



## Fairness

Vol 01 (1) 2025 p. 16-30

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Received 17 April 2025;

Accepted 21 May 2025;

Published 28 May 2025.

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### Conflict of interest statement:

Author(s) reported no conflict of interest

DOI: [http://doi.org/10.70764/gdpu-fr.2025.1\(1\)-02](http://doi.org/10.70764/gdpu-fr.2025.1(1)-02)

# LITERATURE ANALYSIS ON FINANCIAL DISTRESS AND BANKRUPTCY PREDICTION

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## ABSTRACT

**Objective:** This study aims to analyze financial distress prediction models that have been used in various academic studies, evaluate the accuracy of models in various industry sectors, and identify factors that affect the accuracy of predicting corporate bankruptcy.

**Research Design & Methods:** This research uses a systematic literature review (SLR) to evaluate the effectiveness of financial distress prediction models based on studies from reputable journals in the range 2015-2024.

**Findings:** The results show that the Altman Z-Score and Ohlson O-Score have the highest accuracy rate (90.91%), making them the most widely used models in the manufacturing and banking industries. The Zmijewski Model has an accuracy of 86.36%, more suitable for high asset-based sectors such as mining and transportation. The Springate Model, with an accuracy rate of 63.64% - 73.48%, is simpler but less accurate than the other models, especially in the service-based and financial sectors. The research also found that the logit regression-based model (Ohlson O-Score) is superior in considering external factors, such as company size and macroeconomic conditions, compared to other models that focus more on financial ratios.

**Implications & Recommendations:** Any financial distress prediction model has advantages and limitations that depend on industry characteristics. Therefore, their selection should consider the financial structure, industry sector, and external factors such as regulation and economic dynamics. The integration of traditional models with machine learning and artificial intelligence (AI) is recommended to improve the accuracy and effectiveness of early detection.

**Contribution & Value Added:** This research provides insights for academics, practitioners, and regulators on the accuracy of financial distress prediction models and emphasizes the need for an adaptive approach that integrates financial and non-financial factors to improve business resilience.

**Keywords:** Financial distress, Altman Z-Score, Springate Model, Zmijewski Model, Ohlson O-Score.

JEL codes: G32, G33, M41

**Article type:** research paper

## INTRODUCTION

Bankruptcy prediction is an important aspect of financial accounting because it can help companies, investors, and creditors manage financial risks. By accurately predicting bankruptcy, companies can detect early symptoms of financial distress and take strategic steps to avoid bankruptcy, which can have negative impacts on all stakeholders (Mažintienė and Burškaitienė, 2012). Investors and lenders also rely heavily on bankruptcy prediction models to assess a

company's stability before making investments or providing loans, as a company's bankruptcy can result in large financial losses (Panchal et al., 2019). In the world of accounting and finance, bankruptcy prediction has become a primary area of research, with the goal of developing models that can more accurately forecast a company's financial condition (Hess and Huettemann, 2018). Various methods have been developed to improve the accuracy of bankruptcy prediction, including the use of statistical models such as the Altman Z-Score and Ohlson Model and artificial intelligence-based approaches such as artificial neural networks and machine learning algorithms (Hassan and Yousaf, 2022). This model helps company management make better financial decisions, optimize capital structure, and improve financial transparency and accountability.

In addition, bankruptcy prediction also plays an important role in overall economic stability. When a large company goes bankrupt, the impact can spill over to other sectors, causing instability in the financial system (Li & Faff, 2019). Therefore, financial regulators and government agencies use bankruptcy prediction models to monitor high-risk firms and take preventive measures before systemic effects are realized (Karami, 2012). Thus, bankruptcy prediction not only assists companies in managing financial risks but also protects the interests of investors, creditors, and the economy as a whole. The development of more accurate prediction models will continue to be a major focus in accounting and finance to create a more stable and sustainable financial system.

Financial distress has a significant impact on companies, investors, and the economy as a whole. For companies, this condition can lead to difficulties in meeting financial obligations such as debt payments and employee salaries, which ultimately increases the risk of bankruptcy (Rawal et al., 2023). Companies experiencing financial distress also tend to experience a decrease in investment due to a lack of trust from shareholders and creditors (López-Gutiérrez et al., 2015). Additionally, companies under financial stress often resort to debt restructuring or layoffs to reduce operational costs (Erawati et al., 2024). The impact of financial distress on investors is pronounced, as the company's poor financial condition can lead to stock price volatility and reduced investment returns (Robu et al., 2014). Investors tend to avoid companies with high risk, as this can lead to a drastic drop in the share price of the affected company, thereby reducing the value of the investment made (Ha et al., 2023). Additionally, financial distress can lead to a decrease or cessation of dividends received by investors, as the company prioritizes maintaining its internal finances (Manaf et al., 2021).

