057
COLLABRATION	151	3.88	1.119	.091

### One-Sample Test

Test Value = 0

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
OVERALL EFFICIENCY	59.208	150	<.001	4.358	4.21	4.50
TIMELY CAP	61.478	150	<.001	3.185	3.08	3.29
DPTS CO-ORDINATE	37.732	150	<.001	3.377	3.20	3.55
MITIGATE RISKS AND MAINTAINING EFFICIENCY	59.282	150	<.001	3.371	3.26	3.48
COLLABRATION	42.613	150	<.001	3.881	3.70	4.06

### One-Sample Effect Sizes

		Standardizer <sup>a</sup>	Point Estimate	95% Confidence Interval	
				Lower	Upper
OVERALL EFFICIENCY	Cohen's d	.904	4.818	4.250	5.385
	Hedges' correction	.909	4.794	4.228	5.358
TIMELY CAP	Cohen's d	.637	5.003	4.414	5.590
	Hedges' correction	.640	4.978	4.392	5.562
DPTS CO-ORDINATE	Cohen's d	1.100	3.071	2.687	3.451
	Hedges' correction	1.105	3.055	2.674	3.434
MITIGATE RISKS AND MAINTAINING EFFICIENCY	Cohen's d	.699	4.824	4.255	5.392
	Hedges' correction	.702	4.800	4.234	5.365
COLLABRATION	Cohen's d	1.119	3.468	3.044	3.890
	Hedges' correction	1.125	3.450	3.028	3.870

a. The denominator used in estimating the effect sizes.

Cohen's d uses the sample standard deviation.

Hedges' correction uses the sample standard deviation, plus a correction factor.

### INTERPRETATION

All variables have a p-value < 0.001, indicating that their means are significantly different from 0. The t-values are large, meaning strong evidence against the null hypothesis. The 95% confidence intervals do not include 0, further confirming that the variables have **statistically significant positive mean values**. This suggests that each factor (Overall Efficiency, Timely Cap, departments Coordinate, Mitigation of Risks, and Collaboration) has a meaningful presence in the data and **contributes significantly**.

### FINDINGS

**EFFECTIVENESS OF CREDIT RISK MANAGEMENT** - The 5 C's of credit (Character, Capacity, Capital, Collateral, and Conditions) are followed, but inconsistencies in documentation and risk assessment impact efficiency.

**LOAN APPROVAL PROCESS** - The credit approval process shows a positive but weak correlation with overall efficiency, indicating scope for improvement.

**ROLE OF TECHNOLOGY** - Implementation of credit risk software enhances efficiency, but further integration is needed for automation and accuracy.

**IMPACT OF ECONOMIC AND MARKET CONDITIONS** Macroeconomic factors such as inflation and economic slowdowns influence loan repayment behavior, requiring more adaptive risk mitigation strategies.

**BALANCED APPROACH** - The findings demonstrate that effective credit risk management requires a balanced approach combining traditional assessment techniques with modern analytical methods

### SUGGESTION

#### ENCHANCING CREDIT RISK MANAGEMENT SYSTEM



The company can adopt a credit risk management system, integrating measurement and mitigation components, regular monitoring, and advanced machine learning and big data analytics for improved assessment accuracy.

#### **CREDIT STRUCTURING APPROACHES**

Customizing credit structure techniques for borrower profiles and maintaining a balanced approach to the 5 C's of credit, including culturally sensitive character assessment methods, can optimize risk-adjusted returns.

#### **STRENGTHEN CROSS-FUNCTIONAL DEPARTMENT SYSTEMS**

Improved cross-functional collaboration is crucial for operational effectiveness. Establish formal communication protocols for credit processes, implement shared digital platforms, and hold regular working sessions to address process pain points and foster shared ownership of the credit process.

#### **ENHANCING CREDIT TECHNOLOGY INFRASTRUCTURE**

Company has to evaluate current credit management software against industry benchmarks to identify functionality gaps and automate decision support. Implementing machine learning algorithms could accelerate applications and allow human expertise.

#### **ENHANCE CREDIT RISK MODLES**

- Incorporate AI and big data analytics for better predictive risk assessment.
- Use alternative data sources (social media, utility bill payments) for assessing thin-file borrowers.

#### **CONCLUSION**

The study highlights the importance of a strong credit risk management framework in ensuring financial stability at Sakthi Finance Limited. While the company follows structured lending and risk mitigation practices, there is room for enhancing efficiency through technology adoption, better documentation control, and predictive analytics. Strengthening early warning systems and optimizing collection strategies can help reduce NPAs and improve overall profitability. With pro-active risk assessment, enhanced customer engagement, and process automation, Sakthi Finance can achieve sustainable growth and operational excellence in the competitive NBFC sector.

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