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MODELS AND PREDICTIVE FACTORS OF FINANCIAL DISTRESS ACROSS VARIOUS INDUSTRY SECTORS: A SYSTEMATIC LITERATURE REVIEW

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Abstract

Financial distress is a critical issue in accounting and finance literature, as it represents the early stage preceding corporate bankruptcy. This study employs a Systematic Literature Review (SLR) approach on articles published between 2019 and 2025 to identify the most accurate prediction models across different sectors and to analyze both financial and non-financial factors influencing financial distress. The findings indicate that no single prediction model is universally superior across all sectors. The Grover model demonstrates higher accuracy in the retail industry, the Zmijewski model performs better in manufacturing and transportation sectors, while the Springate model shows advantages in specific cases. In terms of financial factors, profitability emerges as the most consistent indicator, followed by liquidity as a short-term protective factor and firm size as a buffer against financial distress. Conversely, leverage and non-financial factors such as corporate governance and credit risk exhibit inconsistent results across studies. This research concludes that financial distress prediction models must be tailored to sector characteristics and specific contexts. These results contribute theoretically and offer practical recommendations for strengthening corporate early warning systems in detecting financial difficulties.

Keywords :
Financial Distress, Prediction Model, Profitability, Liquidity, Leverage, Systematic Literature Review.

Introduction

The phenomenon of financial distress has attracted increasing attention in accounting and finance literature, as it represents the early stage preceding corporate bankruptcy. In an increasingly competitive business environment, companies continuously strive to maintain stable financial performance. However, in practice, many firms fail to sustain their operations due to the inability to meet financial obligations. Financial distress is defined as a stage of declining financial condition before reaching bankruptcy or liquidation (Platt, 2002). Similarly, Ross (2012) describes financial distress as a company's inability to settle its obligations on time, indicating severe financial pressure.

Financial distress generates serious consequences for various stakeholders. Investors may suffer capital losses, creditors face default risk, management may lose professional credibility, and employees are threatened by job termination. Therefore, understanding and early detection of financial distress symptoms are crucial for companies to implement corrective actions before bankruptcy occurs. Financial distress prediction serves as an early warning system that benefits not only internal management but also investors, regulators, and creditors in anticipating financial risk (Muhammad & Zaenal, 2022). The urgency of such prediction becomes more pronounced during global crises, such as the COVID-19 pandemic, which significantly affected almost all industries. Numerous studies have shown that the pandemic triggered substantial financial pressure, reduced revenues, and increased corporate vulnerability to bankruptcy, particularly in the banking, transportation, and retail sectors (Mufidah & Handayani, 2024).

Various models have been developed to predict financial distress. Classical models such as Altman Z-Score, Springate, Zmijewski, Taffler, and Grover remain widely used. Each model applies different combinations of financial ratios, resulting in varying strengths, limitations, and levels of accuracy across industrial contexts. For instance, Mufidah and Handayani (2024) report that the Grover model provides the highest accuracy for the banking sector, while Saputra and Putri (2025) find that the Zmijewski model outperforms others in the transportation and logistics sector. Conversely, Elia and Rahayu (2021), in their study of retail companies, reaffirm that the Grover model produces the most accurate results compared to the Springate and Zmijewski models. These mixed findings indicate that no single prediction model can be considered universally superior across all industries.

Beyond prediction models, internal firm-specific factors also play a significant role in determining the likelihood of financial distress. Financial factors such as profitability, liquidity, leverage, cash flow, and firm size have been shown to influence corporate vulnerability (Ayem et al., 2023). Recent studies further emphasize the importance of non-financial factors, including corporate governance, credit risk, audit quality, and ownership concentration (Fauziah & Husain, 2024). Nevertheless, empirical evidence regarding these variables remains inconsistent. Some studies confirm that leverage increases the likelihood of financial distress, while others reveal the opposite. Similarly, corporate governance and firm size sometimes exhibit significant effects, yet in certain sectors, they appear to have no impact at all.

