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Benchmarking Financial Distress Prediction Models through Outcome Based Validation in Indian Companies

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Abstract. Although many studies have compared financial distress prediction models, most evaluate performance based on agreement among models rather than validation against actual financial outcomes. This limitation makes it difficult to identify which models provide the most reliable early-warning signals in practice. Addressing this gap, this study benchmarks five widely used financial distress prediction models namely the Altman Z-Score, Ohlson O-Score, Zmijewski, Springate, and Grover models through an outcome-based validation framework using real-world financial outcomes of selected Indian companies. Secondary financial data from six companies in the telecommunications, infrastructure, and automobile sectors covering the 2015–2025 period were analyzed. Model predictions were validated against independently verified evidence, including credit ratings, insolvency proceedings, financial restructuring events, and company-specific distress indicators. Predictive performance was evaluated using confusion matrix analysis and multiple classification metrics, including accuracy, sensitivity, specificity, precision, F1 score, and Type II error. The findings reveal substantial variation in model performance. The Springate model achieved perfect sensitivity and identified all distressed observations, whereas the Zmijewski model provided the most balanced overall performance with the highest F1 score. In contrast, the Altman, Ohlson, and Grover models showed higher overall accuracy but missed several actual distress cases. By introducing an outcome-based validation framework, this study advances the evaluation of financial distress prediction models beyond conventional model comparison and provides more reliable guidance for investors, lenders, regulators, and corporate managers in selecting effective early-warning tools.

Keywords: Altman Z-Score; Financial distress prediction; Indian companies; Springate Model; Zmijewski Model

1. Introduction

Financial distress prediction has become a central concern in corporate finance, particularly in emerging economies such as India, where firms operate under conditions of market volatility, economic uncertainty, and rapidly changing business environments (Ahemed et al., 2025; Elhoseny et al., 2025; Farooq et al., 2023; Oware & Appiah, 2022; Sehgal et al., 2021). Financial distress describes a situation in which a firm is unable to

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meet its financial obligations as they fall due and which, if left unaddressed, may culminate in insolvency or bankruptcy. Because firms rarely move directly from financial health to failure and instead pass through a period of measurable deterioration marked by declining profitability, weakening liquidity, and rising leverage, their condition can often be diagnosed well before collapse occurs. The ability to recognise these early warning signals is of considerable value to investors, creditors, managers, and policymakers, since timely identification supports sounder decision-making, limits potential losses, and contributes to broader financial stability.

In the Indian context, the rising volume of corporate insolvency cases resolved under the Insolvency and Bankruptcy Code has sharpened both regulatory and academic interest in detecting financial weakness at an early stage (Baxi, 2023; Ravichandra Rao & Kasture, 2026). To meet this need, researchers have developed a range of quantitative models designed to translate publicly available financial information into an assessment of a firm's likelihood of failure. Among the most influential are the Altman Z-Score (Swalih et al., 2021), the Ohlson O-Score (Lisin et al., 2022), the Zmijewski model (Yendrawati & Adiwafi, 2020), the Springate model (Marsenne et al., 2024), and the Grover model (Nurul CH et al., 2024), each of which draws on financial ratios that capture profitability, liquidity, leverage, and operating performance. Although these models share the common purpose of distinguishing healthy firms from those at risk, they differ substantially in the variables they employ, the statistical techniques on which they are based, and the classification criteria they apply. As a consequence, the same company may be assigned to different risk categories depending on which model is used, a divergence that makes comparative evaluation essential rather than incidental.

This concern is heightened by the fact that most of these models were originally developed and calibrated using data from firms in developed economies, so that their underlying assumptions may not fully reflect the regulatory environment, financial structures, and industry characteristics of Indian companies. A substantial body of literature has compared different financial distress prediction models, yet the findings remain inconsistent. Comparative studies generally conclude that no single model is universally superior across industries and economic environments (Y. Chen et al., 2024; Li & Azman, 2025). The predictive effectiveness of a model often depends on firm characteristics, sector-specific factors, and the economic conditions under which it is applied. Research conducted on Indian stock market companies found that the Altman and Springate models frequently demonstrate strong predictive performance, although their effectiveness varies across firms and industries (Elangovan et al., 2022; Singh Chauhan et al., 2025). Similarly, studies in the retail sector indicate that the Zmijewski model often performs better because of its emphasis on profitability and leverage measures (Chhabra, 2018; Khan et al., 2024).

The COVID-19 pandemic further demonstrated that financial distress models can behave differently during periods of economic disruption. Recent studies have expanded the literature by introducing machine learning and artificial intelligence into financial distress prediction. Barboza & Altman (2024) compared logistic regression and random forest models in Latin American companies and found that advanced methods may improve predictive performance in certain contexts. Likewise, Huang (2024) reported that machine learning approaches can strengthen financial sustainability analysis and enhance distress prediction in emerging markets. At the review level, Zhang et al. (2022) observed that financial distress research is increasingly integrating traditional statistical approaches with artificial intelligence techniques. Similarly, Pandey et al. (2025) found that recent research has become more methodologically diverse and is increasingly focused on improving predictive accuracy and practical applicability. A comparative study of Bangladeshi NBFIs found that the Zmijewski model detected more distressed firms than the Altman, Springate, and Grover models, highlighting differences in model effectiveness (Ghosh, 2019). Predictive performance varies substantially across industries and economic conditions, indicating that no model can be considered universally applicable (Halawi et al., 2022).

Sector-specific studies demonstrate that financial distress prediction varies considerably across industries. Research on Indian companies shows that financial distress models can effectively distinguish between stable and financially weak firms, thereby providing useful early warning signals (Abdullah et al., 2023; Shome & Verma, 2020; Singh & Singla, 2024). Similarly, firm-level studies such as the financial analysis of Dabur India illustrate how financial ratios can be used to evaluate corporate financial health and identify potential warning signs of distress (Thakur, 2019). Research focusing on iron and steel companies indicates that financial distress can occur even in well-established firms when leverage becomes excessive and financial management deteriorates (Chandrasekar et al., 2025; Sun et al., 2019). These findings suggest that model performance is not fixed but depends significantly on the financial structure, operating environment, and risk characteristics of the sector being examined. Taken together, the literature suggests that financial distress prediction remains an active area of research, but model effectiveness is highly sensitive to sector characteristics, economic conditions, and the evaluation methods used.

This study addresses that gap by evaluating and comparing five widely used financial distress prediction models, namely the Altman Z-Score, Ohlson O-Score, Zmijewski, Springate, and Grover models, for six Indian companies drawn from the telecom, infrastructure, and automobile sectors over the period 2015–2025. Rather than relying on model consensus, the study assesses the financial condition of each firm year by year and validates the resulting classifications against independently verified real-world outcomes, thereby grounding model evaluation in actual financial experience rather than mutual agreement. In pursuing this aim, the study compares the distress classifications generated by the five models under identical economic conditions, evaluates their predictive performance using established classification metrics, determines which model offers the most dependable early-warning capability and the best balance between detecting distress and limiting false alarms, and examines whether a multi-model approach yields more reliable insight into distress risk than reliance on any single model. Framing the objectives in this way situates the analysis within the practical decision problems faced by the users of these models.

The originality of the study lies in its combination of a multi-model, cross-sector comparison with outcome-based validation, an approach that remains uncommon in the Indian context. By benchmarking model predictions against confirmed evidence of financial distress, and by applying a comprehensive set of performance measures, the study offers more reliable guidance than analyses grounded in model agreement alone. Its findings are intended to be of practical value to investors, lenders, corporate managers, and policymakers seeking dependable early-warning tools, and to contribute to the academic literature by demonstrating the importance of real-world validation when comparing financial distress prediction models. The theoretical foundations of the study and a detailed review of prior research are presented in the following section.

