

EVALUATION OF FINANCIAL DISTRESS: A CASE STUDY OF SELECTED AUTOMOBILE COMPANIES

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ABSTRACT

Financial distress refers to a situation where a company struggles to meet its financial obligations, which may eventually lead to bankruptcy if not addressed. Accurate prediction of financial distress becomes essential for stakeholders to make informed decisions and manage financial risks effectively. The primary objective of this study is to predict the financial distress of Indian automobile companies by applying the Altman, Springate, and Grover models, and to evaluate the predictive accuracy of these models for firms listed on the National Stock Exchange (NSE) during the period 2014–15 to 2023–24. Adopting a descriptive research design, the study employs both quantitative and panel data approaches. Descriptive statistics, normality tests, and one-way ANOVA were used in the analysis. The empirical findings reveal that the Grover model demonstrates the highest predictive accuracy at 96%, followed by the Springate model at 92%, while the Altman model records a comparatively lower accuracy rate of 68%.

Key Words: Financial Distress, Altman, Springate, Grover

1. INTRODUCTION

The Indian automobile industry has long been seen as a reliable indicator of the economy's health, since it contributes significantly in both macroeconomic growth and technological advancements (IBEF, 2024). In view of India's expanding middle class and a major part of its population being young, the two-wheeler sector equates the industry in terms of volume. (SIAM, 2024). Furthermore, corporations' increased interest in exploring rural markets has significantly contributed to the sector's expansion. The growing logistics and passenger transport sectors are driving demand for commercial vehicles. Future market development is expected to be driven by new trends such as vehicle electrification, particularly for three-wheelers and compact passenger autos (NITI Aayog, 2023). India dominates the worldwide heavy vehicle market, producing the world's largest tractors, second-largest buses, and third-largest heavy trucks. In fiscal year 2023, India produced 25.9 million automobiles. India has a significant local and export market. In December 2024, the overall number of passenger vehicles, three-wheelers, two-wheelers, and quadricycles produced was 19, 21,268 (SIAM, 2024). "This demonstrates the sustained growth of the Indian automobile industry, driven by increasing domestic demand and export opportunities."

India has emerged as a significant automobile exporter, with strong prospects for sustained export growth in the upcoming years. Furthermore, various initiatives introduced by the Government of India—such as the Automotive Mission Plan 2026, the vehicle scrappage policy, and the Production-Linked Incentive (PLI) scheme, are projected to move India to the

forefront of worldwide two- and four-wheeler markets (Ministry of Heavy Industries, 2024; SIAM, 2024.)

By 2030, India is projected to emerge as a global leader in shared mobility, thereby creating significant opportunities for the adoption of electric and autonomous vehicles. In alignment with environmental sustainability goals, policy and industry efforts are increasingly shifting focus toward the promotion of electric mobility as a means to reduce vehicular emissions. During FY 2022–23, India's total automobile exports stood at 4,761,487 units. The sector's contribution to the national GDP has expanded considerably, rising from 2.77% in 1992–93 to approximately 7.1% in recent years, reflecting its growing economic importance (SIAM, 2024). Furthermore, the industry provides direct and indirect employment to over 19 million people, underscoring its critical role in the country's socio-economic development.

By 2030, India is projected to emerge as a global leader in transportation sharing, thereby creating significant opportunities for the integration of electric and autonomous vehicles. In alignment with environmental sustainability goals, policy and industry efforts are increasingly shifting focus toward the advancement of electric mobility as a means to reduce vehicular emissions. During FY 2022–23, India's total automobile exports stood at 4,761,487 units. The sector's share to the national GDP has widened appreciably, increasing from 2.77% in 1992–93 to nearly 7.1% in recent years, indicating its expanding economic contribution (SIAM, 2024). Furthermore, the industry employs over 19 million people, demonstrating its contribution in the country's socio-economic development.

Several financial distress prediction models have been developed, however this study emphasises the Altman Z-score, Springate, and Grover models due to their wide application, reliability, and suitability for analyzing corporate financial performance. Previous studies have highlighted the accuracy and resilience of these models in different contexts. For example, Sari (2018) reported that the Springate model is particularly suitable for transportation firms in Indonesia, due to its higher predictive accuracy compared to other approaches. Similarly, Pakdaman (2018) reported that the Grover model frequently produces the highest accuracy values, positioning it as a strong alternative to the Altman model. Furthermore, Lestari et al. (2021) demonstrated that both the Springate and Grover models perform effectively alongside the Altman model, although their relative accuracy varies across industry and time period.

