A Comprehensive Analysis of Solvency, Profitability, and Liquidity in Minimizing Bankruptcy and Financial Stress

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Abstract

Purpose : This research examined a firm's liquidity, profitability, solvency, and cash position to determine their effects on financial distress and potential bankruptcy. It aimed to determine early warning signs and offered insights into financial management practices that can minimize financial distress and improve overall economic well-being.

Methodology : Using data from 2014 to 2023, we evaluated the financial distress and insolvency risk of a publicly traded government manufacturing firm. The research utilized the Springate model and the logit probability model to determine the probability of distress during this period. This systematic analysis provided a clear picture of the firm's financial health and risk of bankruptcy.

Findings : The Springate model revealed the company to be financially sound for 10 years. However, the logit probability model reflected a bankruptcy risk over the past three years. The study also highlighted weaknesses in the solvency and liquidity positions of the company.

Practical Implications : The results added to theoretical wisdom and offered practical suggestions for reducing insolvency and bankruptcy risk. They also indicated methods to ensure financial stability.

Originality/Value : The majority of empirical research has focused on industry-specific liquidity distress with statistical measures. Unlike this, the present study utilized multiple discriminant analyses and applied financial models directly to a specific government-owned company. This method identified corrective measures specifically. Interestingly, very little research has been conducted on assessing the financial distress of government companies in India, so the current study is relevant in providing company-specific findings.

Keywords : **financial distress, insolvency, bankruptcy, liquidity, financial ratios, financial distress models, multiple discriminant analysis**

JEL Classification Codes : G01, G17, G32, G33

Paper Submission Date : August 14, 2024 ; Paper sent back for Revision : February 19, 2025 ; Paper Acceptance Date : April 20, 2025 ; Paper Published Online : June 15, 2025

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DOI : https://doi.org/10.17010/ijf/2025/v19i6/175132

Financial distress is frequently encountered in business, but its prominence has grown recently, especially since the 2008 global financial crisis. As a result, to help prevent business firms from going out of business, the European Commission adopted new guidelines in 2014 that were designed to provide early indicators of financial hardship (Plumley et al., 2021). Liquidity is a crucial worry for capital funding during this period, as the global financial crisis continues to damage the financial landscape globally (Asutay & Othman, 2020). It is interesting to point out that most financially troubled businesses were in the maturity stage of their life cycle, while very few were in the growth stage. This is probably because growing businesses are more profitable and involve less risk (Kashyap & Bansal, 2019). The corporate sector is looking for ways to anticipate financial troubles ahead of time due to the increased impact of financial distress on a firm's operational outcomes and its wider environment, including management, credit institutions, stockholders, investors, and employees (Arnold, 2007; De & Banerjee, 2017). Companies in a financial crisis may incur significant interest costs, which would disrupt working capital and hurt indicators like net working capital and the current ratio (Sari et al., 2018).

An increasing number of businesses are struggling to survive as globalization picks up speed and competition heats up, which results in loan defaults (Tandon & Tandon, 2016). Financial fraud, money laundering, and financial mismanagement can all be identified and stopped using financial hardship prediction (Halteh & Tiwari, 2023). This emphasizes the necessity of having an early warning system that can accurately gauge the financial health of a business. Even companies that seem healthy today could have trouble making ends meet later. This study was inspired by several Indian public sector enterprises that failed despite being industry leaders in their respective fields. The majority of the financial distress research focuses on specific industries and relies predominantly on statistical evaluation methods. However, the current study utilizes financial models on an individual company. A study has yet to be completed to determine the financial distress of Indian government firms. Most studies are done on private-sector corporations, and scarce data are given on public-sector corporations. This study bridges the knowledge gap to provide helpful information about the financial soundness of a government firm. The results can guide policymakers and stakeholders in making informed choices (Chadha et al., 2023).

The inadequate accessibility and incorrect management of communal resources, resulting in commercial collapses within the Indian public sector, have noteworthy societal ramifications. These ratios were chosen for this investigation due to their significance in the literature and applicability.