With the increasing number of studies related to financial distress, a comprehensive literature review is necessary to identify the latest research trends, assess the effectiveness of various prediction models developed, and evaluate the accuracy of bankruptcy prediction models. Therefore, this study aims to analyze financial distress prediction models used in various academic studies, evaluate the accuracy of these models across different industry sectors, and identify factors that affect the accuracy of corporate bankruptcy predictions. The results of this study are expected to provide valuable insights for academics, financial practitioners, investors, and regulators, enabling a deeper understanding of the risk of financial distress and the mitigation strategies that can be applied.

## LITERATURE REVIEW

Financial distress is a financial condition that indicates the company's inability to meet its financial obligations, which can lead to bankruptcy if not addressed immediately. Patunrui and Yati (2017) define financial distress as a severe liquidity problem that cannot be resolved without changes in the scale of operations or the company's structure. Meanwhile, according to Maulidia and Asyik (2020), financial distress occurs before a company goes bankrupt due to various factors, such as financial crisis, business unhealthiness, or difficulty in maintaining profitability. Financial distress can be categorized into several types (Cipta and Wibowo, 2021):

1. Economic Failure, a condition in which a company's income is insufficient to cover all operating costs, including capital expenditures.
2. Business Failure: The company is forced to cease all operations to minimize losses to creditors.
3. Technical Insolvency, a situation where the company is unable to fulfill its matured financial

obligations.

4. Insolvency in Bankruptcy, a condition where the book value of a company's total liabilities exceeds the market value of its assets.
5. Legal Bankruptcy, a situation in which a company has been declared legally bankrupt by a court decision.

Financial distress is influenced not only by internal conditions, such as liquidity and profitability, but also by external factors, including corporate governance, access to capital markets, and industry and macroeconomic dynamics. Therefore, a comprehensive understanding of financial distress models is essential in developing more effective risk mitigation strategies.

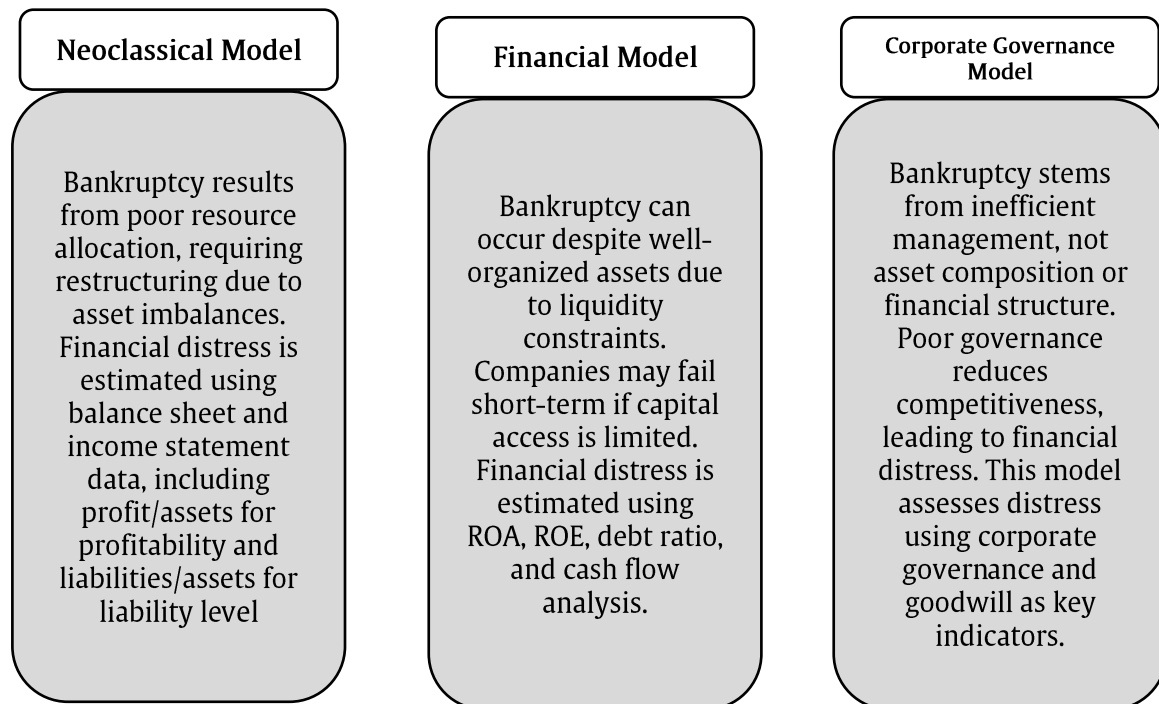


Figure 1. main factors that can cause financial distress and lead to bankruptcy ([Hendra et al. \(2018\)](#))

The term “bankruptcy” has its roots in two Latin words: *bancus*, meaning “bank or table,” and *ruptus*, meaning “broken.” Therefore, it can be translated as “broken table” ([Onakoya and Olotu, 2017](#)). Several sources also mention that the term “bankruptcy” is related to the French phrase “*banque route*,” which metaphorically describes the practice of leaving a trail on the desk of a banker who is no longer in operation. Historically, the term refers to a situation in which a financial institution or business fails and is unable to continue its operations.