Conversely, while models such as Zmijewski and Ohlson are extensively utilized, empirical evidence indicates that they are more frequently applied in banking and service-oriented sectors, while their applicability to manufacturing and automobile industries is relatively limited. Given the study's emphasis on selected automobile companies in India, the Altman, Springate, and Grover models have been selected, as they were consistently validated in manufacturing and other capital-intensive industries. Collectively, these three models provide a comprehensive framework for identifying financial distress through considering profitability, liquidity, solvency, and leverage indicators.

Accordingly, these models have been selected because previous studies have demonstrated their effectiveness, and they relate well with the research objectives and the automobile industry context.

1.1 Financial Distress

Financial distress refers to a decrease in cash flow or liquidity. Inability to cover short-term liabilities is a sign of financial distress and can lead to solvability, where a person or entity cannot pay their obligations on time or has more liabilities than assets. Financial distress as a

company's inability to meet its current obligations, tax, and short-term bank debt. As long as the company's cash flow exceeds its debt commitments, it may pay its creditors (Altman, 1968; Ross et al., 2021). Financial distress relates to a company's unhealthy financial situation. These situations disrupt the company's operations, requiring managerial alertness to prevent an adverse scenario or insolvency.

1.2 Financial Distress Prediction Models

1.2.1 Altman Z score model

The Altman Z-score is a widely recognised financial analysis tool for estimate a company's likelihood of insolvency or financial distress. Edward Altman, an American finance professor, invented it in 1968 and it has since been considered as a reliable indicator of financial health.

Altman pioneered the use of Z-scores, which effectively forecast expected financial outcomes. Altman created the first bankruptcy model by examining various variables and sample sizes. The resulting bankruptcy equation has been created to predict the risk of insolvency of a public manufacturing business. The equation for the Altman model is:

$$Z = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E$$

Variables as follows:

A = Working Capital/Total Assets

B = Retained Earnings/Total Assets

C = Earnings before Interest and Taxes/Total Assets

D = Market Value of Equity/Book Value of Total Liabilities

E = Sales/Total Assets

Classification Zones:

$Z > 2.99$ "safe" zone

$Z > 1.81 < 2.99$ "grey" zone

$Z < 1.81$ "distress" zone

1.2.2 Springate Model

The Springate model is a statistical approach frequently employed to predict the potential of business insolvency. The approach, which was developed by a British statistician named Peter Springate in 1978, has found wide acceptance in the financial domain as a method of recognising financial distress. Notably, the model demonstrates flexibility, as it can be modified to the needs of various sectors and markets. It also enables for adaptations to include industry-specific variables or the macroeconomic factors that may affect a company's financial health.

$$S = 1.03A + 3.07C + 0.66E + 0.4G$$

Where,

A = Working Capital/Total Assets

C = Net Profit before Interest and Taxes/Total Assets

E = Sales/Total Assets

G = Net Profit before Taxes/Current Liabilities

Classification Zones:

S > 0.862 → Safe

S < 0.862 → Failed/Distress

1.2.3 Grover Model

The Grover model was created as an expansion and reconsideration of the Altman Z-score model. In 1968, Jeffrey S. Grover introduced 13 more monetary parameters to the Altman Z-score model. From 1982 to 1996, 70 enterprises were sampled, 35 of which went bankrupt and 35 of which did not. Grover (2001), according to Prihanthini (2013), the study revealed that a simplified version of the model had substantial predictive ability for discriminating between bankrupt and non-bankrupt organisations. The equation for the Grover Model:

$$G = 1.65A + 3.404C - 0.016F + 0.057$$

Where:

A = Working Capital /Total Assets

C = Net Profit before Interest and Tax / Total Assets

F = Return on Assets (ROA)

Classification Zones:

Z > 0.01 → Not Bankrupt

Z ≤ -0.02 → Bankrupt

2. LITERATURE REVIEW

A literature review is a structured overview of previous research on a specific topic. It support researchers in identifying existing knowledge, formulating appropriate research questions, and selecting relevant theories or methods of the study. By situating the present work within previous academic literature, it provides context and establishes the foundation for further research.”