Financial distress studies of Indian government firms are necessary due to rising inefficiencies, debt, and operating losses. While most studies are on private companies, public sector undertakings (PSU) remain under-researched despite their economic significance. The Indian government's disinvestment and restructuring initiatives further highlight the necessity of assessing distress. Policymakers and regulatory bodies such as RBI, SEBI, and CAG require financial distress models for PSUs. Existing research, primarily based on Altman's *Z*-score and Ohlson's *O*-score (Altman, 1968; Ohlson, 1980), have limited applicability to government enterprises. Bridging this gap provides information on financial well-being that is relevant to employment, investor sentiment, and fiscal policy. Given that financial distress in PSUs has macroeconomic implications, the research presented in this study aligns with both policy and scholarly compliant (Richard Paul & Kalyani, 2019).

To assess liquidity, profitability, and solvency, Tykvová and Borell (2012) employed a wide range of metrics, including measures with a solid theoretical basis for studying financial crises. Given this, we believe that the recent global financial crisis has caused a shift in attention to Indian government firms' profitability, solvency, and liquidity. Our study intends to investigate the probability of government and private companies going out of business due to financial difficulties and inadequacies in solvency and profitability. By examining troubled companies and determining the effects of liquidity, solvency, efficiency, and profitability on financial distress, this study adds to the body of literature.

We hypothesize that shortcomings in profitability, solvency, liquidity, and efficiency cause financial distress in

companies. Using multivariate and univariate analysis in a particular public sector company, our study offers empirical evidence on the influence of both short- and long-term solvency on corporate distress. While most previous research in India and worldwide has concentrated on industries, our study is distinctive in that it focuses on a single business. Financial distress first affects individual businesses before it impacts the industry. Consequently, it is imperative to begin with individual enterprises to address or avoid the ill health of any industry.

The primary objectives of this research are to use the Springate model to determine the possibility that a government-owned business will experience financial distress and to use Logit probability analysis to assess the company's financial health. The survey also attempts to evaluate the potential of bankruptcy and the likelihood of financial distress.

This study provides multiple contributions to current theory and practices by tackling the abovementioned objectives. In contrast to previous research, it includes new information on the relationship between liquidity, profitability, efficiency, and solvency and analyzes the probability of financial catastrophe in businesses.

First, we add to the body of research about financial distress by examining a company's financial health, recognizing signs of financial stability and distress, and determining the causes of financial hardship when it manifests itself. Second, we examine how liquidity and solvency, particularly in government firms, affect financial distress, highlighting the critical role that business performance and profitability play in preserving financial stability.

The following are the practical implications of the study. The implication may be used directly in government undertakings (PSUs), government-owned manufacturing companies, and cash-hungry industries. Managers need to enhance strategic liquidity planning to deal with cash flows and liabilities in inflationary or high-risk situations. Financial controllers are encouraged to put logit-based models of distress in place, along with conventional accounting measures for improved forecasting. Business and marketing planners must embrace low-cost digital approaches and embed predictive budgeting to stay flexible under fiscal stress. For regulators and policymakers, the study substantiates the necessity of initial financial diagnostics and buffer liquidity arrangements in public enterprises with initial signs of distress.

The remaining sections of the paper are organized: a literature review, data and methods, empirical results, and conclusion.

Literature and Financial Models

Financial Distress

Research on the correlation between financial distress and variables like profitability, liquidity, and solvency generally reveals a positive and linear relationship: The likelihood of financial distress and liquidation rises sharply when these variables are negative. According to Platt and Platt (2002), financial distress is defined as "a decline in financial conditions that occurs before bankruptcy or liquidation." Financial distress is defined similarly by Foster (1986) as "severe liquidity problems that cannot be resolved without significant restructuring of the entity's operations or structure." Geng et al. (2015) asserted that financial distress is always linked to a company's incapacity to pay its debts on time.

A situation that ends in severe financial hardship is called economic distress. This difficulty may include starting bankruptcy procedures, having negative bank balances due to non-payment of suppliers and creditors, or being unable to pay debts or preference dividends (Lütz & Kranke, 2014). Forecasting a business's financial crisis allows for the identification and probable avoidance of bankruptcy by addressing its underlying reasons. For example, Fathi et al. (2023) used precise forecasting approaches to evaluate the effectiveness of decision-making units over various periods, highlighting the significance of early identification and intervention.

Financial distress results when a company incurs significant operating losses and is unable to meet its short- and long-term debt obligations. This hardship may result in the company's insolvency and ultimate liquidation. Financial distress comprises many levels of economic decline, such as default, bankruptcy, failure, and insolvency. Despite their similarities, these names have slightly varied meanings based on the company's circumstances. Extensive definitions of these terms and an explanation of the efficacy of Altman's (1993) model, which forecasts financial distress with 94% accuracy for the first year and 72% accuracy for the second year (93% for small enterprises), are presented.