2. Methods

2.1. Research Design, Sample Selection, and Data

This study adopts a quantitative, comparative, and analytical research design to examine the effectiveness of financial distress prediction models in the Indian corporate context (Cameron, 2009; S. Chen, 2025). The design is appropriate because the objective of the study is not merely to compute model scores, but to compare how different models classify the same firms under identical economic conditions and to evaluate which model provides the most reliable early-warning signal of distress. Five established financial distress prediction models, namely the Altman Z-Score, Ohlson O-Score, Zmijewski Model, Springate Model, and Grover Model, are applied to the selected Indian companies for the period 2015–2025, and the resulting classifications are compared with independently verified real-world outcomes to evaluate their predictive performance. To operationalize this design, the study uses purposive sampling to select six Indian companies from the telecom, infrastructure, and automobile sectors namely Vodafone Idea, Bharti Airtel, Reliance Infrastructure, Larsen & Toubro, Ashok Leyland, and Maruti Suzuki. These firms were chosen because they represent different financial conditions, capital structures, and industry characteristics, and the sample deliberately includes both financially stable and financially stressed firms so that the models can be tested under contrasting conditions.

The sectoral composition is also intentional namely telecom and infrastructure firms typically carry high leverage and long-term capital commitments, whereas automobile firms operate under different profitability and asset-utilization patterns, making it possible to observe whether model performance changes across distinct business environments (Xu & Pan, 2025). Because the sample is limited to six firms, the findings are intended to be context-specific rather than representative of all Indian companies, a limitation that is acknowledged explicitly. Rather than classifying companies as distressed or financially strong in advance, the study evaluates their financial condition year by year using externally verified real-world outcomes, which are determined from credit ratings, insolvency-related evidence, regulatory filings, restructuring events, and published financial disclosures, as discussed in the findings section. The analysis draws on secondary data collected from the published financial statements of the selected companies, obtained from reliable financial sources such as Moneycontrol and Screener.in for the period 2015 to 2025.

All figures were extracted year-wise and cross-checked for consistency before being used both to calculate the distress prediction models and to validate the model outputs against actual company outcomes. The key variables obtained from these statements include total assets, total liabilities, working capital, retained earnings, EBIT, net income, current assets, current liabilities, sales revenue, and shareholders' equity. From these figures, the financial ratios required for the Altman Z-Score, Ohlson O-Score, Zmijewski, Springate, and Grover models were calculated; the selected ratios primarily measure profitability, liquidity, leverage, and operating performance, which are widely recognized indicators of financial distress.

2.2. Data Analysis and Model Evaluation

The financial data were used to calculate the distress scores for each selected company across the study period 2015–2025, and the resulting classifications were then compared year-wise with the actual financial outcomes established through independent real-world evidence. This validation approach was adopted to assess whether the models produced predictions that matched observed financial conditions, rather than merely agreeing with one another. Model performance was evaluated through confusion matrix analysis and classification metrics including Accuracy, Sensitivity, Specificity, Precision, F1 Score, and Type II Error. These metrics were chosen because distress prediction is an asymmetric classification problem in which failing to identify an actually distressed firm is more serious than generating a false alarm; the use of multiple metrics therefore provides a more reliable basis for comparing model effectiveness. Model performance was assessed using a confusion matrix, in which True Positives (TP) represent correctly identified distress cases, True Negatives (TN) represent correctly identified financially sound cases, False Positives (FP) represent false distress alarms, and False Negatives (FN) represent actual distress cases incorrectly classified as safe. From these four outcomes, the six-evaluation metrics are formally defined as follows. Accuracy = (TP + TN) ÷ (TP + TN + FP + FN), the overall proportion of correctly classified observations.

Sensitivity, also known as Recall or the True Positive Rate, = TP ÷ (TP + FN), the proportion of actual distress cases correctly identified. Specificity, also known as the True Negative Rate, = TN ÷ (TN + FP), the proportion of actual safe cases correctly identified. Precision = TP ÷ (TP + FP), the proportion of predicted distress cases that were genuinely distressed. F1 Score = 2 × (Precision × Sensitivity) ÷ (Precision + Sensitivity), the harmonic mean of Precision and Sensitivity. Type II Error, defined in this study as the false negative rate, = FN ÷ (FN + TP), the proportion of actually distressed firms incorrectly classified as safe. This is stated explicitly because the labelling of Type I and Type II error is not fully standardised in the bankruptcy-prediction literature; some studies use the opposite convention, where Type II error refers to a false positive. In this study it refers specifically to missed distress cases, the more consequential error for creditors, regulators, and investors relying on early-warning signals. Microsoft Excel was used for data organization, financial ratio calculations, model implementation, and performance evaluation. It was also used to construct the validation tables, confusion matrices, and summary statistics, and to generate the charts and tables employed for data visualization and interpretation.

2.3. Financial Distress Models

The study applies five widely recognized financial distress prediction models: Altman Z-Score, Ohlson O-Score, Zmijewski Model, Springate Model, and Grover Model. These models are used to evaluate and compare the financial health of the selected companies.

2.3.1. Altman Z-Score Model (Original — Manufacturing Firms)

The Altman Z-Score Model original is designed for manufacturing firms and uses five financial ratios (Barboza & Altman, 2024). The formula is:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \qquad (1)$$

Where X_1 = Working Capital ÷ Total Assets, X_2 = Retained Earnings ÷ Total Assets, X_3 = EBIT ÷ Total Assets, X_4 = Market Value of Equity ÷ Total Liabilities, X_5 = Sales ÷ Total Assets

2.3.2. Altman Z"-Score *(Modified — Non-Manufacturing Firms)*

The modified Altman Z"-Score is applicable to non-manufacturing and service-sector firms (Swalih et al., 2021). The formula is:

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \qquad (2)$$

Where X_1 = Working Capital ÷ Total Assets, X_2 = Retained Earnings ÷ Total Assets, X_3 = EBIT ÷ Total Assets, X_4 = Book Value of Equity ÷ Total Liabilities

2.3.3. Ohlson O-Score Model

The Ohlson model uses logistic regression to estimate the probability of financial distress (Ohlson, 1980). The simplified four-variable formula applied in this study is:

$$O = -1.32 - 0.407\, ln(TA) + 6.03X_1 - 1.43X_2 + 0.076X_3 - 1.72X_4 \quad (3)$$

Where TA = Total Assets, X_1 = Total Liabilities ÷ Total Assets, X_2 = Working Capital ÷ Total Assets, X_3 = Current Liabilities ÷ Current Assets, X_4 = Dummy variable (1 if Net Income is negative, otherwise 0)

2.3.4. Zmijewski Model

The Zmijewski model is based on probit regression and uses three key financial ratios (Zmijewski, 1984). The formula is:

$$X = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3 \quad (4)$$

Where X_1 = Net Income ÷ Total Assets (ROA), X_2 = Total Liabilities ÷ Total Assets, X_3 = Current Assets ÷ Current Liabilities

2.3.5. Springate Model

The Springate model is a modified version of the Altman model and is given by (Yendrawati & Adiwafi, 2020):

$$S = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4 \quad (5)$$

Where X_1 = Working Capital ÷ Total Assets, X_2 = EBIT ÷ Total Assets, X_3 = EBT ÷ Current Liabilities, X_4 = Sales ÷ Total Assets

2.3.6. Grover Model

The Grover model is an extension of the Altman model designed to improve prediction accuracy by incorporating profitability measures (Nurul CH et al., 2024). The formula is:

$$G = 1.650X_1 + 3.404X_2 - 0.016 \times ROA + 0.057 \quad (6)$$

Where X_1 = Working Capital ÷ Total Assets, X_2 = EBIT ÷ Total Assets, ROA = Net Income ÷ Total Assets

3. Results and Discussion

3.1. Experimental Data and Presentation

The model-wise results show that the same company can receive very different classifications depending on the formula, the financial ratios emphasized, and the cut-off rules applied. This is exactly why comparison across models is necessary. The results also show that some models are more conservative, while others are better at flagging actual distress.