These inconsistencies create a research gap that warrants further investigation. To date, no consensus has been reached regarding the most accurate financial distress prediction model across different industries. Variations in sector characteristics—such as retail, manufacturing, banking, tourism, and property—further complicate the selection of appropriate prediction models. In addition, ongoing debates concerning the most dominant financial and non-financial determinants of financial distress strengthen the need for a comprehensive investigation.

Based on this background, this study is entitled **“Models and Determinants of Financial Distress Across Industry Sectors: A Systematic Review.”** The objectives of this study are to systematically review the literature published between 2019 and 2025 on financial distress prediction, identify the most accurate prediction models across different sectors, analyze both financial and non-financial factors influencing financial distress, and synthesize general patterns that may serve as a foundation for future research and financial management practices. Therefore, this study is expected to contribute both theoretically and practically to strengthening corporate early warning systems for financial difficulties.

KAJIAN LITERATUR

Definition and Concept of Financial Distress

Financial distress is generally defined as a condition in which a company experiences severe financial difficulties that significantly reduce its ability to maintain normal operations and fulfill its financial obligations. Financial distress represents the early stage of bankruptcy, characterized by an imbalance between cash inflows and outflows, an increasing debt burden, and a decline in the firm’s asset value. This condition does not occur suddenly but rather develops gradually, beginning with deteriorating operational performance, profitability, and liquidity (Kuizinienė et al., 2022). Furthermore, financial distress reflects a company’s inability to maintain long-term financial stability, which, if left unaddressed, may lead to legal actions such as debt restructuring or liquidation (Muhani et al., 2022). In the literature, financial distress is also viewed as a signal of declining investor and creditor confidence in the firm’s ability to generate future profits. Companies experiencing financial distress typically exhibit a decline in stock market value, rising leverage ratios, and reduced efficiency in asset utilization (Marsenne et al., 2023). Therefore, early detection of financial distress is essential so that management can implement corrective measures, such as financial restructuring, cost efficiency initiatives, or diversification of revenue sources, before the financial crisis deepens.

Financial Distress Prediction Models

Financial distress prediction models are developed to help identify companies that are potentially facing bankruptcy based on financial indicators. The **Altman Z-Score** is the most well-known classical model, developed by Edward Altman in 1968 using the **Multiple Discriminant Analysis (MDA)** technique. This model combines several financial ratios, including working capital to total assets, retained earnings to total assets, earnings before interest and taxes (EBIT) to total assets, market value of equity to total liabilities, and sales to total assets (Arini, 2021). Marsenne et al. (2023) note that the Altman model is particularly effective for publicly listed manufacturing firms due to its easily measurable data and extensively tested validity. In addition to Altman, the **Zmijewski model** applies a **probit regression** approach to predict bankruptcy using profitability (ROA), leverage (debt ratio), and liquidity (current ratio) as key indicators.

The **Springate model**, an adaptation of the Altman model, modifies the variable composition by placing greater emphasis on profitability and operational efficiency. **Grover (2001)** further refined the Altman model by incorporating **Return on Assets (ROA)** to improve predictive accuracy. Meanwhile, **Ohlson (1980)** developed the **O-Score model** based on **logistic regression**, which estimates the probability of bankruptcy by including variables such as firm size, leverage, and liquidity (Carolina Ety Widjayanti et al., 2024). Each of these models has its own strengths and limitations. The Altman model excels in interpretability and historical validity but is less accurate for non-manufacturing sectors. The Zmijewski and Ohlson models are more flexible and applicable across industries; however, they require comprehensive data and assume normal distribution among variables. The Grover and Springate models are relatively easy to apply, but their accuracy is influenced by economic conditions and the capital structure of the firms under investigation (Marsenne et al., 2023).

Key Predictors of Financial Distress

The primary factors commonly used to predict financial distress are financial ratios that reflect a firm's performance and financial health. **Liquidity ratios**, such as the current ratio and quick ratio, indicate a company's ability to meet its short-term obligations. **Solvency ratios**, including the debt-to-equity ratio and debt ratio, describe the extent to which corporate financing relies on debt. **Profitability** is measured through return on assets (ROA), return on equity (ROE), and net profit margin (NPM), which demonstrate a firm's ability to generate earnings from its available resources (Carolina Ety Widjayanti et al., 2024). In addition, **activity ratios** such as total asset turnover (TATO) are used to assess how efficiently assets are utilized to generate sales. **Capital structure** and **firm size** are also important variables because they influence financial stability and a firm's resilience to external pressures. Marsenne et al. (2023) argue that the combination of these ratios reflects liquidity, efficiency, and profitability, which collectively serve as the main indicators of financial distress risk. Moreover, several recent studies have incorporated **non-financial variables** such as corporate governance, firm age, and macroeconomic conditions to enhance the predictive power of financial distress models.