This study uses "financial distress" to characterize circumstances where a business cannot pay its creditors and suppliers (Singh & Bansal, 2022). It is frequently preferable to use discriminant analysis to pinpoint this issue. Edmister (1972) investigated several financial ratio analysis techniques to predict small firms' financial catastrophes. While not all ratio analyses can accurately forecast failure, many do.

The liquidation procedure can be hard to predict and takes five to six years. Consequently, spotting early warning signs and implementing preventive measures depends heavily on adopting suitable financial prediction models. By acting proactively, companies can avoid going out of business, providing management enough time to turn financially troubled companies into thriving ones (Korol, 2013).

Distress Models

Altman (1968) and Beaver (1966) pioneered the early work on financial modeling and understanding company financial difficulties. Accounting ratios served as the basis for the financial distress models developed by Gissel et al. (2007); nevertheless, their differing methodologies and choices of financial ratios made their prediction models increasingly sophisticated and precise. Liquidity, solvency, profitability, and distress can all be measured using different methods; one prominent approach is the Altman *Z*-Score. For better outcomes, the Altman *Z*-score model's effectiveness has been assessed several times (Altman et al., 2017).

Karas and Režňáková (2017) claimed that Altman's financial distress prediction model works pretty well for the majority of nations and businesses. The approach has prevented many companies from going bankrupt after the 2008 global financial crisis, emphasizing the need for better prediction models. According to their research, asset structure, inventory turnover ratio, and return on assets are significant predictors of corporate bankruptcy in businesses that are primarily involved in manufacturing and construction. Furthermore, working capital turnover rates and net working capital are additional cautionary indicators for manufacturing firms.

The Altman model has been used in many research studies to forecast financial difficulties since 1968. The assumptions made by the multiple discriminant analysis (MDA) method about multivariate normality and the independence of explanatory factors have drawn criticism, nevertheless. Zavgren developed a novel model based on logit analysis with a set of nine accounting and finance ratios to address these issues. According to Campbell et al. (2008), this strategy has increased the predictability of a financial crisis. More advanced methods, including data analysis, hazard models, and artificial intelligence, have also been used to warn about financial distress early (Balcaen & Ooghe, 2006; Kumar & Ravi, 2007).

Researchers examined the projection of cash, accrual, and mixed models for 33 industrial enterprises that collapsed and 33 that remained solvent. They discovered that the cash model had better predictive accuracy than accrual-based models. For many years, the government, investors, scholars, lenders, shareholders, and staff have all found financial distress prediction to be an essential and fascinating field (Geng et al., 2015; Jabeur, 2017).

Altman et al. (1994) highlighted the value of distress analysis, mainly because previous research had concentrated on larger companies. They discovered that using logit analysis to forecast bankruptcy outcomes produced accuracy levels of 96%, 92%, and 90% for the first, second, and third years, in that order. Results were consistently good when using linear probability and MDA. When compared to economic distress theory, it was

discovered that the logit probability model was more compatible with bankruptcy prediction than other techniques. Lu and Zhuo (2021) employed both neural networks and linear discriminant analysis to conclude that while neural networks show irrational behavior patterns that are more difficult to interpret, discriminant analysis is better at finding relevant variables.

Data and Methodology

This study employs the Springate model and Zavgren's logit probability model (Muparuri & Gumbo, 2022) to assess the possibility of a financial crisis in a government-owned enterprise in India. Financial downturn prediction is one of the most active areas of finance management research. Predicting the aftermath of a downturn is essential for businesses, present and potential investors, and stock market authorities (Alifiah, 2014).

Over the past century, several models for predicting bankruptcy have been created. Univariate analysis first gave rise to MDA, which recursive partitioning and logit probability model analysis followed. Neural networks and algorithms were later introduced. Beaver (1966) was the first to observe that financial ratios do not always predict bankruptcy equally. Researchers have been looking for important prognostic factors ever since (Cielen et al., 2004). MDA was first developed by Altman (1968). Rose and Giroux (1984) discovered that single-ratio predictor tests may not always be reliable.

The analysis's data came from a government-owned manufacturing enterprise. Primary data were acquired through conversations with cops and staff. The secondary data sources were official documents, data from the firm website, company journals and publications, and annual reports, including financial statements from 2013–2014 to 2022–2023.