Bankruptcy occurs when a company is unable to fulfill its obligations, both in debt payments and business operations ([Putro and Pratama, 2017](#)). Based on Law No. 4 of 1998, a company can be declared bankrupt if it has two or more creditors and fails to pay off its overdue debts. Bankruptcy is also associated with a company's failure to generate profits, which often leads to liquidation or cessation of business ([Fanny and Retnani, 2017](#)). Bankruptcy information plays an important role for various parties. Lenders use it to assess credit risk. Investors use it in their investment strategy to anticipate losses. The government has an interest in detecting signs of bankruptcy early to take supervisory measures. Accountants assess business continuity based on bankruptcy information, while company management can mitigate through mergers or restructuring to avoid bankruptcy costs ([Cipta and Wibowo, 2021](#)).

According to [Saragih et al. \(2019\)](#), bankruptcy causes can be categorized into general, external, and internal factors. General factors include economic conditions such as inflation, social

changes that affect market demand, technological advances that increase operational costs, and government regulations related to export-import tariffs and banking policies. External factors include customers, suppliers, and competitors. A company's inability to understand customer behavior, maintain relationships with suppliers, and effectively manage market competition can accelerate its bankruptcy. Internal factors, such as over-lending, poor business strategies, and capital structure imbalances, are related to financial and operational management and can hamper the company's financial stability (Saragih et al., 2019). Bankruptcy is not just a financial issue, but also a combination of economic conditions, business competition, governance, and managerial strategies. Therefore, companies need to implement effective risk management systems and financial strategies to prevent bankruptcy and maintain business continuity (Saragih et al., 2019).

## METHODS

This research uses the Systematic Literature Review (SLR) approach to analyze various studies that discuss financial distress prediction models. This method enables the identification of trends, assessment of model accuracy, and its application in various industries, as informed by previous research. The literature reviewed was selected based on several criteria, including the publication period from 2015 to 2024, to ensure relevance to the latest developments in this field.

The data sources were obtained from journal articles indexed in Scopus, Web of Science, and Google Scholar, ensuring the quality and credibility of the references used. The literature search process was conducted using several specific keywords, including "financial distress prediction", "bankruptcy models", "Altman Z-Score", "Springate Model," and "financial distress in industries". This data indicate that the topic of financial distress and bankruptcy prediction models remains a focus of attention in the academic literature, with various studies examining the effectiveness of different methods. Through the SLR approach, this research aims to summarize and compare the most relevant prediction models across different industry sectors and specific economic conditions.

## RESULT

Financial challenges can arise in organizations of all sizes, from large corporations to small enterprises. Such difficulties are characterized by volatile financial situations or crises that can precede bankruptcy. Companies facing these challenges often exhibit weaknesses in their corporate governance structures. Improved corporate governance usually correlates with improved organizational performance. Therefore, it is essential for companies to implement effective corporate governance practices within their management systems, as this fosters a stable and healthy financial environment. Between 2015 and 2024, there has been a significant increase in both the quantity of research focused on "financial distress" and the diversity of thematic areas associated with scholarly output. The research encompasses more than 51 distinct thematic areas, totaling 62. The main focus of this research is within the domains of Economics, Business Finance, and Management.

Financial distress is a condition in which a company experiences financial difficulties that could potentially lead to bankruptcy. Based on the results of the bibliometric analysis using VOSviewer software, it was found that the concept of financial distress is closely related to various aspects, such as bankruptcy prediction, company performance, financial impact, and likelihood. This indicates that research in this field primarily focuses on developing methods and prediction models to anticipate and analyze the risk of bankruptcy. One of the primary approaches in financial distress research is the development of bankruptcy prediction models that aim to identify companies with high financial risk prior to bankruptcy. Some models frequently used in this research include the Zmijewski Model, the Ohlson Model, and various score models, such as the Altman Z-Score and the Springate Model. The Zmijewski Model emphasizes the probability of bankruptcy by considering financial variables, such as the level of leverage and return on assets. Meanwhile, the Ohlson Model considers a combination of financial and non-financial factors to assess the likelihood of a company's bankruptcy. On the other hand, various score models, including the Altman Z-Score, rely on financial ratio analysis to assess an entity's financial health and determine its risk of bankruptcy.