Statistical and Machine Learning Techniques in Prediction

Advances in data analytics technology have encouraged the use of statistical and machine learning methods to improve the accuracy of financial distress prediction models. Classical approaches such as **logistic regression**, **probit regression**, and **discriminant analysis** remain widely applied because they produce easily interpretable results and allow researchers to assess the influence of each predictor variable (Muhani et al., 2022). However, over the past decade, a variety of **machine learning techniques** have emerged, including **random forest**, **support vector machine (SVM)**, **gradient boosting**, **decision tree**, and **artificial neural network (ANN)**. These methods are capable of capturing nonlinear patterns, managing complex inter-variable interactions, and performing well on large datasets (big data). According to Jati (2024), **ensemble-based techniques** such as boosting and bagging often demonstrate higher predictive accuracy compared to conventional statistical models. Nevertheless, machine learning methods also present several limitations, including limited interpretability due to the **black-box problem**, the requirement for large, high-quality datasets, and the risk of overfitting if proper cross-validation is not applied. Therefore, many studies integrate classical statistical approaches for interpretability with machine learning techniques for accuracy optimization.

Differences in Financial Distress Characteristics Across Industry Sectors

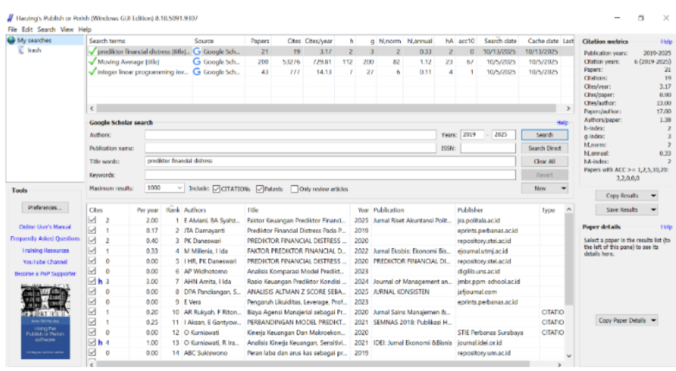
The characteristics of financial distress vary across industry sectors due to differences in cost structures, revenue patterns, and sources of risk. In the manufacturing sector, financial distress is commonly triggered by declining production efficiency, rising raw material costs, and increasing long-term debt pressure. Profitability and solvency ratios are the most significant factors in detecting potential bankruptcy within this sector (Carolina Ety Widjayanti et al., 2024). In the financial and insurance sectors, financial distress risk is more strongly influenced by liquidity ratios, claim levels, and investment exposure. Meanwhile, in the service sector, variables such as operating margin and revenue growth serve as the primary indicators, reflecting the relatively low proportion of fixed assets in this industry. Marsenne et al. (2023) emphasize that applying the same model across all sectors without proper adjustment may lead to biased predictions. Therefore, prediction models must be calibrated according to industry-specific characteristics to achieve more accurate and relevant results. Based on the literature, early detection of financial distress carries important implications for various stakeholders. For management, prediction outcomes provide a foundation for financial planning, cost efficiency initiatives, and debt restructuring. For investors and creditors, financial distress models assist in assessing investment risk and formulating risk mitigation strategies. Both Marsenne et al. (2023) and Jati (2024) highlight the importance of combining classical and modern approaches in developing effective early warning systems. Models that integrate financial and non-financial variables and are calibrated by industry sector are believed to yield the most accurate predictive outcomes.