Table 1 Vodafone Idea Ltd

Year	Altman Z	Status	Springate	Status	Grover	Status	Zmijewski	Status	Ohlson	Status
2015	6.7398	Safe	0.9115	Safe	0.6115	Safe	-1.0119	Safe	-2.0618	Safe
2016	4.6265	Safe	0.6639	Distress	0.3237	Safe	-0.4297	Safe	-1.2783	Safe
2017	4.6014	Safe	0.3382	Distress	0.2563	Safe	-0.0415	Safe	-2.9062	Safe
2018	4.8665	Safe	-0.0988	Distress	0.2569	Safe	0.0092	Distress	-3.1694	Safe
2019	3.1780	Safe	-0.2624	Distress	-0.1386	Distress	0.2047	Distress	-3.0026	Safe
2020	1.2236	Grey	-0.5038	Distress	-0.2891	Distress	2.7142	Distress	-0.4836	Safe
2021	1.2425	Grey	-0.3665	Distress	-0.0802	Distress	3.4483	Distress	0.3873	Safe
2022	0.8287	Distress	-0.2079	Distress	-0.0372	Distress	3.8743	Distress	0.9066	Distress
2023	0.6886	Distress	-0.2218	Distress	-0.0328	Distress	4.0805	Distress	1.1514	Distress
2024	-0.1206	Distress	-0.2247	Distress	0.0061	Safe	5.3684	Distress	2.4856	Distress
2025	1.2199	Grey	-0.0846	Distress	0.1648	Safe	4.0464	Distress	0.8109	Distress

Table 1 presents a clear picture of the progressive financial deterioration of Vodafone Idea and highlights important differences in the behaviour of the five distress prediction models. The Altman Z"-Score classified the company as financially safe during FY2015–FY2019, moved into the grey zone during FY2020–FY2021, and entered the distress zone from FY2022 onward. The delayed distress signal is partly attributable to the model's reliance on operating profitability, which remained positive despite severe losses and increasing leverage. In contrast, the Springate model identified distress as early as FY2016 and maintained this classification throughout the remaining period, indicating a much more conservative and sensitive approach to financial deterioration. The Zmijewski model began signaling distress from FY2018 onward and showed a pattern broadly consistent with the company's worsening leverage and profitability position.

The Grover model produced mixed results, classifying the company as distressed during the middle years but returning to a safe classification in FY2024 and FY2025. This suggests that the model may place greater weight on short-term improvements in operating performance and may therefore understate distress in highly leveraged firms. Similarly, the Ohlson model remained in the safe zone for most of the study period and only shifted to distress from FY2022, indicating a relatively conservative response to the company's deteriorating condition. Taken together, the results demonstrate that the timing and severity of distress signals vary considerably across models because they emphasize different financial characteristics. However, despite these differences, the models increasingly converge toward a distress classification in the later years, which is consistent with Vodafone Idea's real-world financial condition, including persistent losses, technical insolvency, and external evidence of financial distress. The company therefore provides a useful case for illustrating why model evaluation should consider both the ability to detect distress early and the extent to which model predictions align with actual outcomes.

Table 2 Bharti Airtel Ltd

Year	Altman Z	Status	Springate	Status	Grover	Status	Zmijewski	Status	Ohlson	Status
2015	4.5865	Safe	0.6348	Distress	0.2863	Safe	0.0276	Distress	-1.0301	Safe
2016	4.9746	Safe	0.6170	Distress	0.3087	Safe	-0.4352	Safe	-1.7489	Safe
2017	5.2558	Safe	0.5109	Distress	0.2529	Safe	-0.3383	Safe	-1.5705	Safe
2018	4.4942	Safe	0.3454	Distress	0.1713	Safe	-0.2295	Safe	-1.6158	Safe

Year	Altman Z	Status	Springate	Status	Grover	Status	Zmijewski	Status	Ohlson	Status
2019	4.4795	Safe	0.1682	Distress	0.0148	Safe	-0.1148	Safe	-1.4442	Safe
2020	4.6441	Safe	0.0381	Distress	0.1534	Safe	0.5574	Distress	-2.9609	Safe
2021	5.0610	Safe	0.3301	Distress	0.2326	Safe	0.5839	Distress	-2.7556	Safe
2022	5.4800	Safe	0.5135	Distress	0.3156	Safe	0.2445	Distress	-1.2527	Safe
2023	5.6574	Safe	0.5577	Distress	0.3631	Safe	0.2792	Distress	-1.3326	Safe
2024	6.6289	Safe	0.5497	Distress	0.3565	Safe	0.2535	Distress	-1.3052	Safe
2025	7.0694	Safe	0.5644	Distress	0.2604	Safe	-0.2185	Safe	-1.6464	Safe

Table 2 presents a largely stable financial profile for Bharti Airtel and illustrates how different distress models can produce contrasting classifications for the same firm. The Altman Z"-Score remained comfortably within the safe zone throughout the study period and exhibited a gradual upward trend, suggesting improving financial strength over time. Similarly, the Grover and Ohlson models consistently classified the company as financially sound in every year, indicating no meaningful evidence of financial distress. The Zmijewski model, however, produced distress signals in FY2015 and again during FY2020–FY2024 before returning to the safe zone in FY2025. These temporary classifications appear to be associated with periods of weaker profitability and increased leverage rather than persistent financial deterioration.

The most notable divergence came from the Springate model, which classified Bharti Airtel as distressed throughout the entire study period despite the company's relatively stable operating and financial performance. This suggests that the Springate model may be overly conservative for firms operating in capital-intensive industries such as telecommunications, where high leverage and temporary earnings fluctuations do not necessarily imply financial distress. Overall, the evidence indicates that Bharti Airtel maintained a financially stable position throughout the study period, a conclusion that is supported by its real-world financial condition and by the classifications of four of the five models for most of the sample period. The company therefore provides an important example of how certain models may generate false distress signals and highlights the importance of evaluating model performance using actual outcomes rather than relying solely on model classifications or agreement among models.