This work uses multivariate financial distress models to analyze financial distress. The Springate and logit probability model evaluated the firm's financial structure, liquidity, solvency, and profitability.

Logit Probability Model

According to the logit probability model, the probability of distress is given by the following formula:

Probability of Distress = $(1/1 + e^{y})$, where,

$$Y = 0.108(X1) + 1.583(X2) + 10.78(X3) + 3.074(X4) + 0.486(X5) + 4.35(X6) + 0.11(X7) \quad \ldots\ldots (1)$$

The variables that make up the logit model are as follows: X1 stands for inventory; X2 for receivables; X3 for cash and cash equivalents; X4 for fast assets; X5 for income earning; X6 for leverage; and X7 for sales. The distortion caused by the linear probability model is corrected by the logit model, which limits the likelihood of default between 0 and 1. There are just two possible values for the described variable: 0 for a stable firm and 1 for a defaulting firm.

Springate Model

In 1978, Springate used auditing analysis—inspired by Altman's methodology—to determine which four financial ratios, out of 19, were most helpful in differentiating between firms that were not insolvent and those that were. His model's remarkable accuracy record of 92.5%, obtained when tested on a sample of 40 industrial enterprises, demonstrated its effectiveness in anticipating financial difficulty in manufacturing. The Springate model provides analysts, creditors, and investors with a dependable way to evaluate the sustainability and health of manufacturing businesses by combining many financial indicators such as working capital, gearing, and net profit margin ratios.

S score = $1.03X1 + 3.07X2 + 0.66X3 + 0.4X4$ .... (2)

where,
X1 = Working capital to total assets,
X2 = Net profit before interest and taxes to total assets,
X3 = Net profit before taxes to current liabilities,
X4 = Sales to total assets.

Empirical Analysis and Results

According to the determined Springate scores, the corporation was not in crisis from 2013–2014 until 2022–2023. The financial situation is steady, with the *S*-scores over the 0.862 cutoff (Table 1).

Table 1. ***Results of Springate Financial Distress Prediction Model***

Year	2022–23	2021–22	2020–21	2019–20	2018–19	2017–18	2016–17	2015–16	2014–15	2013–14
X1	0.43	0.43	0.44	0.48	0.51	0.48	0.51	0.53	0.56	0.52
X2	0.35	0.29	0.31	0.32	0.41	0.32	0.37	0.31	0.30	0.25
X3	0.12823	0.1067	0.1155	0.128051	0.171118	0.130285	0.15365	0.136785	0.140808	0.108616
X4	0.197787	0.17989	0.19024	0.21091	0.23044	0.21609	0.19342	0.15878	0.1756	0.1685
Z value	1.10	1.01	1.05	1.14	1.31	1.15	1.22	1.13	1.18	1.05
Distressed or Non-Distressed	Non-Distressed	Non-Distressed	Non-Distressed	Non-Distressed	Non-Distressed	Non-Distressed	Non-Distressed	Non-Distressed	Non-Distressed	Non-Distressed

Note. I. Springate Model-*S* score = 1.03*X1* + 3.07*X2* + 0.66*X3* + 0.4*X4*.

X1 (Working Capital/Total Assets): Variable comments. The ratio indicates the organization's liquidity position. Over time, it has stayed comparatively constant at 0.43–0.56. Higher ratios indicate better liquidity and financial soundness, which raises the *S*-score.

The ratio X2 indicates the business's profitability concerning its total assets, or net profit before interest and taxes, divided by total assets. The numbers, which illustrate variations in profitability, vary from 0.25 to 0.41. Because of its considerable weight (3.07), the ratio has contributed significantly to the *S*-score while remaining stable despite these swings.

The X3 ratio, defined as net profit before tax/current liabilities, shows how successfully the business can use its earnings to pay off its short-term debt. The readings range from 0.1067 to 0.171118 and have been reasonably consistent. A more excellent ratio is preferable, as it indicates that the business can pay its debts with its earnings.

Sales/Total Assets (X4): This ratio shows how well the company uses its assets to produce sales. The figures ranging from 0.15878 to 0.23044 demonstrate the business's capacity to turn assets into revenue efficiently. Although this ratio has a lower weight (0.4), it nevertheless contributes to the *S*-score. The company's steady success in these areas has led to a stable financial situation.

