International Journal of Technology, Leadership and Sciences (IJTLS)

ISSN: 3107-9083
www.ijtls.com
Research Paper
DOI: https://doi.org/10.5281/zenodo.19396272

CREDIT RISK MODELS IN COOPERATIVE BANKS AT BANDHAN BANK

***[1]Mr VR Ramakrishna, Associate Professor,**
***[2]Shaik Kalandar, MBA Student,**

Department of MBA, Viswam Engineering College (Autonomous), Angallu, Madanapalle, AP.

ABSTRACT:

This research evaluates cooperative bank credit risk models, focusing on Bandhan Bank. Financial institutions, especially cooperatives, worry about credit risk—the loss that may result from a borrower's failure to meet financial obligations. The study examines credit risk assessment models including PD, LGD, and EAD to preserve financial stability and manage non-performing assets. Direct data from Bandhan Bank's lending operations and secondary data from financial reports and scholarly literature are used to assess existing credit risk management practices' pros and cons. Bandhan Bank and other cooperative banks are using data-driven, technology-based solutions to improve credit assessments and minimize default rates, even while standard risk appraisal approaches are structured. Research supports this. This research suggests ways to improve credit risk modeling for sustainable development and integrate international risk management practices into cooperative banking.

Keywords: Credit Risk Management, Probability of Default (PD), Loss Given Default (LGD), Exposure at Default (EAD), Non-Performing Assets (NPAs),

Received Date: 5 March-April 2026; **Accepted Date:** 15 March-April 2026;; **Published Date:** 20 March-April 2026

1. Introduction

Credit risk, or the potential loss a lender may suffer when a borrower defaults on their loan, is a major worry for all financial organizations. Cooperative banks help farmers, small businesses, and rural and semi-urban residents with financial needs since they are community-oriented. Cooperative banks must manage credit risk because, unlike commercial banks, they lend to customers without collateral or credit histories. These organizations can enhance regional economic growth and financial stability by detecting, measuring, and reducing defaults using structured credit risk models.

Credit risk models estimate a borrower's default risk and lender portfolio impact. Cooperative banks evaluate borrowers quantitatively and qualitatively. Credit scoring, logistic regression, and probability of default evaluations are quantitative models. Instead, qualitative methods consider the borrower's socioeconomic condition, management skills, and reputation. Combining these tactics can help cooperative banks enhance lending, reduce NPAs, and comply with regulations.

Cooperative banking has different credit risk issues than commercial banking. Due to their regional economies, weak capital bases, and limited funding sources, these financial institutions are very vulnerable to borrower defaults. Small business owners and farmers are another type of borrower cooperative banks aid because their income is sensitive to market swings and natural disasters. Cooperative banks' credit risk models must be tailored to each industry and economic condition.

Recent advances in technology and data analytics have helped cooperative banks enhance their credit risk models. Machine learning algorithms, big data analytics, and automated credit scoring systems let banks analyze huge borrower data and improve default risk forecasts. These technology advances enable constant creditworthiness monitoring, which speeds up payback resolution. Therefore, cooperative banks can increase portfolio quality, manage resources more efficiently, and optimize lending methods.

2. Literature Survey

Patel, R., & Mehta, V. (2025): Patel and Mehta examined Gujarat and Maharashtra cooperative banks' credit assessment methods for farm and small company loans. They examined over 5,000 loan accounts from various businesses and individuals. Default risk was calculated using the Altman Z-score, KMV model, and traditional credit rating procedures. The study indicated that borrower demographics, cash flow estimates, and collateral valuation affected loan repayment. The authors observed that complicated scoring models using these parameters outperformed ratio-based models.

Sharma, A., & Gupta, N. (2024): Sharma and Gupta compared cooperative bank statistical and machine learning-based credit risk models. They used 15 years of rural and urban loan data to test logistic regression, random forests, and gradient boosting for loan default detection. Their study found machine learning models better at detecting loan account stress early. The study underlined that predictive models must contain financial markets and non-financial behavioral variables. They also noted that cooperative banks' poor digital infrastructure may hinder AI use.

Verma, P., & Joshi, K. (2023): Verma and Joshi investigated how ensemble learning, support vector machines, and neural networks can forecast cooperative company credit risk using artificial intelligence. They examined 12-year loan-level data on small business, microfinance, and agriculture loans. The study suggests that AI models could detect tiny borrower trends that traditional models overlook, improving default warning indications. The writers underlined the importance of combining traditional financial parameters with AI discoveries for a complete credit assessment. They also discussed execution issues like digital infrastructure and data standardization in cooperative banks.

Chakraborty, A., & Sen, R. (2022): Credit risk models for West Bengali community bank farmer loans were examined by Chakraborty and Sen. They calculated 4,500 accounts' loan default risk using discriminate analysis and logistic regression. The study improved forecasts with seasonal currency flows, financial ratios, and farm-level output data. Their research demonstrated that sector-specific risk models outperformed generic score techniques.

Rao, S., & Menon, A. (2021): Rao and Menon examined how Maharashtra cooperative banks assess farmer and small company lending risk. Altman Z-score and logistic regression models examined 7,000 loan accounts from various firms. The study underlined the importance of combining financial ratios and collateral evaluation to predict failure. They found that organized credit rating systems enhanced loan portfolios and reduced non-payment.

Iyer, M., & Natarajan, V. (2020): Iyer and Natarajan examined Tamil Nadu cooperative bank credit risk models based on scenarios. Possible defaults were simulated in response to economic shocks like droughts, commodity price shifts, and rising interest rates. They examined how these issues affected farming and microfinance portfolios using prior loan data. Results demonstrated that scenario-based models helped institutions restructure loans and reduce failure risk.