Table 3 Reliance Infrastructure Ltd

Year	Altman Z	Status	Springate	Status	Grover	Status	Zmijewski	Status	Ohlson	Status
2015	5.0788	Safe	0.2215	Distress	0.1650	Safe	-0.8839	Safe	-2.1354	Safe
2016	4.6264	Safe	0.2869	Distress	0.2649	Safe	0.1400	Distress	-1.2685	Safe
2017	4.6629	Safe	0.2844	Distress	0.2517	Safe	-0.0220	Safe	-1.3876	Safe
2018	4.4562	Safe	0.2051	Distress	0.1937	Safe	-0.0109	Safe	-1.3858	Safe
2019	3.5294	Safe	-0.1043	Distress	-0.1566	Distress	0.3644	Distress	-2.6475	Safe
2020	4.0968	Safe	0.2372	Distress	0.1825	Safe	0.4722	Distress	-0.7178	Safe
2021	3.9228	Safe	0.1844	Distress	0.0796	Safe	0.1712	Distress	-0.8893	Safe
2022	4.3895	Safe	0.2397	Distress	0.2144	Safe	0.3250	Distress	-2.6470	Safe
2023	4.0861	Safe	0.1781	Distress	0.1451	Safe	0.7156	Distress	-2.2459	Safe
2024	4.3130	Safe	0.2720	Distress	0.2088	Safe	0.6404	Distress	-2.2781	Safe
2025	5.0570	Safe	0.5920	Distress	0.3962	Safe	-0.4813	Safe	-1.5210	Safe

Table 3 presents a mixed and borderline financial profile for Reliance Infrastructure and highlights substantial differences in the way the five models interpret financial vulnerability. The Altman Z"-Score remained in the safe zone throughout the study period, with values ranging from 3.52 to 5.08 and no movement into either the grey or distress zones. Similarly, the Ohlson model consistently classified the company as financially sound in every year, while the Grover model largely maintained a safe classification and signalled distress only in FY2019. In contrast, both the Springate and Zmijewski models identified considerably higher levels of financial risk. The Springate model classified Reliance Infrastructure as distressed throughout the entire period, suggesting that it is highly sensitive to relatively weak profitability and operating performance. The Zmijewski model also produced repeated distress signals, particularly from FY2019 to FY2024, before returning to the safe zone in FY2025. These classifications broadly coincide with periods of weaker profitability and negative operating performance identified in the ratio analysis. The substantial divergence among the models suggests that Reliance Infrastructure occupies a borderline position between financial stability and financial distress. Models such as Altman, Ohlson, and Grover appear to place greater emphasis on the company's ability to maintain a broadly stable balance sheet, whereas Springate and Zmijewski respond more strongly to profitability deterioration and periods of operational weakness.

This case therefore illustrates that financial vulnerability may exist even when traditional solvency measures remain relatively stable. Overall, the evidence indicates that Reliance Infrastructure experienced recurring financial stress rather than persistent severe distress. The company represents an important test case for evaluating the ability of distress prediction models to identify early warning signs in firms that exhibit intermittent financial weakness. It also demonstrates the importance of validating model classifications against actual outcomes rather than relying solely on agreement among models.

Table 4 Larsen & Toubro Ltd

Year	Altman Z	Status	Springate	Status	Grover	Status	Zmijewski	Status	Ohlson	Status
2015	8.9027	Safe	0.5928	Distress	0.4804	Safe	0.0730	Distress	-1.6469	Safe
2016	8.7733	Safe	0.6345	Distress	0.5187	Safe	-0.0090	Safe	-1.7793	Safe
2017	8.7075	Safe	0.6707	Distress	0.5759	Safe	-0.0963	Safe	-1.9472	Safe
2018	6.8990	Safe	0.6351	Distress	0.5208	Safe	-0.0397	Safe	-1.8742	Safe
2019	6.6056	Safe	0.6398	Distress	0.5321	Safe	-0.0491	Safe	-1.9405	Safe
2020	6.0973	Safe	0.6272	Distress	0.5332	Safe	-0.0050	Safe	-1.9447	Safe
2021	6.5875	Safe	0.6801	Distress	0.6201	Safe	-0.1878	Safe	-2.2223	Safe
2022	6.4979	Safe	0.6476	Distress	0.5680	Safe	-0.2246	Safe	-2.2432	Safe
2023	6.6480	Safe	0.7329	Distress	0.6378	Safe	-0.3207	Safe	-2.3904	Safe
2024	5.9678	Safe	0.7229	Distress	0.5461	Safe	-0.2604	Safe	-2.2284	Safe
2025	5.8885	Safe	0.7427	Distress	0.5533	Safe	-0.2829	Safe	-2.2829	Safe

Table 4 presents a consistently strong financial profile for Larsen & Toubro and highlights a significant divergence between the Springate model and the remaining distress prediction models. The Altman Z"-Score remained comfortably within the safe zone throughout the study period, despite declining from 8.90 in FY2015 to 5.89 in FY2025. This downward movement indicates some moderation in financial strength over time but does not suggest any meaningful deterioration toward financial distress.

Similarly, the Grover and Ohlson models classified the company as financially sound in every year of the study period. The Zmijewski model produced a distress signal only in FY2015 and subsequently classified the company as safe from FY2016 onward, indicating that the temporary signal was not supported by persistent weakness in the firm's financial condition. In contrast, the Springate model classified L&T as distressed throughout all eleven years, making it a clear outlier among the five models. Given L&T's stable profitability, positive operating performance, and strong real-world financial position, these classifications suggest that the Springate model may be overly conservative for large, capital-intensive firms and may generate false distress signals when applied without considering industry characteristics.

L&T emerges as one of the financially strongest companies in the sample, with four of the five models consistently supporting a safe classification. The company therefore provides an important example of how model performance can vary across industries and demonstrates the importance of validating model predictions against actual company outcomes rather than relying on a single model's classification.

Table 5 Ashok Leyland Ltd

Year	Altman Z"	Status	Springate	Status	Grover	Status	Zmijewski	Status	Ohlson	Status
2015	2.3370	Grey	0.5389	Distress	0.2951	Safe	0.1308	Distress	-2.2946	Safe
2016	2.5659	Grey	0.9238	Safe	0.5616	Safe	-0.1051	Safe	-0.8425	Safe
2017	2.6255	Grey	0.8408	Distress	0.4929	Safe	-0.2499	Safe	-1.0014	Safe
2018	2.3106	Grey	0.8722	Safe	0.5007	Safe	-0.1157	Safe	-0.9335	Safe
2019	2.0734	Grey	0.8793	Safe	0.5327	Safe	-0.1309	Safe	-1.0469	Safe
2020	1.7010	Distress	0.5375	Distress	0.3677	Safe	0.1772	Distress	-0.7896	Safe
2021	1.5294	Distress	0.3545	Distress	0.2443	Safe	0.3381	Distress	-2.3787	Safe
2022	1.7333	Distress	0.4285	Distress	0.2730	Safe	0.4700	Distress	-2.2769	Safe
2023	2.0135	Grey	0.6909	Distress	0.4275	Safe	0.3927	Distress	-0.7082	Safe
2024	1.9497	Grey	0.7661	Distress	0.5117	Safe	0.4568	Distress	-0.6964	Safe
2025	2.1732	Grey	0.7961	Distress	0.5963	Safe	0.3531	Distress	-0.9715	Safe

Table 5 presents a financially vulnerable but not persistently distressed profile for Ashok Leyland and demonstrates considerable variation in model classifications. The Altman Z"-Score remained predominantly in the grey zone and moved into the distress zone during FY2020–FY2022, indicating a period of heightened financial pressure. The scores declined from 2.34 in FY2015 to a low of 1.53 in FY2021 before recovering to 2.17 by FY2025, suggesting that the company experienced temporary deterioration rather than a continuous decline into severe distress. The Grover and Ohlson models, in contrast, classified the company as financially safe throughout the entire study period. These classifications imply that, despite periods of weaker profitability and increased leverage, the firm's overall financial position remained sufficiently strong to avoid a persistent distress classification.

The Springate model, however, signalled distress in most years, while the Zmijewski model identified distress in FY2015 and consistently from FY2020 onward. Notably, these distress signals coincide with the period in which the Altman Z"-Score reached its lowest levels and when the ratio analysis indicated weaker profitability and financial pressure. The divergence among the models suggests that Ashok Leyland occupied an intermediate position between financial stability and financial distress. Models such as Springate and Zmijewski appear to respond more strongly to short-term deterioration in profitability and leverage, whereas Grover and Ohlson place greater emphasis on the firm's broader financial resilience. Consequently, the company provides an important example of how firms can experience periods of significant financial stress without necessarily entering persistent distress.