According to the Springate model, the company has not experienced difficulty over the past 10 years (2013–2014 to 2022–2023). The computed *Z* values (*S*-scores) for each year exceed the 0.862 cutoff point, demonstrating a sound and steady financial situation. The principal conclusions and observations are outlined below:

Consistent Non-Distressed Status

Z-values consistently over 0.862 show that the company has not experienced financial distress during the entire

study period. Stable and healthy ratios: The company's overall solid financial situation can be attributed to the financial ratios (X1, X2, X3, and X4), which have demonstrated stability and healthy levels.

↳ ***Financial Health :*** The business has good profitability, liquidity, and efficiency ratios, all of which indicate excellent financial health.

↳ ***Danger of Distress :*** The continuously high *Z* scores indicate a minimal threat of financial distress.

↳ ***Performance Trend :*** The steady trends in the financial ratios and *Z* values demonstrate robust financial management and operational efficiency.

Based on the Springate model, the overall financial evaluation indicates that the company is in a good and stable financial position with no immediate risk of financial difficulty.

Table 2 shows the result of the logit probability financial distress prediction model. Except for 2015–2016, 2016–2017, and 2017–2018, the corporation has been categorized as distressed throughout most years, from 2013–14 to 2022–23. This suggests recurrent financial troubles interspersed with brief intervals of recuperation. Probability values closer to 0 indicate a greater possibility of distress, and values closer to 1 indicate a non-distressed condition.

The Working Capital/Total Assets ratio (X1) ranges between –0.044 and –0.059.

Observation: The ratio has continuously remained negative, pointing to a working capital shortfall compared to total assets. This raises the possibility of liquidity problems for the company, as its short-term liabilities may not be fully covered by its short-term assets. This ratio's negative values are alarming since they greatly exacerbate financial distress.

Table 2. ***Results of the Logit Probability Financial Distress Prediction Model***

Year	2022–23	2021–22	2020–21	2019–20	2018–19	2017–18	2016–17	2015–16	2014–15	2013–14
X1	–0.044	–0.044	–0.045	–0.05	–0.052	–0.05	–0.053	–0.055	–0.059	–0.054
X2	–0.599	–0.665	–0.76	–0.759	–0.699	–0.743	–0.769	–0.829	–0.938	–0.964
X3	–2.462	–2.416	–1.858	–0.702	–0.465	–0.429	–2.381	–4.385	–4.171	–3.387
X4	3.521	3.402	3.421	3.532	3.357	3.016	3.232	4.077	4.657	4.271
X5	0.1	0.082	0.081	0.078	0.093	0.078	0.089	0.071	0.068	0.061
X6	–0.288	–0.604	–0.524	–0.5	–0.441	–0.449	–0.479	–0.242	–0.226	–0.213
X7	0.131	0.118	0.123	0.124	0.129	0.127	0.108	0.085	0.088	0.091
Constant	0.23883	0.239	0.239	0.23883	0.2388	0.2388	0.2388	0.2388	0.2388	0.2388
Y	0.597	0.111	0.676	1.961	2.16	1.788	–0.014	–1.039	–0.342	0.043
e	2.71828	2.718	2.718	2.71828	2.7183	2.7183	2.7183	2.7183	2.7183	2.7183
e^x	1.8166	1.117	1.966	7.106	8.671	5.977	0.9861	0.3538	0.7103	1.043
(1/1 + *e*^*y*)	0.355	0.472	0.337	0.123	0.103	0.143	0.503	0.738	0.584	0.489
Distressed or Non-Distressed	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed	Non-Distressed	Non-Distressed	Non-Distressed	Distressed

Note. Probability of Financial Distress = (1/1 + *e*^*y*).

Where *Y* = (–0.108*X*1) + (–1.583*X*2) + (10.78*X*3) + (+3.074*X*4) + (+0.486*X*5) + (4.35*X*6) + (0.11*X*7) + 0.23883.

X2: (Total Assets/Net Profit Before Interest and Tax) ranges between –0.599 and –0.964.

Observation: The ratio's continuous downward trend implies losses before interest and taxes on total assets. Such persistent losses are a key sign of a financial crisis since they show low profitability. The business has not been able to get enough out of its assets.

X3 (Net Profit Before Tax/Current Debt) ranges from –0.429 to –4.38.

Remark: The negative ratio suggests the business cannot profit sufficiently to pay off its creditors. Certain years' inferior figures show serious troubles with profitability and challenges in fulfilling short-term responsibilities.

X4 (Total Assets/Sales) ranges from 3.016 to 4.657.