3. Principles Of Credit Risk Management

Proper Credit Risk Environment: The initial step in effective risk management is to establish a strong credit risk framework. It requires creating a company culture where everyone, from entry-level workers to management, takes chances. Policies and techniques should clearly state who is responsible for what, how much risk is acceptable, and who decides. Strong risk settings ensure that credit-related operations follow clear rules and who is responsible for what. Institutions can avoid giving money without thinking and maintain stable portfolios by fostering this climate.

Effective Credit-Granting Process: Loans and credits are granted through credit-granting. A loan applicant's creditworthiness must be properly examined before approval. This includes reviewing collateral, business developments, the borrower's ability to repay the loan, and financial records. Checklists, credit rating models, and standardized processes aid fair and consistent decision-making. By creating a good process, banks can reduce failures and ensure their loans match their risk tolerance.

Efficient Administrative System: Effective administrative systems are essential to manage all credit risk operations. This involves timely report filing, record keeping, loan tracking, and proper documentation. Automation and digital technologies reduce errors, speed up processes, and provide real-time credit account views. Well-organized administrative systems provide seamless work, rule compliance, and precise performance tracking. It also allows speedy problem-solving.

Deploying Apt Controls in Place: Installing controls to stop, find, and reduce credit risks is called "deploying appropriate controls." Internal controls include credit limitations, employment separation, permission hierarchies, and audits. Risk-reducing procedures include agreements, guarantees, and collateral management. Enough controls detect and correct policy deviations fast, reducing risk and maintaining portfolio quality.

Accurate Supervising: Accurate credit portfolio management requires constant monitoring to identify new risks and ensure compliance with company policy and the law. This entails monitoring the borrower's performance, loan covenants, and early signals of danger. Supervisors must notice trends, assess risk, and act fast to resolve issues. Good guidance reduces defaults, enhances risk management, and makes individuals more responsible.

4. Results and Interpretation

Table 1: Credit Risk Models Used in Cooperative Banks

Model Type	Description	Common Techniques	Purpose
Statistical Models	Based on historical data and probability	Logistic Regression, Discriminant Analysis	To estimate probability of default
Machine Learning Models	Use AI to identify patterns	Decision Trees, Random Forest, Neural Networks	To improve prediction accuracy
Behavioral Models	Focus on borrower repayment behavior	Credit Scoring, Transaction Analysis	To assess borrower's future behavior
Hybrid Models	Combine statistical & ML methods	Ensemble Learning	To enhance prediction reliability

Table 2: Borrower Risk Classification Matrix

Risk Category	Credit Score Range	Probability of Default (PD)	Loss Given Default (LGD)	Exposure at Default (EAD) ₹ Lakhs	Risk Weight (%)
Low Risk	750 – 900	0.50%	20%	500	20
Moderate Risk	650 – 749	2.00%	35%	800	50
High Risk	550 – 649	6.00%	50%	300	100
Very High Risk	Below 550	15.00%	70%	150	150

Table 3: Portfolio Distribution By Sector (Bandhan Cooperative Segment)

Sector	No. of Borrowers	Total Exposure ₹ Cr	Share of Portfolio (%)	Average PD (%)	Average LGD (%)
Agriculture	8,500	1,200	30	3.5	45
MSME	5,200	1,000	25	2	35
Housing Loans	3,100	800	20	1.2	20
Personal Loans	2,600	600	15	4	50
Others (Gold, etc.)	1,400	400	10	1.8	25

Table 4: Historical Default Rates (3-Year Trend)

Year	No. of Accounts	Defaults	Default Rate (%)	Recovery Rate (%)
2022	18,000	720	4	60
s2023	20,300	610	3	65
2024	21,000	504	2.4	68

Table 5: Bandhan Bank Loan Portfolio Composition

5. Conclusion

To conclude, cooperative banks need credit risk models to operate effectively and maintain financial stability. Rural and semi-urban banks struggle because their customers have unstable incomes, poor paperwork, and short credit histories. These organizations may frequently monitor clients' creditworthiness, predict loan defaults, and save losses by utilizing sophisticated credit risk models. Logistic regression, decision trees, and machine learning-based predictive models are more accurate and flexible in financial situations. Traditional approaches including credit scoring, financial ratio analysis, and the "5 Cs of Credit" provide a foundation for appraising debtors.

References

1. Chakraborty, A., & Sen, R. (2022). Credit risk models for agricultural loans in cooperative banks in West Bengal. Indian Journal of Rural Finance, 8(1), 33–50.
2. Desai, M., & Rao, L. (2024). Regulatory credit risk frameworks and cooperative banks in southern India. Journal of Banking Regulation, 15(3), 120–138.
3. Iyer, M., & Natarajan, V. (2020). Scenario-based credit risk modeling in Tamil Nadu cooperative banks. Asian Journal of Cooperative Finance, 6(2), 88–105.
4. Nair, S., & Pillai, K. (2022). Behavioral scoring and credit risk prediction in Kerala cooperative banks. South Asian Journal of Banking and Finance, 11(2), 34–52.
5. Patel, R., & Mehta, V. (2025). Credit scoring models for small business and agricultural loans in cooperative banks. Journal of Cooperative Banking Research, 14(1), 23–45.

6. Rao, S., & Menon, A. (2021). Credit risk assessment models for SME and agricultural loans in Maharashtra cooperative banks. Journal of Rural Finance and Banking, 8(4), 72–91.
7. Reddy, T., & Srinivasan, P. (2024). Credit portfolio models to improve loan approval strategies in cooperative banks. Journal of Banking and Risk Analytics, 12(2), 35–54.
8. Shukla, R., & Deshmukh, P. (2021). Machine learning approaches for credit risk prediction in cooperative banks. Journal of Financial Technology, 9(3), 51–70.