The evidence indicates that Ashok Leyland faced recurring financial vulnerability, particularly during FY2020–FY2022, but subsequently showed signs of recovery. This case reinforces the importance of using multiple models and validating their classifications against actual company outcomes, as reliance on any single model could either overstate or understate the true level of financial risk.

Table 6 Maruti Suzuki India Ltd

Year	Altman Z"	Status	Springate	Status	Grover	Status	Zmijewski	Status	Ohlson	Status
2015	11.3503	Safe	1.5602	Safe	0.7220	Safe	-3.1216	Safe	-3.9672	Safe
2016	10.9182	Safe	1.5663	Safe	0.6544	Safe	-3.2663	Safe	-4.0464	Safe
2017	14.6703	Safe	1.5568	Safe	0.5964	Safe	-3.3202	Safe	-4.1179	Safe
2018	10.4729	Safe	1.4959	Safe	0.5337	Safe	-3.2172	Safe	-4.0126	Safe
2019	10.8198	Safe	1.5352	Safe	0.5973	Safe	-3.3379	Safe	-4.3895	Safe
2020	12.3507	Safe	1.1988	Safe	0.3748	Safe	-3.4311	Safe	-4.5199	Safe
2021	9.4334	Safe	0.8799	Safe	0.3701	Safe	-3.0739	Safe	-4.4021	Safe
2022	10.3435	Safe	0.8887	Safe	0.3133	Safe	-3.0626	Safe	-4.3679	Safe
2023	11.2493	Safe	1.1916	Safe	0.3336	Safe	-3.2025	Safe	-4.2671	Safe
2024	9.7538	Safe	1.4015	Safe	0.5575	Safe	-3.3632	Safe	-4.6611	Safe
2025	11.4296	Safe	1.3494	Safe	0.5638	Safe	-3.2550	Safe	-4.6564	Safe

Table 6 presents a remarkably consistent picture of financial strength and stability for Maruti Suzuki throughout the study period. The Altman Z"-Score remained comfortably within the safe zone in every year and at exceptionally high levels, indicating strong solvency and a substantial buffer against financial distress. Similarly, the Springate, Grover, Zmijewski, and Ohlson models all classified the company as financially sound throughout the entire period, with none of the models generating a single distress signal. The complete agreement among the five models is noteworthy because such unanimity is rarely observed in financial distress prediction studies, where differences in model structure and sensitivity often lead to conflicting classifications. In the case of Maruti Suzuki, the company's low leverage, consistently positive profitability, and stable operating performance produced a financial profile that was recognised as healthy regardless of the methodology applied.

Unlike the other firms in the sample, Maruti Suzuki exhibits no meaningful evidence of financial vulnerability or temporary financial stress. The consistency of the model classifications also suggests that the company represents a benchmark case of financial stability against which the predictive performance of the models can be assessed. Because all five models correctly identified the firm as financially healthy, Maruti Suzuki provides important evidence that the models are capable of producing highly reliable classifications when a company's financial condition is unambiguously strong. Overall, the results indicate that Maruti Suzuki was the financially strongest and most stable company in the sample throughout the study period. The company's unanimous safe classification also reinforces the importance of real-world validation, as model agreement in this case is fully consistent with the firm's observed financial performance and market position.

3.2. Ground truth validation

It constitutes one of the most important components of this study because the predictive ability of financial distress models cannot be evaluated solely on the basis of agreement among the models themselves. A model may classify a company as distressed or financially healthy, but such classifications are meaningful only if they correspond to independently verifiable financial outcomes. Therefore, this study adopts a real-world validation approach by constructing a year-wise benchmark of actual company financial status using external evidence rather than relying on model consensus alone. The ground truth benchmark classifies Vodafone Idea as financially distressed from FY2017 onward and Reliance Infrastructure as distressed during FY2019–FY2024, while Bharti Airtel, Larsen & Toubro, Ashok Leyland, and Maruti Suzuki are classified as financially sound throughout the study period.

These classifications are based on independently verified evidence, including India Ratings (IND-D designation), CRISIL credit ratings, IBC insolvency filings, Aranca Research reports, and Business Standard disclosures. By comparing model predictions against this external benchmark, the study evaluates not only whether the models agree with one another but also whether they accurately reflect actual financial conditions. This validation approach directly addresses an important limitation identified in previous Indian studies, many of which compare model classifications without testing their consistency with real-world outcomes. Consequently, the ground truth benchmark provides a more rigorous basis for assessing model performance and allows the study to distinguish between genuine distress signals and potential false classifications.

Table 7 Ground Truth Validation — Year-Wise Real-World Financial Status (2015–2025)

Company	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Vodafone Idea	S	S	D	D	D	D	D	D	D	D	D
Bharti Airtel Ltd	S	S	S	S	S	S	S	S	S	S	S
Reliance Infrastructure	S	S	S	S	D	D	D	D	D	D	S
Larsen & Toubro	S	S	S	S	S	S	S	S	S	S	S
Ashok Leyland	S	S	S	S	S	S	S	S	S	S	S
Maruti Suzuki India	S	S	S	S	S	S	S	S	S	S	S

S = Safe (financially sound); D = Distress (real-world distress evidence)

Sources: India Ratings (IND-D), CRISIL, Aranca Research, Business Standard (2024–2025).

Table 7 presents the year-wise real-world financial status of each company based on independently verified evidence. The benchmark was developed using publicly available information on credit ratings, insolvency proceedings, regulatory disclosures, and financial performance indicators. Vodafone Idea is classified as distressed from FY2017 onward due to persistent net losses, continuous deterioration in profitability, and a highly leveraged financial position that eventually resulted in liabilities exceeding total assets from FY2021. Reliance Infrastructure is classified as distressed during FY2019–FY2024, corresponding to six consecutive years of India Ratings' 'IND-D' designation and evidence of severe financial stress, before returning to the safe category following its credit-rating upgrade in July 2025. The remaining firms are classified as financially sound throughout the study period, supported by investment-grade credit ratings, positive operating performance, and the absence of insolvency proceedings or significant evidence of financial distress. The year-wise classifications presented in Table 7 serve as the benchmark against which the predictive performance of the five financial distress models is evaluated in the subsequent analysis.

3.3. Model Performance Evaluation

The performance evaluation shows that model ranking changes depending on the metric used, which is a crucial finding. Accuracy alone is not enough in distress prediction because a model can look strong overall while still missing many actual distressed firms. For that reason, sensitivity and Type II error are especially important in this study.

Table 8 Confusion Matrix Analysis

Rank	Model	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)
1	Springate	15	15	36	0
2	Zmijewski	14	36	15	1
3	Grover	6	51	0	9
4	Ohlson	4	51	0	11
5	Altman	3	40	3	9