Tariq et al. (2025) examined data from 21 non-financial organisations over the period from 2014-15 to 2022-23, employing Altman's Z-score as a proxy for financial distress. The study applying Panel Least Squares (PLS), Fixed Effect, and Random Effect models. It is found that low profitability, large debt, and inadequate liquidity significantly increase the probability of financial distress. The study concludes that continuous monitoring of financial indicators can assist stakeholders in managing financial risks efficiently. **Aravam Dhanunjayulu and K Jayachandra Reddy (2025)** sought to examine the financial health of six selected Indian cement companies for the period 2012-13 and 2021-22 using the Altman Z-Score model. The analysis revealed that UltraTech Cement and Ambuja Cement fall within the safe zone, indicating strong financial position, while Dalmia Cement and JK Cement lie in the grey zone, implying moderate financial risk. Birla Cement and India Cements are positioned in the distress zone, indicating serve financial risk. However, the study's dependence exclusive on the Altman model, without cross-validation using alternative models such as Springate or Zmijewski, limits the robustness and generalizability of its conclusions. **Asad Mehmood and Francesco De Luca (2023)** employed a sample comprising of 312 distressed and 312 non-distressed enterprises to enhance the predictive capability of the original Z"-Score model. By applying Linear Discriminant Analysis (LDA),

the study modified the model and develop a TDR (Troubled Debt Restructuring) probability index through logistic regression. The finding reveal that the improved Z"-Score model significantly enhance prediction accuracy by successfully discriminating between distressed and non-distressed enterprises. The study indicates that the model serve a reliable tool for early detection of financial distress, thereby supporting timely TDR interventions. **Hasna Kurnia Ulfah and Abdul Moin (2022)** examined the predictive accuracy of distress models using data from five tobacco companies listed on Indonesia Stock exchange over the period from 2017-18 to 2020-21. The models were tested with Excel and SPSS. It is found that the Springate S-Score model achieved the highest accuracy (80%) in predicting financial distress. The observation emphasises that, the Springate model demonstrates strong predictive capability, and broader research are required for more rigorous validation. **Patel et al. (2021)** evaluated the financial distress of the Indian automobile industry over the period from 2015 -16 to 2019 - 20. The study employs purposive sampling, selecting ten of the largest automobile companies listed on the Bombay Stock Exchange (BSE) by market capitalisation. The study Used Altman, Grover, Springate, and Zmijewski models, to evaluate financial distress scores. The finding demonstrate that the financial performance of the firms was relatively stable during the study period, and a comparison across the models indicates that the predicted distress levels for the selected companies were considerably comparable. **Mr. Taj Baba (2019)** examined the financial distress of selected automobile companies in India using Altman's Z-score method. The study, descriptive-explanatory in nature, employed a purposive sampling method and considered 6 companies from the period 2015 - 16 to 2018-19. The findings indicate that Bajaj Auto Ltd. and Hero MotoCorp Ltd. are financially healthy and stable, while Tata Motors Ltd. falling in to the distress zone, showing an adverse outlook for the company and its stakeholders. The study concludes that Altman's Z-score provides valuable insights into financial soundness and bankruptcy evolution of risk within the automobile sector. **M. Fakhri Husein and Galuh Tri Pambekti (2015)** developed financial distress models as early warning systems to anticipate potential bankruptcy conditions. The study employed a quantitative research approach, pooled data, and dummy variables, using a sample of 132 enterprises listed on the Daftar Efek Syariah (DES) between 2009-10 to 2011-12. Considering Binary Logistic Regression as the analytical tool, the findings indicate that all four models—Altman, Springate, Zmijewski, and Grover—are effective in predicting financial distress. However, the Zmijewski model has the highest degree of significance, which render it the most accurate predictor. The study implies that Zmijewski's stronger emphasis on leverage ratios enhances its reliability in identifying financial distress. **Ng et al. (2013)** examined financial health of PN17 and non-PN17 enterprises for the period 2003-04 to 2008-09. The result indicated that not all PN17 firms were financially distressed—some were categorised due to technical or regulatory issues—and that other non-PN17 enterprises displayed indicators of distress despite the lack of official categorisation. The study's limitations include its dependence on a restricted collection of financial measurements and a single model, which may limit the depth and breadth of its analysis. The finding highlights the need for a more complete approach that incorporates different models and indicators for a holistic assessment. **Hazem B. Al-khatib and Alaa Al-Horani (2012)** examined 56 publicly traded corporations using logistic regression and discriminant analysis to identify determinates of financial distress. The finding revealed that profitability, liquidity, leverage, and activity ratios had a substantial impact on financial distress. However, the study's reliance on quantitative data and concentration on a single stock exchange restrict the conclusions' broader relevance. It is found that financial ratios are effective instruments for early detection and timely intervention. **N.VenkataRamana et al. (2012)** analysed the financial health of Dalmia