METHOD

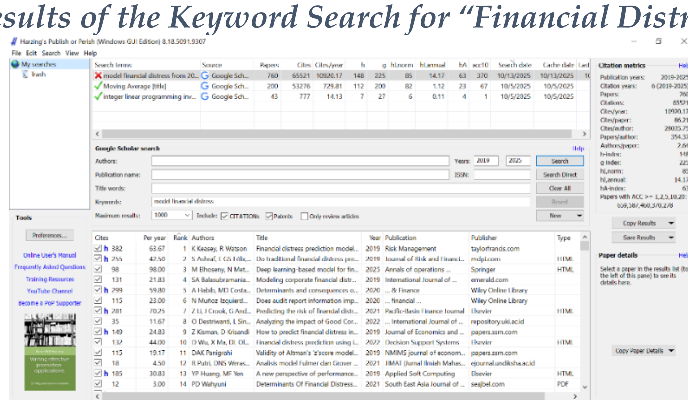
The research approach employed in this study is a **Systematic Literature Review (SLR)**. The objective of a systematic literature review is to provide a comprehensive summary of all relevant studies on a particular topic in a structured and transparent manner (Phua, 2010). SLR follows standardized methodological procedures consisting of three main stages: **preparation, review implementation, and results reporting**. In line with this, Sánchez et al. (2021) state that the main strength of SLR lies in its ability to reduce researcher bias through clearly defined and replicable literature selection procedures. The data sources for this study were obtained from the **Google Scholar database** with the assistance of the **Publish or Perish** software. The dataset consists of peer-reviewed journal articles indexed and relevant to the topic of financial distress. The selected articles were published between **2019 and 2025**, in accordance with the study's objective to examine recent developments in financial distress prediction models across various industry sectors. To select the literature, this study applied **inclusion and exclusion criteria**. The inclusion criteria were as follows:

1. Articles discussing financial distress prediction using both classical models (Altman Z-Score, Springate, Zmijewski, Taffler, and Grover) and modern approaches.
2. Articles examining both financial and non-financial factors.
3. Articles published between 2019 and 2025.

The exclusion criteria consisted of articles that were purely opinion-based, lacked empirical data, or did not focus on financial distress. The literature selection process followed the stages proposed by Sánchez et al. (2021): **identification, screening, eligibility, and final selection**. During the identification stage, keywords such as *financial distress prediction*, *bankruptcy models*, *Altman Z-Score*, *Springate*, *Grover*, *financial ratios*, and *corporate governance* were used. The retrieved articles were then screened based on topic relevance and publication year. At the eligibility stage, articles were further reviewed to ensure the suitability of their methodologies and variables. The final stage involved selecting the articles that constituted the sample for the review.



Figures 1. *Results of the Keyword Search for "Financial Distress Predictors*



Figures 2. *Results of the Search Using the Keyword "Financial Distress Model"*

Figures 1 and 2 present a summary of the search results using the keywords "financial distress predictors" and "financial distress model." The search identified 781 articles with a total of 65,540 citations, including citation metrics such as the h-index and g-index.

RESULT DAN DISCUSSION

From the initial broad search results, only a limited number of articles met the predefined criteria, including publication period, indexation status, and topic relevance to financial distress prediction models and their determining factors. These selected articles were drawn from various indexed journals published between 2019 and 2025 and focused on the application and comparison of prediction models such as Altman Z-Score, Springate, Zmijewski, Grover, Taffler, and Fulmer, as presented in Table 1.

Table 1. List of Articles Meeting the Inclusion and Exclusion Criteria

No	Year	Title	Journal	Sinta
1	2021	Accuracy Analysis of Financial Distress Prediction Models	Journal of Management Science	3
2	2020	Comparative Analysis of Financial Distress Condition Prediction Using the Altman, Springate, and Zmijewski Models	Journal of Accounting Studies	4
3	2024	Financial Ratios as Predictors of Financial Distress During the COVID-19 Pandemic in Property and Real Estate Companies	Journal of Management and Business Review	3
4	2022	Predictor Factors of Financial Distress in Tourism, Restaurant, and Hospitality Subsector Companies Listed on the Indonesia Stock Exchange	Journal of Economics, Business, and Management	4
5	2022	Financial Distress Prediction Analysis: A Comparison Between Empirical Models and the Altman Model	Selekta Management: Journal of Business and Management Students	3
6	2024	Analysis of Financial Distress Predictions Using Altman, Zavgren, Fulmer, Ohlson, Taffler, and Ca-Score Models as Early Warning Systems in Manufacturing Companies	Nominal Journal of Accounting Research Barometer	3
7	2021	Comparison of the Accuracy Levels of Financial Distress Prediction Models in	MEA Scientific Journal	4