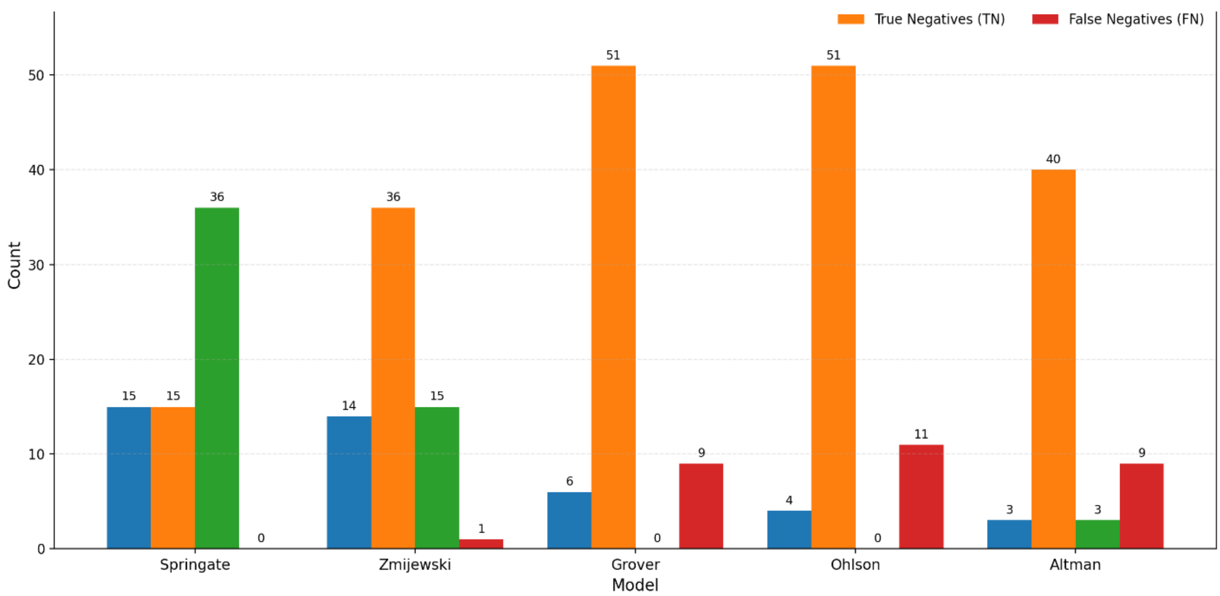

Figure 1 Confusion Matrix Analysis by Model

Table 8 and Figure 1 presents the confusion matrix results for the five financial distress prediction models by comparing model classifications with the independently verified ground truth benchmark. True Positives (TP) represent correctly identified distress cases, True Negatives (TN) represent correctly identified financially sound observations, False Positives (FP) indicate false distress alarms, and False Negatives (FN) represent actual distress cases that were incorrectly classified as safe. The results reveal substantial differences in predictive behaviour among the models and highlight the trade-off between early distress detection and classification accuracy. The Springate model achieved the highest distress detection capability by correctly identifying all distressed observations (TP = 15) and recording zero false negatives (FN = 0). However, this strong sensitivity came at the cost of a large number of false alarms (FP = 36), suggesting that the model is highly conservative and tends to overclassify firms as distressed. The Zmijewski model provided a more balanced performance, correctly identifying 14 of the 15 distressed observations while generating considerably fewer false positives (FP = 15).

This indicates that the model was able to maintain high distress detection ability without producing excessive false alarms. In contrast, the Grover and Ohlson models generated no false positives, indicating excellent performance in identifying financially healthy firms. However, both models failed to identify a substantial number of actual distress cases, producing nine and eleven false negatives, respectively. Similarly, the Altman Z"-Score generated relatively few false positives (FP = 3) but missed nine distress observations, suggesting that it is comparatively conservative in issuing distress classifications. Grey zone observations produced by the Altman model were excluded from confusion matrix counts as they do not constitute a definitive distress or safe classification.

These findings demonstrate that no single model performs best across all evaluation criteria. Models that maximise distress detection tend to generate more false alarms, whereas models that minimise false alarms often fail to identify genuine distress cases. Consequently, the choice of model depends on the objectives of the decision-maker. For creditors, regulators, and investors seeking early warning signals, a higher sensitivity and lower false negative rate may be preferable. Conversely, managers and analysts concerned with avoiding unnecessary distress classifications may prefer models with lower false positive rates. The confusion matrix therefore provides important evidence that financial distress prediction involves an inherent trade-off between sensitivity and specificity rather than a single measure of overall accuracy.

3.4. Performance Metrics Analysis

No single model is universally superior across all evaluation criteria. Models that maximise distress detection generally sacrifice specificity and generate more false alarms, whereas models with very high accuracy and specificity often fail to identify genuine distress cases. Therefore, the selection of an appropriate financial distress prediction model depends on the objectives of the user and the relative importance assigned to early warning capability, classification accuracy, and the cost of prediction errors.

Table 9 Performance Metrics Summary

Model	True Accuracy	Sensitivity	Specificity	Precision	Type II Error	F1 Score
Springate	45.5%	100.0%	29.4%	29.4%	0.0%	45.5%
Zmijewski	75.8%	93.3%	70.6%	48.3%	6.7%	63.6%
Grover	86.4%	40.0%	100.0%	100.0%	60.0%	57.1%
Ohlson	83.3%	26.7%	100.0%	100.0%	73.3%	42.1%
Altman	78.2%	25.0%	93.0%	50.0%	75.0%	33.3%

Table 9 explain a comprehensive evaluation of model effectiveness, performance metrics including Accuracy, Sensitivity, Specificity, Precision, Type II Error, and F1 Score were calculated. The primary objective of financial distress prediction is to identify firms at risk before severe deterioration occurs, sensitivity and Type II Error are particularly important metrics, as they measure a model's ability to detect distress and avoid missed distress cases. The results demonstrate that model ranking changes substantially depending on the evaluation criterion used. The Grover model achieved the highest overall accuracy (86.4%) and perfect specificity (100.0%), indicating excellent performance in identifying financially healthy firms. However, its sensitivity was only 40.0%, meaning that it failed to identify the majority of actual distress cases and produced a relatively high Type II Error of 60.0%.

A similar pattern is observed for the Ohlson and Altman models, both of which exhibited strong specificity but weak sensitivity, suggesting that these models are comparatively conservative and less effective as early-warning tools. The Springate model achieved perfect sensitivity (100.0%) and recorded zero Type II Error, demonstrating exceptional ability to identify distressed firms and ensuring that no actual distress cases were missed. However, this performance came at the expense of very low specificity (29.4%) and precision (29.4%), indicating that the model generated a large number of false distress alarms. Consequently, although Springate is the strongest early-warning model in terms of distress detection, its practical usefulness may be limited when avoiding false classifications is also an important objective. The Zmijewski model delivered the most balanced performance among the five models. It combined high sensitivity (93.3%) with acceptable specificity (70.6%) and achieved the highest F1 Score (63.6%), which reflects the best balance between identifying distressed firms and maintaining overall classification reliability. The relatively low Type II Error of 6.7% further indicates that the model missed very few actual distress cases while avoiding the excessive false alarms generated by the Springate model.

3.5. Model Effectiveness Analysis

One possible explanation is that the Springate model employs a relatively conservative threshold and places considerable emphasis on profitability and operating performance. Consequently, firms operating in capital-intensive industries or experiencing temporary earnings weakness may be classified as distressed even when their overall financial condition remains stable. This pattern was particularly evident in the cases of Bharti Airtel and Larsen & Toubro, which were repeatedly classified as distressed despite exhibiting strong real-world financial performance. The Zmijewski model provided the most balanced performance in the study, achieving high sensitivity (93.3%), acceptable specificity (70.6%), and the highest F1 Score (63.6%). The model's relatively strong performance may be attributed to its simultaneous consideration of profitability, leverage, and liquidity, which were the three financial dimensions that most clearly distinguished distressed firms from financially healthy firms in the sample. By maintaining a low Type II Error while avoiding the excessive false alarms generated by the Springate model, the Zmijewski model appears to provide the most practical balance between early warning capability and classification reliability. The Grover model achieved the highest overall accuracy (86.4%) and perfect specificity (100.0%), suggesting excellent performance in identifying financially healthy firms.