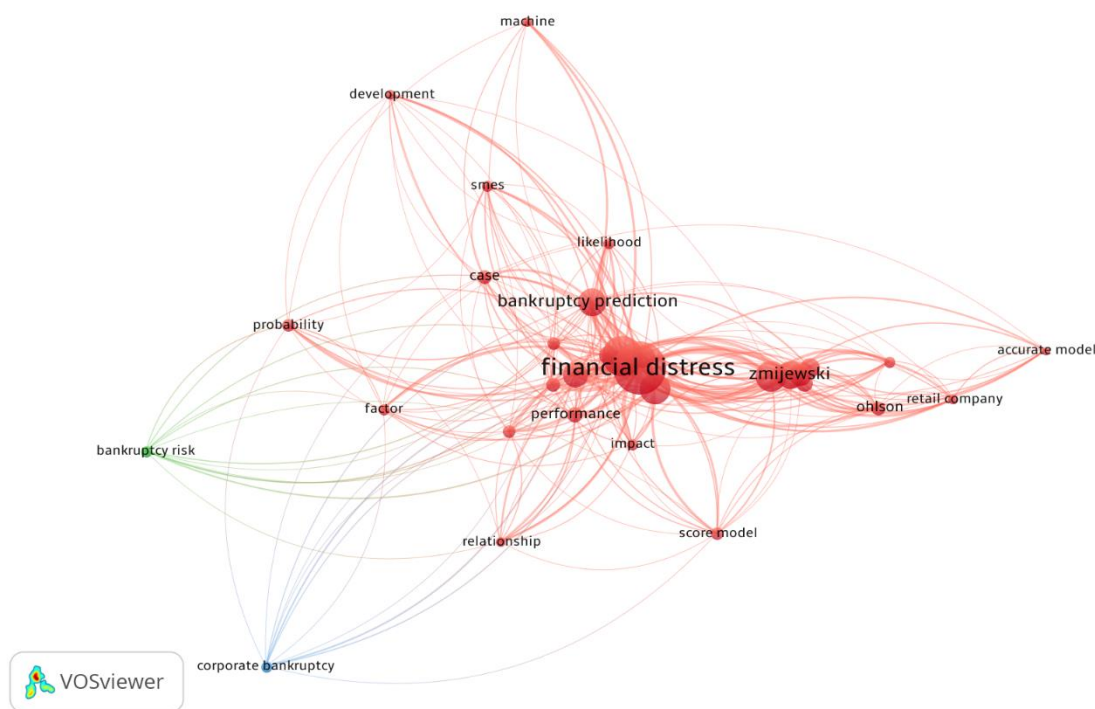


Figure 2. The main key concepts regarding the risk of bankruptcy used in the most relevant

Furthermore, the results of the bibliometric analysis show that factors such as corporate bankruptcy, bankruptcy risk, probability of bankruptcy, and relationships between various financial factors are closely related to the concept of financial distress ([Gajdosikova and Gabrikova, 2023](#)). This finding indicates that research on financial distress does not only focus on large companies but also encompasses the small and medium-sized enterprises (SMEs) sector, the retail industry, and other sectors vulnerable to financial stress ([Kuiziniene et al., 2022](#)). In terms of methodology, financial distress research is growing by adopting technology-based approaches, such as machine learning and statistical modeling, to improve the accuracy of bankruptcy prediction ([Shi and Li, 2019](#)). This is evident from the association between financial distress and terms such as accurate model and machine development in the bibliometric analysis results ([Gomes et al., 2024](#)). The utilization of artificial intelligence in financial distress prediction enables more in-depth and accurate data analysis, allowing companies to take early mitigation steps and reduce the risk of bankruptcy ([Kuiziniene et al., 2022](#)). Overall, research on financial distress continues to evolve in line with the increasing complexity of the financial system and the growing digitalization of the business world. With the widespread application of financial technology innovations, future research may further explore how these technologies can help firms manage financial risks and improve business resilience amid global economic uncertainty ([Ramesh et al., 2024](#)).



