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Comparison of financial distress prediction methods: Altman Z-Score, Zmijewski, Springate, and Grover in Indonesian retail trading companies

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ABSTRACT
This study seeks to identify the most accurate method for predicting financial distress among retail trade sub-sector companies listed on the Indonesia Stock Exchange by comparing the Altman Z-Score, Zmijewski, Springate, and Grover methods. The research population comprises retail trade sub-sector companies listed on the Indonesia Stock Exchange during the 2019-2021 period, encompassing a total of 18 companies. A purposive sampling technique was employed, resulting in a sample size of 18 companies. The study utilized a four-mean difference test alongside an accuracy level test to evaluate the predictive performance of each method. The findings indicate that the Altman Z-Score method outperforms the Grover, Zmijewski, and Springate methods in accurately predicting financial distress within the examined companies.

KEYWORDS
Financial Distress Prediction; Altman Z-Score; Zmijewski Model; Springate Model; Grover Model

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Introduction

Indonesia, with a population of approximately 250 million, is the fourth most populous country globally, and presents a considerable market opportunity for retail entrepreneurs. Recent years have witnessed notable growth in Indonesia's retail sector, reinforcing its status as a major player in the global retail industry. The retail sector's sales have reached a significant $369 billion, positioning Indonesia as the fifth largest retail market worldwide, according to Kearney's 2019 report. This expansion underscores the substantial prospects available in the Indonesian market for retail enterprises aiming to leverage its growing consumer base. The expansion period has seen a surge in diverse retail enterprises and a notable influx of international retailers entering the Indonesian market. A pivotal factor driving this growth is the burgeoning middle-class demographic, which is nearing 60 million individuals (Ministry of Finance of the Republic of Indonesia, 2019).

From 2012 to 2014, the retail industry experienced a remarkable growth rate exceeding 12%. However, this upward trend began to decelerate in 2016, with the growth rate falling to around 8%. By 2017, the decline became more pronounced, with the growth rate plummeting to 3.6%, marking the lowest growth rate in the past decade. Recent years have been marked by a troubling trend of numerous store closures among retail sub-sector companies across various Indonesian regions. This decline is particularly concerning given Indonesia's economic growth averaged approximately 5% between 2015 and 2019 (Badan Pusat Statistik, 2020). The slowdown in the retail sector's growth, despite a relatively stable economic environment, underscores the pressing need for effective strategies to sustain and enhance sector performance.

According to Widowati (2019), several retail sub-sector firms closed stores between 2017 and 2019. For example, PT Mitra Adiperkasa Tbk (MAPI) closed 321 outlets in 2017, including Lotus Department Store, Debenhams, and New Look. PT Hero Supermarket Tbk (HERO) shut down six Giant Supermarket outlets and 26 Hero Supermarket outlets, leading to the layoff of 532 employees and a loss of IDR 191 billion in 2017 due to declining sales in the food sector. The company continued restructuring in 2018, incurring a net loss of IDR 1.25 trillion. Similarly, PT Ramayana Lestari Sentosa Tbk (RALS) closed eight outlets in 2017 and one additional outlet in Jakarta in May 2019. PT Matahari Department Store Tbk (LPPF) faced significant challenges, closing four outlets in 2017 and two more in 2018 due to expired leases and underperformance. This trend extends to numerous retail firms listed on the Indonesia Stock Exchange, which have consistently reported declining net incomes in recent years.

Given the high number of store closures and declining net incomes among retail firms listed on the Indonesia Stock Exchange, it is crucial for these companies to explore proactive strategies to sustain their operations. The persistent decline in sales poses a serious risk of financial distress, potentially leading to bankruptcy if not addressed effectively. Therefore, it is essential for Indonesian retail companies to focus on stabilizing their financial health through innovative and robust strategies to navigate the challenging market environment. To evaluate and predict financial distress, various methodologies can be employed, including the Altman Z-Score, Zmijewski X-Score, Springate, Grover models, and a range of financial ratios. Previous studies, such as those by Trisnaningsih (2011) and Trisnaningsih & Saputri (2009), have utilized financial ratios encompassing liquidity, activity, solvency, profitability,

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and market ratios to analyze financial distress. These studies, however, have produced inconsistent results regarding the effectiveness of different prediction methods.

For instance, Aryo & Trisnaningsih (2021) and Damayanti et al. (2019) found that the Altman Z-Score method achieved the highest accuracy in forecasting financial distress. In contrast, Listyarini (2020) and Nilasari & Haryanto (2018) argued that the Zmijewski method provided better accuracy. Furthermore, Edi & Tania (2018) and Azizah (2017) highlighted the Springate method as the most precise, while Prasetianingtias & Kusumowati (2019) and Sudrajat & Wijayanti (2019) determined that the Grover method was the most reliable. These conflicting results underscore the necessity for a detailed approach when selecting and employing financial distress prediction models, emphasizing the need for further research to identify the most effective methods for accurately predicting financial stability in the retail sector.