However, its low sensitivity indicates that it failed to identify a substantial proportion of actual distress cases. This finding illustrates an important limitation of relying exclusively on overall accuracy when evaluating financial distress prediction models. A model may appear highly accurate while still failing to perform effectively in its primary objective of identifying financially distressed firms. The Ohlson and Altman models exhibited relatively conservative classification behaviour and generated comparatively high numbers of missed distress cases. In the case of the Ohlson model, the inclusion of firm-size effects and its probabilistic structure may contribute to delayed distress classification for large firms experiencing financial deterioration. Similarly, the Altman Z"-Score relies heavily on operating profitability through the EBIT-to-total-assets ratio and may therefore respond more slowly to situations in which firms continue to generate operating earnings despite experiencing severe net losses or increasing financial obligations. The experience of Vodafone Idea illustrates this limitation, as several models continued to classify the company as financially sound during periods in which its overall financial condition had already deteriorated substantially.

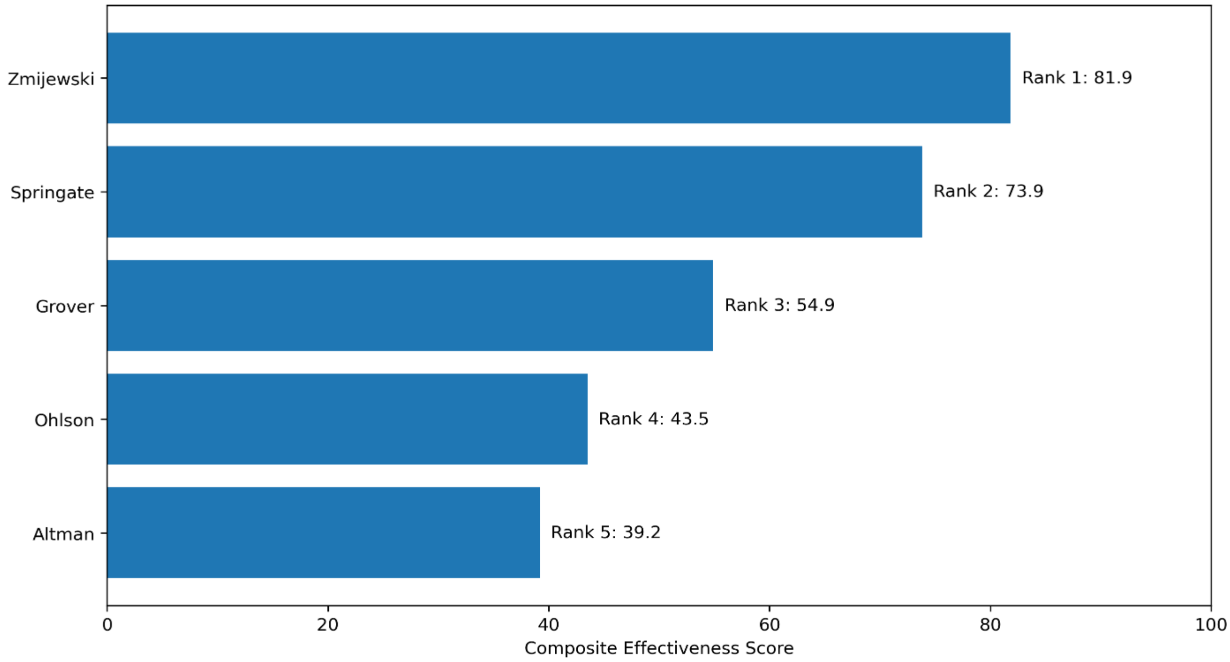

Figure 2 Overall Effectiveness Ranking of Financial Distress Prediction Models

Figure 2 indicate that the effectiveness of financial distress prediction models depends not only on their statistical accuracy but also on the type of prediction errors they produce and the financial characteristics they emphasise. The findings demonstrate that different models capture different dimensions of financial weakness and therefore vary considerably in their practical usefulness. Among the five models, the Springate model emerged as the strongest early-warning model because it achieved perfect sensitivity (100.0%) and failed to miss any distressed observations. However, this superior distress detection capability was accompanied by a substantial number of false positive classifications.

No financial distress prediction model is universally superior across all circumstances. Models that maximise distress detection generally produce more false alarms, whereas models that minimise false classifications often fail to identify genuine distress cases. Therefore, the choice of model should depend on the objectives of the user and the relative importance assigned to early warning capability, classification reliability, and the costs associated with prediction errors. From a practical perspective, the Springate model appears most useful when the primary objective is to avoid missing distressed firms, whereas the Zmijewski model provides the most reliable overall balance between detecting financial distress and maintaining classification accuracy.

4. Conclusions

This study examined the effectiveness of five widely used financial distress prediction models as Altman Z"-Score, Springate, Grover, Zmijewski, and Ohlson using six selected Indian companies from the telecom, infrastructure, and automobile sectors over the period 2015–2025. Unlike many previous comparative studies that evaluate models primarily through agreement among classifications, this research validated model predictions against independently verified real-world financial outcomes and assessed performance using multiple classification metrics, including Accuracy, Sensitivity, Specificity, Precision, F1 Score, and Type II Error. This outcome-based approach provides a more rigorous assessment of predictive effectiveness and represents an important contribution to the Indian financial distress literature.

The findings demonstrate that financial distress prediction cannot be evaluated solely on the basis of overall accuracy. Models that appeared highly accurate, such as the Grover, Ohlson, and Altman models, failed to identify a substantial proportion of actual distress cases and therefore exhibited limited effectiveness as early-warning tools. In contrast, the Springate model successfully identified all distressed observations and achieved perfect sensitivity, making it the strongest model for early detection despite generating a large number of false alarms. The Zmijewski model provided the most balanced performance, combining high sensitivity with acceptable specificity and achieving the highest F1 Score among the five models. These results indicate that model rankings change considerably depending on the performance criterion used and that no single model is universally superior under all decision-making contexts. The study also demonstrates that financial distress prediction is highly sensitive to industry characteristics, financial structure, and model design. The different classifications observed across the selected companies confirm that models emphasizing profitability, leverage, liquidity, and operating performance may respond differently to the same underlying financial conditions. Consequently, financial distress prediction should be viewed as a risk-screening and decision-support exercise rather than a source of absolute judgments regarding corporate failure.

The findings suggest that investors, lenders, regulators, and corporate managers should avoid relying on a single prediction model when assessing financial risk. A multi-model approach, combined with external evidence and real-world validation, provides a more reliable basis for identifying financially vulnerable firms and supporting timely intervention. The Springate model offers the strongest early-warning capability, whereas the Zmijewski model provides the most balanced and reliable overall performance within the context of the selected Indian companies. More importantly, the research demonstrates that independently validated real-world outcomes and multiple performance measures provide a more meaningful framework for evaluating financial distress prediction models than model agreement or overall accuracy alone. This study therefore contributes to both the academic literature and practical financial analysis by highlighting the importance of context-specific model evaluation and evidence-based assessment of financial distress prediction tools.

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Declaration of conflicting interests

All authors declare that they have no conflicts of interest.