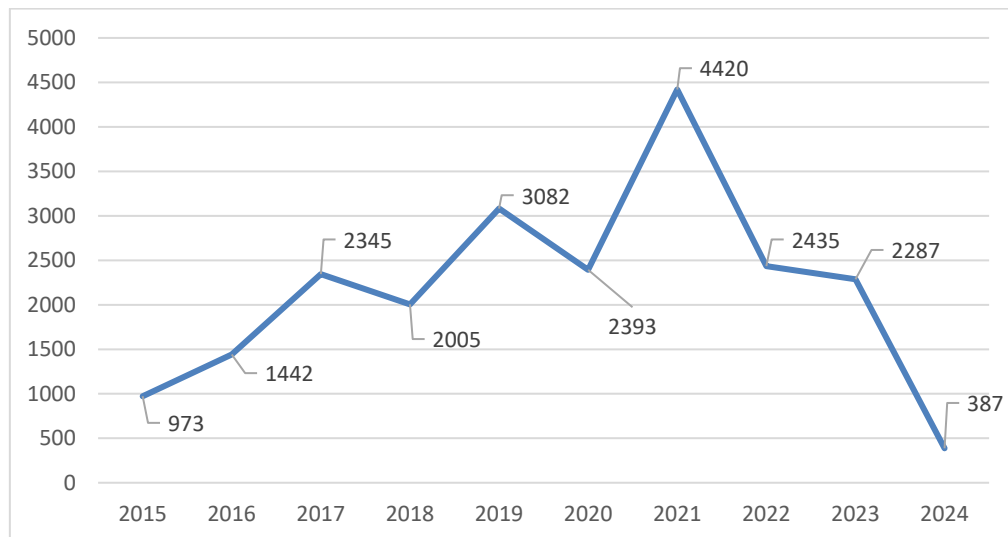


Figure 3. Research papers in the period 2015-2024

The financial distress of economic entities has been studied in various fields, with the primary focus remaining on Economics, Business Finance, and Management. Based on the keyword “financial distress”, the number of studies in this field has fluctuated over time, reaching its highest value in 2021 (4,420 articles). And reached its lowest value in 2024 with 387 research articles. For a clearer understanding and overview of the poor economic situation caused by Financial Distress and the models used, we consider it necessary to conduct a meta-analysis based on research papers in the period 2015-2024. This meta-analysis is presented in Table 1.

Table 1. Meta-Analysis on the Concept of Financial Distress

Authors	Concept and Definition	Research Purpose	Results	Research Impact
(Ghasemi et al., 2018)	Financial distress is a financial condition in which a company faces difficulties in meeting its financial obligations.	Applying metaheuristic models to predict financial distress	More complicated and technology-based prediction models can improve the accuracy of financial distress prediction.	Helping decision-makers detect and avoid bankruptcy earlier.
(Harahap, 2015)	Financial distress in foreign exchange banking companies is influenced by risk analysis, corporate governance, income, and capital.	Examine the factors that influence financial distress in the banking sector.	Good corporate governance and certain financial ratios play an important role in preventing financial distress.	Provide insights for the banking sector to improve risk management.
(Amalia and Kartikasari, 2023)	Financial distress prediction utilizes artificial intelligence methods, including Support Vector Machine (SVM) and Artificial Neural Network (ANN).	Analyzing the effectiveness of machine learning algorithms in detecting financial distress in the mining sector.	SVM and ANN have higher accuracy than traditional statistical models.	Leading to the development of a more efficient technology-based prediction model.
(Jiang et al., 2023)	Using semantic features in patent documents as an	Analyzing the Relationship between	Companies with fewer innovations in patents are more	Demonstrate the importance of R&D and innovation in

Authors	Concept and Definition	Research Purpose	Results	Research Impact
	indicator of financial distress.	Technological Innovation and Bankruptcy Prediction	prone to financial distress.	business sustainability.
(Kamau and Murori, 2024)	The impact of financial distress on earnings management practices before and after the COVID-19 pandemic.	Examines the relationship between financial distress and earnings management in companies listed on the Nairobi Securities Exchange.	Companies with high financial distress are more likely to do earnings management.	Provide an understanding of the impact of COVID-19 on corporate financial policy.
(Ananto, 2020)	Financial Distress in the Mining Sector: An Application of the Springate Model.	Analyzing the accuracy of the Springate model in detecting declining financial performance.	The Springate model is effective for industries with high fixed assets but less accurate for service-based sectors.	Strengthen the use of financial ratio-based prediction models for specific sectors.
(Munawarah and Hayati, 2019)	Comparison of Springate, Zmijewski, and Grover models in detecting financial distress.	Measuring the Accuracy of Prediction Models in the Financial Sector.	Zmijewski has the highest accuracy in predicting financial distress.	Contribution in determining the most appropriate model for the financial sector.
(Saputri and Krisnawati, 2020)	Comparison between Altman Z-Score, Springate, Zmijewski, and RGEK in the banking sector.	Determine the most accurate prediction model for the banking sector on the Indonesia Stock Exchange (IDX).	The Zmijewski and RGEK models are more accurate than Altman and Springate in detecting financial distress in the banking sector.	Assist financial authorities in improving bank risk evaluation models.