Bharat Ltd, KCP Ltd, and Kesoram Industries Ltd during the period 2001-02 to 2009-10, by employing liquidity, working capital, and solvency ratios along with Altman's Z-score model. The findings indicated weak financial performance across the selected firms, with KCP Ltd and Kesoram Industries Ltd identified as financially weak and at high risk of bankruptcy, while Dalmia Bharat Ltd was found to be near financial distress. It concludes that early detection of financial distress through such models is vital for effective financial management and long-term stability.

2.2 Research Gap

Existing studies on financial distress in India have predominantly examined sectors such as banking, textiles, and general manufacturing, while the automobile industry has received comparatively limited attention. Furthermore, much of the prior research has relied on a single prediction model and relatively short study periods, thereby constraining the robustness and generalizability of the findings. To date, limited study has systematically applied Altman, Springate, and Grover models over a ten-year horizon to evaluate distress levels in Indian automobile companies. Addressing this gap is crucial, as a comprehensive and long-term assessment can generate valuable insights for investors, policymakers, and corporate decision-makers.

2.3 Objective of the Study

1. To predict the financial distress in selected Indian automobile companies using suitable financial distress prediction models.
2. To check accuracy of models used and predict suitable financial distress model.

2.4 According with the theoretical background, the study's hypothesis are given as follows:

H01: There is no significant difference in mean scores among the distress models.

Ha1: There is significant difference in mean scores among the distress models.

3. RESEARCH METHODOLOGY

The present empirical study relies exclusively on secondary data, and the sample firms were selected using purposive sampling technique. The study focusses on Indian automobile industry, especially the **top five NSE-listed companies based on market capitalization as of March 2024**. The data gathered from the annual reports of the selected automobile companies and the CMIE Prowess IQ database of information covering a ten-year period of (2014–15 to 2023–24). The Altman, Springate, and Grover models are used to identify early warning signs of financial distress, which may then be addressed or reversed through appropriate managerial and financial interventions. The normality test, variance homogeneity test, and overall significance test (F-test) were additionally employed within the study for statistical validation. Data computation and statistical analysis were carried out using Microsoft Excel and SPSS software packages. This approach indicates that only relevant and representative firms—those with the highest market capitalization—are considered in the analysis. The companies with highest market capitalization as of 2024 are as follows:

Rank	Company Name	Market Capitalization (in crores)
1	Bajaj Auto Ltd.	255397.8
2	Mahindra & Mahindra Ltd.	238925.4
3	Maruti Suzuki India Ltd.	396158.2

4	T V S Motor Co. Ltd.	102231.6
5	Tata Motors Ltd.	329980.8

3.1 Variable of the Study

For evaluating the financial performance and determine the distress level, the following factors and parameters are stated:

- A = Working Capital/Total Assets
- B = Retained Earnings/Total Assets
- C = Earnings before Interest and Tax/Total Assets
- D = Market Value of Equity/Total Liabilities
- E = Sales / Total Assets
- F = Return on Assets (ROA)
- G = Net Profit before Taxes to Current Liabilities

4. RESULT AND DISCUSSION

This section presents the results of the analysis, followed by a discussion that reconciles the empirical findings with theoretical predictions and evaluate the financial health of the selected 5 Automobile Companies.