	Companies Included in Kantar's 2020 Top 30 Global Retailers	(Management , Economics, and Accounting)

Table 2 presents the differences in the examined sectors (retail, banking, tourism, logistics, manufacturing, and listed companies on the Indonesia Stock Exchange), the analytical methods applied (linear regression, logistic regression, and comparative analysis), as well as the models and factors tested.

Table 2. Main Findings of Each Article

No	Autohor (Year)	**Sector**	**Method**	**Models / Variables Tested**	**Main Results**
1	Arini (2021)	Global retail	Model comparison	Altman, Springate, Taffler, Grover	Grover was the most accurate (76.67%)
2	Listyarini (2020)	Indonesian manufacturin g	Model comparison	Altman, Springate, Zmijewski	Zmijewski achieved the highest accuracy (100%)
3	Arnita & Ida (2024)	Property & real estate	Logistic regression	CR, TATO, DER, ROA, operating cash flow	TATO (+) and ROA were significant; others were not
4	Millenia & Ida (2022)	Tourism, restaurant, hotel	Logistic regression	Profitability, liquidity, leverage	Profitability and liquidity were significant; leverage was not
5	Muhamma & Zaenal (2022)	Manufacturin g	Discrimina nt regression	Financial ratios (liquidity, leverage, profitability)	Profitability was dominant; leverage showed mixed effects
6	Erfina (2024)	Mixed industries	Logistic regression	Altman & financial factors	Altman showed moderate accuracy; profitability was significant
7	Trias (2021)	Listed companies (IDX)	Comparativ e analysis	Altman, Springate	Springate performed better than Altman on a limited sample

It can be observed that there is considerable diversity in the focus and findings of the reviewed articles. Some studies indicate that the Grover model provides the highest accuracy, while others emphasize the superiority of the Zmijewski model. In addition, several studies highlight profitability, firm size, and credit risk as significant determinants of financial distress, whereas other factors such as leverage and corporate governance (GCG) do not consistently exhibit significant effects.

Profitability as the Primary Indicator

Profitability is the most consistently influential variable affecting financial distress. Arini (2021) demonstrates that the **Grover model** outperforms others because it prioritizes operating profit in its calculation, which aligns with the characteristics of the retail industry that is highly sensitive to profit margins. Listyarini (2020) also finds that profitability is a critical variable in the **Zmijewski model**, which proves to be highly accurate in Indonesian manufacturing firms. In the tourism and hospitality sector, Millenia and Ida (2022) reveal that profitability significantly reduces distress risk, as stable earnings enable firms to cover operational costs even when demand declines. However, Arnita and Ida (2024) uncover an interesting phenomenon in the property sector during the COVID-19 pandemic. Despite increased sales, not all companies were able to maintain profitability (ROA). As a result, firms remained vulnerable to financial distress even with high sales activity. This finding confirms that profitability is not merely about sales volume but also about the effectiveness of converting assets into profits. Therefore, profitability can be regarded as a **"universal predictor"** across industries; however, its mechanism differs by sector. In retail and manufacturing, profitability is closely associated with operational efficiency, whereas in the service sector, profitability reflects resilience in facing demand fluctuations.

Liquidity as a Short-Term Safeguard

Liquidity emerges as a significant factor in several studies, particularly within the service sector. Tourism, restaurant, and hospitality firms with high liquidity are more resilient in facing pandemic-related shocks. The ability to meet short-term obligations enables firms to maintain the confidence of creditors and suppliers while reducing the risk of default (Millenia & Ida, 2022). However, contrasting results are observed in the property sector, where liquidity does not significantly affect financial distress. This can be explained by the capital-intensive and long-term nature of the property industry (Arnita & Ida, 2024). Temporary liquidity is insufficient to protect firms when property demand declines structurally. Therefore, liquidity can be viewed as a **short-term protective indicator**. Its relevance is stronger in sectors with rapid cash flow cycles, such as retail and tourism, but less meaningful in industries characterized by long-term investments, such as property and manufacturing.