## DISCUSSION

### Altman Z-Score Prediction Model

Altman discriminant analysis is one of the statistical techniques used to predict the likelihood of bankruptcy in a company. Altman has integrated several ratios into a prediction method using statistical techniques. This discriminant analysis method is commonly referred to as the Z-score (Hutauruk et al., 2021). The Z-score formula was first developed by Altman in 1968. This formula was created through various studies conducted on manufacturing companies in the United States listed on the stock exchange. Therefore, this formula is very suitable for predicting the sustainability of manufacturing companies listed on the stock exchange. Altman (1968) used a stepwise multivariate discriminant analysis (MDA) model in the study. Similar to logistic regression, this statistical technique is commonly used to develop models where the dependent variable is qualitative (Rahayu et al., 2016). The output of the MDA technique is a linear equation that can distinguish between two states of the dependent variable. The Altman Z-Score model is one of the most widely used methods in predicting financial distress and corporate bankruptcy. Since its development by Edward Altman in 1968, the model has undergone various adaptations and validations in various industry contexts and economic regions.

Research shows that the Altman Z-Score is not only useful in detecting financial distress but can also identify indications of fraud in financial statements, making it an important tool for auditors, regulators, and financial analysts in objectively assessing the financial health of companies (Mahama, 2015). The model has also been tested in various industries, including telecommunication companies on the Indonesia Stock Exchange, where research shows that Z-Score has a high level of accuracy in classifying companies at risk of bankruptcy. However, there are challenges in applying it to industries with more dynamic financial characteristics (Rahayu et al., 2016). In addition, the model remains a standard tool in evaluating the financial health of companies, especially in unstable economic conditions, as seen in the study of PT Garuda Indonesia Tbk during and after the COVID-19 pandemic, which compared five bankruptcy prediction methods and still found the relevance of Z-Score as the main method (Seto, 2022). One of the reasons this model remains widely used is its empirical validity, which has been tested across various economic sectors. Studies comparing the Altman Z-Score with the Grover Score and Zmijewski show that the Z-Score remains the most effective model in the consumer goods industry, as it can more accurately predict a company's financial stability based on financial ratios (Primasari, 2017). The effectiveness of this model is also evident in the banking industry, where research indicates that the Altman Z-Score has an accuracy rate of up to 94% in predicting bank bankruptcies in Lebanon, demonstrating its ability to assess risk in the financial sector (Elia et al., 2021). However, in the pharmaceutical industry, the accuracy of the model is more variable, as it is influenced by the company's financial structure, which suggests the need for sector-specific customization of the model (Panigrahi, 2019). Other studies have also highlighted the role of the Altman Z-Score in helping companies and investors anticipate bankruptcy risk, as the model considers key financial ratios such as liquidity, profitability, leverage, and operational efficiency, which can serve as early indicators of a potential financial crisis (Altman, 2018).

Although the Altman Z-Score is recognized as one of the most widely used financial distress prediction models, it also has several limitations that must be considered when applying it. One of its weaknesses is that it is less accurate in service and technology-based industries. This model is more suitable for manufacturing companies and asset-based industries, where the financial structure is more stable and can be measured through financial ratios. However, for service-based companies that have irregular cash flows and fewer tangible assets, the accuracy of the Altman Z-Score is lower. Additionally, the Altman Z-Score does not account for external factors or market trends. The model focuses solely on a company's historical financial data, excluding macroeconomic factors, government regulations, and industry dynamics that may influence bankruptcy risk. Global economic conditions, monetary policy, and industry competition are often the primary factors that determine a company's sustainability. Another limitation is the Altman Z-Score's inaccuracy in assessing companies with unique financial strategies. A study conducted by Panigrahi (2019) found that some pharmaceutical companies with high leverage but implementing aggressive growth strategies were still able to survive, despite their Z-Score scores indicating that the companies were at risk of bankruptcy. This suggests that the model lacks flexibility in analyzing companies with unconventional business strategies. Therefore, while the Altman Z-Score remains a useful tool in bankruptcy prediction, its use should be tailored to industry characteristics and considered in conjunction with other models that can complement its analysis.

### Springate Prediction Model

The Springate Model is one of the bankruptcy prediction methods developed by Gordon L.V. Springate (1978). This model utilizes four key financial ratios to evaluate a company's financial condition and determine whether it is at risk of financial distress. Several studies have evaluated the effectiveness of this model across various industry sectors, with results showing varying levels of accuracy depending on the company's characteristics and the economic conditions it faces.