References

Abdullah, M., Gulzar, I., Chaudhary, A., Tabash, M. I., Rashid, U., Naaz, I., & Ali, A. (2023). Dynamics of speed of leverage adjustment and financial distress in the Indian steel industry. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(4). https://doi.org/10.1016/j.joitmc.2023.100152

Ahemed, A. M., Iqbal, U., & Atif, M. M. (2025). Asymmetric cost behavior and financial distress. *Economics Letters*, *247*. https://doi.org/10.1016/j.econlet.2024.112121

Barboza, F., & Altman, E. (2024). Predicting financial distress in Latin American companies: A comparative analysis of logistic regression and random forest models. *North American Journal of Economics and Finance*, *72*. https://doi.org/10.1016/j.najef.2024.102158

Baxi, A. (2023). Interim Finance in Creditor-Oriented Bankruptcy Codes: A Study in the Context of Insolvency & Bankruptcy Code, India. *Vikalpa*, *48*(3). https://doi.org/10.1177/02560909221150689

Cameron, R. (2009). A sequential mixed model research design: Design, analytical and display issues. *International Journal of Multiple Research Approaches*, *3*(2). https://doi.org/10.5172/mra.3.2.140

Chandrasekar, V., Ashraf, S., Naresh, N. R., Piradeep, S., Muralidhar, S., & Poornima, J. (2025). A Study on the Plausibility of Financial Distress Due to Covid 19: Evidence from Nifty Fifty Companies. In *Studies in Systems, Decision and Control* (Vol. 555). https://doi.org/10.1007/978-3-031-67890-5_91

Chen, S. (2025). *Quantitative Trading* (pp. 161–167). https://doi.org/10.1007/978-981-95-3064-9_16

Chen, Y., Xu, J., Wang, S., & Xu, S. (2024). Economic environment uncertainty and financialization of real estate firms. *International Review of Economics and Finance*, *93*. https://doi.org/10.1016/j.iref.2024.05.011

Chhabra, B. (2018). Impact of core-self evaluation and job satisfaction on turnover intentions: A study of Indian retail sector. *Organizations and Markets in Emerging Economies*, *9*(2). https://doi.org/10.15388/omee.2018.10.00015

Elangovan, R., Irudayasamy, F. G., & Parayitam, S. (2022). Testing the market efficiency in Indian stock market: evidence from Bombay Stock Exchange broad market indices. *Journal of Economics, Finance and Administrative Science*, *27*(54). https://doi.org/10.1108/JEFAS-04-2021-0040

Elhoseny, M., Metawa, N., Sztano, G., & El-hasnony, I. M. (2025). Deep Learning-Based Model for Financial Distress Prediction. *Annals of Operations Research*, *345*(2–3). https://doi.org/10.1007/s10479-022-04766-5

Farooq, M., Hunjra, A. I., Ullah, S., & Al-Faryan, M. A. S. (2023). The determinants of financial distress cost: A case of emerging market. *Cogent Economics and Finance*, *11*(1). https://doi.org/10.1080/23322039.2023.2186038

Ghosh, T. (2019). Corporate Governance and Audit Fees Evidence from Bangladeshi Listed Banks and NBFIs. *Journal of Corporate Governance Research*, *3*(1). https://doi.org/10.5296/jcgr.v3i1.15638

Halawi, L., Clarke, A., & George, K. (2022). Evaluating Predictive Performance. In *Harnessing the Power of Analytics* (pp. 51–59). Springer International Publishing. https://doi.org/10.1007/978-3-030-89712-3_4

Khan, M. A., Farooqi, M. R., Ahmad, M. F., Haque, S., & Alkhuraydili, A. (2024). Influence of Compensation, Performance Feedback on Employee Retention in Indian Retail Sector. *SAGE Open*, *14*(2). https://doi.org/10.1177/21582440241236615

Li, D., & Azman, N. H. N. (2025). Digital Financial Inclusion Promotes Economic Environment-Inclusive Growth-in Underdeveloped Regions: Evidence from Gansu, China. *Chinese Journal of Urban and Environmental Studies*, *13*(1). https://doi.org/10.1142/S2345748125500071

Lisin, A., Kushnir, A., Koryakov, A. G., Fomenko, N., & Shchukina, T. (2022). Financial Stability in Companies with High ESG Scores: Evidence from North America Using the Ohlson O-Score. *Sustainability (Switzerland)*, *14*(1). https://doi.org/10.3390/su14010479

Marsenne, M., Ismail, T., Taqi, M., & Hanifah, I. A. (2024). Financial distress predictions with Altman, Springate, Zmijewski, Taffler and Grover models. *Decision Science Letters*, *13*(1). https://doi.org/10.5267/j.dsl.2023.10.002

Nurul CH, F., Sulistyowati, S., Rusli, D., Rohmah, A., & Suprati, D. (2024). Accuracy of the Financial Distress Model in Transportation Firms: Altman, Springate and Grover Model. *Taxation and Public Finance*, *2*(1). https://doi.org/10.58777/tpf.v2i1.362

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, *18*(1). https://doi.org/10.2307/2490395

Oware, K. M., & Appiah, K. (2022). CSR assurance practice and financial distress likelihood: evidence from India. *Meditari Accountancy Research*, *30*(6). https://doi.org/10.1108/MEDAR-10-2020-1055

Pandey, C. S., Mishra, P., Pandey, S. R., Singh, R. D., & Pandey, S. (2025). Research paradigms: a systematic literature review of methodological shifts and interdisciplinary approaches in research. *Quality & Quantity*, *60*(1), 2297–2325. https://doi.org/10.1007/s11135-025-02359-5

Ravichandra Rao, N., & Kasture, J. (2026). Sectoral insights into corporate insolvency: a comprehensive analysis of Corporate Insolvency Resolution Process (CIRP) outcomes in India. *International Journal of Law and Management*, *68*(2). https://doi.org/10.1108/IJLMA-08-2024-0291

Sehgal, S., Mishra, R. K., Deisting, F., & Vashisht, R. (2021). On the determinants and prediction of corporate financial distress in India. *Managerial Finance*, *47*(10). https://doi.org/10.1108/MF-06-2020-0332

Shome, S., & Verma, S. (2020). Financial Distress in Indian Aviation Industry: Investigation Using Bankruptcy Prediction Models. *Eurasian Journal of Business and Economics*, *13*(25). https://doi.org/10.17015/ejbe.2020.025.06

Singh Chauhan, S., Suri, P., Alam, F., Hani, U., Johri, A., & Ali, F. (2025). A causality investigation into stock prices and macroeconomic indicators in the Indian stock market. *F1000Research*, *13*. https://doi.org/10.12688/f1000research.157041.3

Singh, G., & Singla, R. (2024). Logit model for predicting financial distress in Indian corporate sector. *International Journal of Business and Globalisation*, *37*(4). https://doi.org/10.1504/IJBG.2024.140052

Sun, J., Zhou, M., Ai, W., & Li, H. (2019). Dynamic prediction of relative financial distress based on imbalanced data stream: from the view of one industry. *Risk Management*, *21*(4). https://doi.org/10.1057/s41283-018-0047-y

Swalih, M. M., Adarsh, K. B., & Sulphey, M. M. (2021). A study on the financial soundness of indian automobile industries using altman z-score. *Accounting*, *7*(2). https://doi.org/10.5267/j.ac.2020.12.001

Thakur, Dr. S. (2019). A Study on Financial Performance Analysis of Dabur India Limited. *International Journal of Scientific & Engineering Research*, *10*(9). https://doi.org/10.14299/ijser.2019.09.01

Xu, Y., & Pan, H. (2025). The Effects of Enterprises' E-Business Adoptions on Cross-Border Firm Internationalization. *Systems*, *13*(2). https://doi.org/10.3390/systems13020084

Yendrawati, R., & Adiwafi, N. (2020). Comparative analysis of Z-score, Springate, and Zmijewski models in predicting financial distress conditions. *Journal of Contemporary Accounting*, *2*(2). https://doi.org/10.20885/jca.vol2.iss2.art2

Zhang, Z., Wu, C., Qu, S., & Chen, X. (2022). An explainable artificial intelligence approach for financial distress prediction. *Information Processing and Management*, *59*(4). https://doi.org/10.1016/j.ipm.2022.102988

Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research*, *22*, 59. https://doi.org/10.2307/2490859