Leverage

Leverage is the variable that most frequently produces mixed empirical findings. High leverage is shown to be significant in the Zmijewski model because Indonesian manufacturing firms are capital-intensive and heavily dependent on debt financing. Consequently, debt ratios serve as an important signal of financial distress in this sector (Listyarini, 2020). However, leverage is not significant in the tourism and hospitality sectors. Firms in these industries are more strongly affected by external factors such as travel restrictions and declining demand (Arnita & Ida, 2024). In this context, debt is not the primary cause of distress; rather, the sharp decline in revenue plays a more decisive role. High leverage does not necessarily indicate distress if a firm can maintain positive operating cash flows, and conversely, firms with low leverage may still experience distress when profitability deteriorates significantly. These findings indicate that leverage cannot be treated as a standalone indicator. Its relevance is stronger in capital-intensive sectors during stable periods, but it loses explanatory power during crisis conditions when financial distress is driven primarily by external shocks (Elia & Rahayu, 2023).

Firm Size as a Buffer Against Financial Distress

Only a limited number of studies have examined firm size, one of which focuses on foreign exchange banking. The findings indicate that larger banks are more resilient to financial distress (Dahari et al., 2023). This occurs because large banks benefit from business diversification, easier access to capital, and higher levels of public trust. However, this evidence has not been extensively tested in non-financial sectors. It is plausible that firm size also plays a significant role in industries such as manufacturing and property, as larger firms are typically more capable of achieving economies of scale and possess stronger bargaining power with creditors and suppliers (Erfina, 2024). In other words, firm size functions as a **buffer** that enhances resilience against financial shocks. There remains considerable scope for future research to expand the examination of this variable across industries, particularly to assess whether firm size can reduce distress risk in vulnerable sectors such as tourism and retail.

Prediction Model

Comparative analysis across studies reveals that no single prediction model outperforms others across all sectors. The **Grover model** demonstrates higher accuracy in global retail. Although the **Altman model** remains classical and widely used, it tends to be less accurate without modification. This is because the model was originally developed in the United States using manufacturing samples and therefore may not be directly applicable to different countries or industry contexts (Trias, 2021). The **Springate model**, which is simpler in structure, sometimes produces better accuracy because it focuses on key financial ratios that are more relevant to specific conditions. The implication is that the selection of a prediction model must be tailored to industry sector, time period, and local context. Relying on a single model without proper adaptation increases the risk of producing misleading predictions.

Non-Financial Factors (Corporate Governance and Credit Risk)

The non-financial factors examined include **good corporate governance (GCG)** and **credit risk**. The findings are somewhat surprising, as both factors are not statistically significant. Instead, **profitability**, **capital adequacy ratio (CAR)**, and **bank size** emerge as more dominant determinants. Two possible explanations can be proposed. First, the measurement of GCG in the study remains limited and may not fully capture the overall quality of corporate governance. Second, in the foreign exchange banking sector, financial distress is more strongly influenced by internal financial factors such as capital strength and profitability rather than governance mechanisms (Fauziah & Husain, 2024). Although these non-financial factors are not significant in this particular study, they remain important and warrant further investigation. Future research could examine more detailed non-financial indicators, such as audit quality, board independence, or macroeconomic factors, to complement financial ratio-based prediction models and enhance their explanatory power.

CONCLUSION

Based on the results and discussion, it can be concluded that financial distress prediction cannot rely on a single universal model. The **Grover**, **Zmijewski**, and **Springate** models each demonstrate advantages in different sectors, reflecting distinct industry characteristics. **Profitability** is confirmed as the most consistent predictor, while **liquidity** and **firm size** function as additional protective factors. **Leverage** and non-financial variables continue to exhibit inconsistent effects, indicating the need for further research employing more detailed indicators. Therefore, the selection of prediction models and supporting factors must consider industry context and external conditions to produce an effective early warning system capable of preventing corporate bankruptcy.

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