The Springate Model has proven to be quite effective in detecting declining financial performance in mining sector companies listed on the Indonesia Stock Exchange (IDX), especially in identifying companies with high levels of leverage that are at risk of financial distress (Ananto, 2020). However, in the context of the manufacturing industry, this model has limitations, as shown in a study that found a significance value of 0.175 ( $>0.05$ ), indicating that it is less accurate in



predicting bankruptcy among manufacturing companies in Indonesia ([Robiansyah et al., 2022](#)). In a comparison of several prediction models, the Zmijewski Model has a higher accuracy rate than the Springate Model in predicting financial distress in the financial sector, making the Springate Model less recommended for more complex and service-based industries ([Munawarah and Hayati, 2019](#)). In addition, research comparing the Springate Model with the Altman Z-Score, Zmijewski, Bankometer, Grover, and RGEC models in the banking sector shows that the Springate and Zmijewski Models more often categorize companies as being in distress than other models. However, these models also tend to produce many false positives, i.e., classifying companies as high risk when, in reality, this is not the case ([Saputri and Krisnawati, 2020](#)). Other studies in the retail sector also show that the Springate Model has a lower accuracy rate than the Grover Model, which is considered more accurate in identifying companies that are truly in financial distress ([Munira et al., 2021](#)).

In general, the primary advantage of the Springate Model is its simplicity, as it utilizes fewer variables than other models, such as Ohlson and Zmijewski, making it easier to apply across various industry sectors. However, the primary limitation of this model is its lack of consideration for external factors, such as macroeconomic conditions and government policies, which can significantly impact the company's financial stability. Additionally, the model overlooks company size and long-term leverage, which are crucial factors in determining the likelihood of bankruptcy.

### **Zmijewski Model and Ohlson O-Score**

The Zmijewski Model and the Ohlson O-Score are two financial distress prediction models widely used in accounting and finance research. These two models have different approaches in identifying companies at risk of bankruptcy. Based on the analyzed research results, it was found that the Zmijewski Model is superior in the manufacturing and mining sectors. At the same time, the Ohlson O-Score is more effective in the financial and services sectors.

The Zmijewski Model was developed by Mark Zmijewski (1984) using a probit regression model approach, which assesses the probability of bankruptcy based on profitability, leverage, and liquidity ([Salim and Ismudjoko, 2021](#)). In a study of mining companies listed on the Indonesia Stock Exchange (IDX), this model achieves an accuracy rate of 86.36%, which is higher than the Springate Model but still lower than the Ohlson O-Score. In addition, a study of soccer clubs in the English Premier League found that the Zmijewski Model has an accuracy of 72% in detecting financial distress in the sports industry, demonstrating its versatility across various sectors ([Lutfiyyah and Bhilawa, 2021](#)). Another study found that the Zmijewski Model is the most accurate method for predicting financial distress at PT Garuda Indonesia (Persero) Tbk, with an accuracy of 100%, significantly outperforming the Altman, Springate, and Ohlson Models ([Mirza and Tojibussabirin, 2022](#)).

On the other hand, the Ohlson O-Score was developed by James Ohlson (1980) using a logit regression model approach. Unlike the Zmijewski Model, which considers only a few financial ratios, the Ohlson O-Score utilizes more variables, including company size, leverage, liquidity, cash flow, and profitability, thereby providing a more comprehensive analysis ([Salim and Ismudjoko, 2021](#)). The research reveals that the Ohlson Model achieves the highest accuracy rate (90.91%) among other models in the mining sector, confirming its effectiveness in identifying financial distress in high-asset-based companies. In addition, a comparison between the Springate, Ohlson, Zmijewski, and Grover Models found that the Ohlson Model is superior in detecting financial distress in service-based companies, where non-financial factors have a greater impact on the company's financial stability ([Piscestalia and Priyadi, 2019](#)). Other research on commercial Islamic banks also indicates that the Ohlson Model is more accurate than the Zmijewski Model in predicting bankruptcy, as it considers a wider range of external factors that impact the financial health of banks ([Utama and Hamidah, 2024](#)).

Based on the comparison of the two models, the Zmijewski Model is superior in detecting financial distress in the manufacturing, transportation, and mining sectors, whereas the Ohlson O-Score is more accurate for the services and banking sectors, as it considers a broader range of external factors. The main advantage of the Zmijewski Model is its ease of implementation, as it

uses fewer variables than the Ohlson Model. However, the Ohlson Model offers a more comprehensive approach, which can lead to more accurate predictions, particularly for industries heavily influenced by macroeconomic factors.

Based on the analysis of Table 2, the accuracy of various financial distress prediction models shows significant variation depending on the method and industry sector analyzed. Altman Z-Score and Ohlson O-Score have the highest accuracy rate (90.91%), making them more reliable methods in predicting bankruptcy risk, especially for manufacturing companies and the financial sector. The main advantage of the Altman Z-Score lies in its simple and financial ratio-based application. However, it is less accurate in the services and technology sectors, which have different financial structures. The Ohlson O-Score, on the other hand, offers a wider range of variables by considering external factors such as company size and macroeconomic conditions. However, the model is more complex in its application.