4.1 Altman Z score

Table 1 - Altman Z score

Year	Bajaj Auto	M&M	Maruti Suzuki	TVS Motors	Tata Motors
2015	5.00	2.91	3.48	4.27	1.83
2016	5.22	2.99	3.64	4.63	1.81
2017	4.84	2.85	4.17	4.55	1.75
2018	4.21	2.73	4.54	4.82	1.64
2019	3.96	2.53	3.76	4.07	1.58
2020	3.52	1.82	2.65	2.80	0.39
2021	4.03	2.11	2.96	3.48	1.14
2022	3.91	2.30	3.18	3.45	1.93
2023	4.26	2.90	3.45	4.44	2.48
2024	6.90	3.64	3.86	6.30	4.45
Avg. value	4.58	2.68	3.57	4.28	1.90
Status	Healthy	Grey Zone	Healthy	Healthy	Grey Zone

Source: Computed by Authors, Averaged values for study period.

As shown in the table 1 it can be observe that the Z-Score research from 2014-15 to 2023-24 shows that Bajaj Auto, Maruti Suzuki, and TVS Motors have continuously maintained robust financial health, with Z scores usually over 3, which indicates minimal bankruptcy risk. M&M stayed in the Grey Zone for the majority of the time, but showed remarkable progress by 2024, moving into the Healthy Zone. Tata Motors experienced financial difficulties between 2015 and 2021, with its lowest score in 2020, but slowly improved, attaining a high score of 4.45 in 2024. Overall, despite some short-term effects from the COVID-19 pandemic, all corporations except Tata Motors and M&M had stable condition.

4.2 Springate Score

Table 2 - Springate score

Year	Bajaj Auto	M&M	Maruti Suzuki	TVS Motors	Tata Motors
2015	2.83	1.20	1.49	1.34	-0.18
2016	3.11	1.22	1.55	1.47	0.30
2017	2.67	1.21	1.62	1.30	0.08
2018	2.34	1.17	1.49	1.22	0.26
2019	2.16	1.20	1.53	1.29	0.58
2020	2.50	1.17	1.20	0.94	-0.26
2021	1.92	0.93	0.85	0.96	0.01
2022	2.16	1.02	0.84	1.03	0.19
2023	2.29	1.23	1.17	1.26	0.48
2024	2.21	1.43	1.44	1.49	0.95
Avg. value	2.42	1.18	1.31	1.23	0.24
S-Score Status	Healthy	Healthy	Healthy	Healthy	Unhealthy

Source: Computed by Authors, Averaged values for study period.

According to the data presented in the table 3 the Springate S-Score values for five Indian automobile companies from 2014-15 to 2023-24. Bajaj Auto regularly achieves the best markings, remaining above the 1.0 level throughout the time, indicating robust financial health. M&M, Maruti Suzuki, and TVS Motors stay in the "Healthy" zone, despite periodic changes and mild drops, particularly between 2020 and 2021. On the other hand, Tata Motors' financial situation reflect potentially unstable, with numerous years of low or barely positive ratings, ending in a score of 0.95 in 2024—still categorised as "Unhealthy." Overall, while most companies remain financially stable, Tata Motors gazes to be in financial distress over the examined time.

4.3 Grover Score

Table 3 - Grover Score

Year	Bajaj Auto	M&M	Maruti Suzuki	TVS Motors	Tata Motors
2015	1.36	0.49	0.69	0.24	-0.24
2016	1.02	0.45	0.39	0.24	0.02
2017	1.10	0.45	0.36	0.16	-0.09
2018	0.95	0.48	0.32	0.08	-0.07
2019	0.76	0.52	0.44	0.19	0.04
2020	0.82	0.61	0.27	0.05	-0.29
2021	0.89	0.55	0.30	0.12	-0.09
2022	0.78	0.52	0.23	0.07	-0.09
2023	0.79	0.58	0.19	0.14	-0.15
2024	0.75	0.60	0.32	0.25	0.19
Avg. Value	0.92	0.52	0.35	0.15	-0.07
G-Score Status	Healthy	Healthy	Healthy	Healthy	Distressed

Source: Computed by Authors, Averaged values for study period.

Based on the findings it can observe that the Grover G-Score values for selected Indian automobile companies for the period 2014-15 and 2023-24. Bajaj Auto regularly has the best financial status, with G-Scores well above the usual distress threshold (typically > 0.75 , signifying health). M&M, Maruti Suzuki, and TVS Motors continue in the "Healthy" zone,

but with lower scores that fluctuate over time—particularly for Maruti and TVS, which experience a persistent decrease until a minor turnaround in 2024. Tata Motors, on the other hand, reveals ongoing financial challenges throughout the time, with numerous years of negative G-Scores and a mere slight improvement to 0.19 by 2024, retaining its "Distressed" status. Overall, the Grover model shows that most corporations are financially healthy while Tata Motors appears to be financially distress.