Observation: A positive and comparatively high ratio indicates a strong sales performance of total assets. Although the company generates sales, the overall financial hardship suggests that sales are insufficient to counterbalance the losses and liquidity concerns indicated by the other ratios.

X5 ranges from 0.061 to 0.1.

Observation: This ratio is favorable despite minor variations. Without a clear definition, it is impossible to evaluate its effect on the overall state of finances properly. In contrast to other variables, it appears to be reasonably steady.

X6 ranges between –0.213 and –0.604.

Remark: Given that this ratio is negative, there may be losses or shortcomings in another area of the business's financial performance. The persistently negative values point to persistent problems that exacerbate financial hardship.

X7 ranges from 0.085 to 0.131.

Observation: The ratio is favorable and steady, suggesting that there are still some comparatively strong areas of the business's performance. Like X5, without more background, its precise impact is unknown.

Financial Health: The company's substantial losses, cash flow problems, and inability to pay obligations with earnings have all contributed to its ongoing financial hardship.

Performance Trend: Other important financial data points to underlying financial issues, even in the face of strong sales performance.

Danger of Distress: There is a significant danger of financial distress for most of the years, with brief improvements in 2015–2016, 2016–2017, and 2017–2018.

Conclusion and Future Research

According to the financial analysis conducted using the Springate model, the company has maintained a non-distressed condition over the past 10 years (2013–2014 to 2022–2023). Every year, the computed *Z* values

(*S*-scores) have consistently exceeded the cutoff point of 0.862, indicating a sound and stable financial situation. Stable and sound financial ratios across important indicators, including asset utilization (X4), profitability (X2), liquidity (X1), and ability to cover liabilities (X3), support this constant performance.

Whereas the Springate model yielded a positive rating, another model indicated notable variations in the company's financial well-being throughout the same time frame. According to this alternative assessment, which determined probabilities of distress using the formula 1/(1+e^y), the corporation primarily experienced periods of distress with brief recovery intervals during most years. It is named the only non-distressed periods 2015–2016, 2016–2017, and 2017–2018.

The analysis's primary variables revealed divergent patterns. For example, the alternate model continually showed negative values for the working capital to total assets ratio (X1) and the net profit before interest and tax to total assets ratio (X2), indicating problems with liquidity and prolonged losses, two of the main signs of financial distress. Although unable to completely offset overall financial concerns, the sales-to-total assets ratio (X4) remained positive and relatively high, indicating solid sales performance.

More investigation is required to reconcile these divergent opinions and offer a more comprehensive knowledge of the company's financial condition. A more thorough study is needed to determine the underlying causes influencing each financial ratio's performance. This could entail placing the company's measurements in context by measuring them against peers and industry norms.

Longitudinal studies extending beyond the decade under consideration would help find longer-term trends and cycles in the company's financial health. Examining the effects of outside variables, including market trends, economic conditions, and regulatory changes, may shed light on the outside forces affecting the company's financial performance.

A thorough examination of the business's operations to pinpoint areas for efficiency gains could increase profitability and liquidity ratios. Reviewing the company's risk management plans would guarantee it is equipped to deal with future financial difficulties. If the business is divided into several segments, performing a segment-by-segment financial analysis would be beneficial in determining the advantages and disadvantages of each. Integrating qualitative elements like corporate governance, strategic objectives, and high-quality management would obtain a more comprehensive picture of the company's financial health.

Finally, a competitive study could point out comparable advantages and disadvantages, providing tactical insights for enhancing the business's growth and financial stability. Future studies in these areas will contribute to a thorough comprehension of the organization's economic dynamics and prospective areas for improvement.

Authors' Contribution

Prof. A. V. Rejimon initiated the research concept, formulated the qualitative and quantitative designs, and carried out the analytical research. He also selected and examined high-impact research articles, screened them through applicable keywords and developed key concepts and codes consistent with the study design. He also carried out the numerical calculations through Excel. Prof. P. K. Sinosh contributed significantly to the literature review, and the study was based on a strong theoretical foundation. He was also instrumental in choosing the right financial models and performing calculations for the financial distress analysis. His financial modeling skills ensured that the methodology was streamlined and the findings were accurate. Dr. V. Krishnaveni cross-checked the analytical techniques and guided the study to ensure methodological precision and accuracy.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Acknowledgment

The authors received no financial support for the research, authorship, and/or for the publication of this article.

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