Table 2. Model Accuracy in Various Industries

Prediction Model	Accuracy (%)	Excellence	Weaknesses	External Factors Affecting	Research References
<b>Altman Z-Score</b>	90,91%	<ul style="list-style-type: none"> <li>• Easy to implement and use across multiple industries.</li> <li>• High empirical validity since 1968.</li> <li>• Provides early warning of bankruptcy risk.</li> </ul>	Less accurate for service & technology industries; does not consider external factors.	Changes in financial regulations, global economic conditions	(Altman, 1968; Murthy et al., 2018; Panigrahi, 2019; Salim and Ismudjoko, 2021; Saputri and Krisnawati, 2020)
<b>Springate Model</b>	63.64% 73.48%	<ul style="list-style-type: none"> <li>• More simple than the Altman Z-Score and more accurate in the manufacturing sector.</li> </ul>	Less effective in service & financial industries, does not consider long-term leverage.	Manufacturing industry volatility, trade policy.	(Mulyani et al., 2019; Munira et al., 2021)
<b>Zmijewski Model (1984)</b>	86,36% 100%	<ul style="list-style-type: none"> <li>• More suitable for the finance and banking sector, considering leverage</li> </ul>	<ul style="list-style-type: none"> <li>• Less accurate for companies with aggressive growth strategies.</li> <li>• Not considering the operational efficiency of the company.</li> </ul>	Interest rate stability, monetary policy.	(Lutfiyyah and Bhilawa, 2021; Mirza and Tojibussabirin, 2022; Salim and Ismudjoko, 2021; Saputri and Krisnawati, 2020)
<b>Ohlson O-Score</b>	73% 90,91%	<ul style="list-style-type: none"> <li>• Utilizes a wide range of variables suitable for a wide range of company sizes</li> </ul>	<ul style="list-style-type: none"> <li>• More complex model than others.</li> <li>• Interpretation is more difficult than Z-Score or Springate.</li> </ul>	Capital market conditions, fiscal policy.	(Ohlson, 1980; Piscestalia and Priyadi, 2019; Rachman et al., 2023; Salim and Ismudjoko, 2021)

Meanwhile, the Zmijewski Model has an accuracy rate of 86.36%, making it a more suitable method for high asset-based industries such as mining and transportation. It is simpler than the

Ohlson O-Score but does not consider global economic volatility, which may affect the accuracy of predictions in dynamic economic conditions. The Springate Model, with the lowest accuracy rate (63.64%-73.48%), is more widely used in the manufacturing sector due to its ease of application. However, this model has limitations as it does not consider non-financial factors, making it less optimal in predicting bankruptcy in industries with more complex financial structures.

From the results of this comparison, it is evident that no single model can be applied universally across all sectors. The selection of the right model must consider the industry's characteristics, the company's financial structure, and external factors that affect the risk of bankruptcy. To improve prediction accuracy, integrating traditional models with machine learning and artificial intelligence (AI)- based technologies can be a solution to overcoming existing limitations. The combination of financial ratios with non-financial indicators, such as corporate governance and business innovation, can also strengthen the early warning system against financial distress. Therefore, the results of this study provide insights for academics, investors, and regulators in selecting the prediction method that best suits the company's conditions and the business environment it faces.

## CONCLUSION

Financial distress is a significant challenge for companies, which can lead to bankruptcy, influenced by both internal factors, such as profitability and leverage, and external factors, including economic conditions and regulations. Financial distress prediction is important in financial accounting to anticipate risks and assist strategic decision-making. Various models have been developed, including the Altman Z-Score, the Springate Model, the Zmijewski Model, and the Ohlson O-Score, with varying levels of accuracy across different industry sectors.

This study employs a systematic literature review (SLR) to assess the effectiveness of financial distress prediction models, drawing on studies published in reputable journals between 2015 and 2024. The analysis shows that the Altman Z-Score and Ohlson O-Score have the highest accuracy rate (90.91%), followed by the Zmijewski Model (86.36%), while the Springate Model has the lowest accuracy rate (63.64% -73.48%), but it is still relevant in the manufacturing sector. The Ohlson O-Score is more flexible, as it considers external factors such as macroeconomic conditions and company size. In contrast, the Zmijewski Model is more suitable for high-asset-based sectors.

Each of these models has limitations, making them unsuitable for universal application. The Altman Z-Score is less accurate in the service and technology sectors. The Zmijewski Model does not consider economic volatility, and the Ohlson O-Score is more complex in its application. Therefore, model selection should be tailored to the industry's characteristics for more accurate predictions. Going forward, the integration of traditional models with machine learning and artificial intelligence (AI) has the potential to improve prediction accuracy. The combination of financial ratios with non-financial indicators such as corporate governance and business innovation can strengthen the early warning system against financial distress. The results of this study offer valuable insights for academics, practitioners, investors, and regulators in developing effective risk mitigation strategies and promoting the financial stability of companies.

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