4.4 Test of Normality

The normality test indicates that useful data is consistently distributed, with a significance level (Sig) greater than 0.05. This study employed the Shapiro Wilk technique, which was produced using SPSS software.

Table 4 - Shapiro- Wilk Test

	Shapiro-Wilk		
	Statistic	df	Sig.
Z SCORE	.986	50	.816
SPRINGATE	.963	50	.124
GROVER	.981	50	.589

*. This is a lower bound of the true significance.

Lilliefors Significance Correction

The results of the Shapiro-Wilk normality test for the financial distress prediction models Z-Score, Springate, and Grover shows that the significance values for each model are more than the threshold value of 0.05. It can be concluded that the data is normally distributed.

4.5 Test of Homogeneity of Variances

The Levene's test was used to determine variance equality between groups for the Z-Score, Springate, and Grover models. The **Levene Statistic** table using SPSS can be seen as follows.

Table 5 - Levene Statistic

	Levene Statistic	df1	df2	Sig.
Z SCORE	.589	9	40	.798
SPRINGATE	.261	9	40	.982
GROVER	.370	9	40	.943

As per the above table of **Levene Statistic** test, the values of Z-Score (0.798), Springate (0.982), and Grover (0.943) are significantly higher than the 0.05 level. This implies that the assumption of variance homogeneity is fulfilled, implying that the variance remains the same across the groups and that parametric tests such as ANOVA may be executed with reliability.

4.6 Overall Significance test (F-test)

The ANOVA outcome indicates that there are statistically significant differences in mean scores between the three models: Z-Score, Springate, and Grover. The results of F test analysis table using SPSS are as follows.

Table 6 - One way ANOVA

		Sum of Squares	df	Mean Square	F	Sig.(p-value)
Z SCORE	Between Groups	24.281	9	2.698	1.884	.083
	Within Groups	57.278	40	1.432		
	Total	81.559	49			
SPRING ATE	Between Groups	1.661	9	.185	.286	.975
	Within Groups	25.845	40	.646		
	Total	27.506	49			
GROVER	Between Groups	.198	9	.022	.140	.998
	Within Groups	6.310	40	.158		
	Total	6.508	49			

As per the findings there is no significant difference in the mean across the groups, yet it is near the threshold of significance. The p- values for the Z score, Springate and Grover models are 0.083, 0.975 and 0.998, respectively, which are significantly higher than 0.05. We fail to reject (H0) the null hypotheses, it means there is no significant difference in mean scores among the distress models.

Finally, the ANOVA findings reveal that none of the models have substantial variance in scores across the ten groups, revealing that financial distress prediction has been consistent among the selected organisations.

4.7 Accuracy Evaluation of Financial Distress Models

The accuracy level in this study was tested using an updated method based on Husein and Pambekti (2014), with the real condition of the company established using net profit as the classification criterion. In this framework, the dependent variable was coded as a dummy variable, with "0" indicating a non-distressed (healthy) company with positive net profit and "1" indicating a financially distressed company with negative net profit. The predictive accuracy of each model has been assessed by comparing the predicted classification with its actual classification based on net profit data.

The model accuracy test provides both accurate and inaccurate estimations. The accuracy level represents the percentage that of the model predicts correctly as opposed to wrongly from the complete existing dataset.

According to Altman (2000), the method for measuring accuracy is as follows:

$$\text{Accuracy Level} = \frac{\text{Total Correct Predictions}}{\text{Total Samples}} \times 100\%$$

The level of inaccuracy from prediction models has been divided into two main categories (Altman, 2000).

Type I Error

Type I error occurs when a measuring model predicts absence of distress but actually experiences distress. The type I error rate can be identified as follows:

$$\text{Type I Error} = \frac{\text{Total Type I error}}{\text{Total Sample}} \times 100\%$$

Type II Error

Type II error occurs when a measuring model predicts distress but the sample fails to experience distress. The type II error rate can be identified as follows:

$$\text{Type II Error} = \frac{\text{Total Type II error}}{\text{Total Sample}} \times 100\%$$

4.7.1 Accuracy Test of Altman Z score Model

The following are the outcomes of calculating the accuracy of the Altman model.

Table 7 - Altman Model Accuracy Calculation Result

	Total Sample	Correct Prediction	Wrong Prediction	Gray Zone	Type Error	
Distress	7	5	0	2	Type 1 Error	0.00%
Non-Distress	43	29	1	13	Type 2 Error	2.33%
Total	50	34	1	15	32.00%	
Accuracy Level	68.00%					

Based on the results, the model accurately predicted 34 of 50 enterprises, resulting in a 68% accuracy rate. In the distress group, 5 out of 7 firms were properly classified, with 2 falling into the grey zone, obtaining a Type I error of 0%. In the non-distressed group, 29 of 43 firms were correctly categorised, one was misclassified, and 13 went into the grey zone, resulting in a Type II error of 2.33%. Although the model performs relatively well, the significant number of grey zone indications shows significant discrepancies in predictions.

4.7.2 Accuracy Test of Springate S score Model

The following are the outcomes of calculating the accuracy of the Springate model.

Table 8- Springate Model Accuracy Calculation Result

	Total Sample	Correct Prediction	Wrong Prediction	Type Error	
Distress	7	7	0	Type 1	0.00%
Non-Distress	43	39	4	Type 2	09.30%
Total	50	46	4		8.00%
Accuracy Level	92.00%				

Based on the results, the Springate model had a 92% accuracy rate, correctly predicting 46 of 50 enterprises. Within the distress group, all seven firms were correctly identified, obtaining a Type I error rate of 0%, indicating high reliability in detecting financial distress. In the non-distressed group, 39 of 43 companies were correctly identified, while 4 were misclassified, obtaining a Type II error rate of 9.30%.

4.7.3 Accuracy Test of Grover G score Model

The following are the outcomes of calculating the accuracy of the Grover model.

Table 9 – Grover Model Accuracy Calculation Result

	Total Sample	Correct Prediction	Wrong Prediction	Type Error	
Distress	7	6	1	Type 1	14.28%
Non-Distress	43	42	1	Type 2	2.32%
Total	50	48	2		4.00%
Accuracy Level	96.00%				

Based on the results, the Grover model scored an overall accuracy rate of 96%, accurately predicting 48 of 50 enterprises. 6 out of 7 distressed companies were correctly identified, with 1 classified incorrectly, yielding a Type I error rate of 14.28%. In the case of non-distressed companies, 42 of 43 were properly recognised, with a single misclassification, resulting in a Type II error rate of 2.32%.

4.7.4 Comparison of the Accuracy and Error Rate of Financial Distress Prediction Models

The table below compares the accuracy and error rates of three different financial distress prediction models:

Table 10 - Accuracy Level Percentage

	Altman Z score	Springate S score	Grover G score
Accuracy Level Percentage	68.00%	92.00%	96.00%
Error Rate	32.00%	8.00%	4.00%

Based on the results of calculating the accuracy values of the three models, the Grover G-Score model was found to be the most accurate, with an accuracy percentage of 96% (error rate 4%). This is followed by the Springate S-Score model with an accuracy rate of 92% (error rate 8%), while the Altman Z-Score model had the lowest prediction performance with an accuracy of 68% (error rate 32%).

5. CONCLUSION

Thus, this study is consistent with prior findings, which indicate that the Grover model is the most accurate model in predicting the potential for financial distress of Indian Automobile Companies listed on the national stock exchange with an accuracy percentage 96%.

This study evaluated the accuracy of three financial distress prediction models—Altman Z-Score, Springate S-Score, and Grover G-Score—on selected Indian enterprises. The results show that all three models are successful in predicting economic crises, while their levels of accuracy vary. Among these, the Grover model scored the greatest accuracy level of 96%, followed by the Springate model at 92%, and the Altman Z-Score at 68%.

The findings indicate that in the Indian context, the Grover and Springate models are especially strong and produce highly dependable forecasts. At the same time, the Altman Z-Score remains a significant standard model with extensive global relevance, ensuring its continuing use in financial research.

These findings are consistent with previous research, such as Meiliawati and Isharjadi (2016), who highlighted the good performance of the Springate model in the cosmetic sector, as well as other studies that support the Grover model's robustness in emerging countries. This study expands to the literature by enhancing the contextual applicability of multiple distress prediction models and emphasising the significance of employing them as complementary tools in financial decision-making.

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