This study aims to rigorously evaluate the effectiveness of four prominent financial distress prediction models—Altman Z-Score, Zmijewski, Springate, and Grover—specifically in the context of retail sub-sector companies listed on the Indonesia Stock Exchange. The primary research question seeks to determine which of these models provides the most accurate and reliable forecasts of financial distress within this sector. By systematically comparing these models, the research aims to identify which method offers the highest precision in predicting financial instability. This evaluation is crucial for understanding the relative strengths and limitations of each model in the retail industry, thereby contributing to a more nuanced understanding of their applicability and effectiveness. The study will provide insights into how well each model performs in real-world scenarios, particularly for companies operating in the dynamic and competitive retail sector.

The implications of this study are significant both theoretically and practically. Theoretically, it enriches the existing literature by offering a comparative analysis of these financial distress prediction models, thus providing a valuable reference point for future academic inquiries into financial forecasting methods. Practically, the findings are expected to aid companies in more accurately assessing their financial health, which can help mitigate the risk of financial distress and potentially prevent bankruptcy. Additionally, the insights derived from this research are crucial for investors, as they enable more informed decision-making and enhance the quality of investment choices. By better evaluating the financial health of potential investment opportunities, investors can make more strategic decisions, ultimately contributing to more stable and informed financial markets.

Literature review

Financial distress

Financial distress, as conceptualized by Brigham and Daves (2003), occurs when an organization is unable to meet its payment obligations or when forecasts indicate an imminent inability to fulfill financial commitments. According to Gamayuni (2011), financial distress can manifest in five distinct forms: economic failure, business failure, technical insolvency, insolvency in bankruptcy, and legal bankruptcy. Each form represents a different stage or aspect of financial distress, highlighting the various degrees and dimensions through which financial instability can affect a company.

Economic failure arises when a company's revenues fall short of covering its costs, leading to financial losses. Business failure is marked by a company's inability to operate profitably, eventually resulting in the cessation of operations. Technical insolvency occurs when a company cannot meet its short-term obligations despite possessing assets that exceed its liabilities. Insolvency in bankruptcy refers to a legal status where a company is unable to pay its debts as they become due, often leading to formal bankruptcy proceedings. Legal bankruptcy is the formal court declaration of insolvency, necessitating either reorganization or liquidation. Each of these manifestations represents an escalating level of financial distress, reflecting increasing severity in the company's financial challenges.

Fahmi (2011) further refines the concept by categorizing financial distress into four distinct levels: A (severe), B (high), C (moderate), and D (low). Each level necessitates specific interventions tailored to address the particular financial issues faced by the company. Hanafi and Halim (2016) identify several key indicators of financial distress, including cash flow analysis, evaluation of business strategies, assessment of management quality, and cost control measures. These indicators are essential for diagnosing the extent of financial distress and developing effective strategies to mitigate its impact.

Financial distress analysis methods

The Altman Z-Score model, conceived by Edward Altman in 1968, is a well-regarded and widely applied tool for predicting bankruptcy. This model utilizes multiple discriminant analysis to amalgamate several key financial ratios into a composite score, which aids in assessing the likelihood of a company experiencing financial distress. As articulated by Darsono et al. (2004), the Altman Z-Score relies on five critical financial ratios: Working Capital to Total Assets (WCTA), Retained Earnings to Total Assets (RETA), Earnings Before Interest and Taxes to Total Assets (EBITTA), Market Value of Equity to Book Value of Liabilities (MVEBVL), and Sales to Total Assets (STA). Collectively, these ratios provide a thorough overview of a company's financial health.

Despite its extensive application and the broad spectrum of financial indicators it incorporates, the Altman Z-Score model is not without limitations. A notable drawback is the susceptibility to biases introduced by accounting adjustments, which can undermine the accuracy of the Z-Score. Additionally, the model's effectiveness may diminish when applied to newly established or unprofitable companies that lack the requisite financial history for accurate analysis. Furthermore, the reliability of the model can fluctuate with quarterly financial results, particularly in scenarios involving significant write-offs at the fiscal year's end, as highlighted by Nurcahyanti (2015). These limitations indicate that, while the Altman Z-Score is a potent tool for bankruptcy prediction, it should be employed with caution and complemented by other analytical methods to enhance its accuracy and reliability.

The Zmijewski model, introduced in 1984, provides a critical advancement over earlier sampling techniques by employing random sampling to evaluate financial distress. This model emphasizes three key financial areas—leverage, profitability, and liquidity—to assess a company's financial condition. By focusing on these indicators, the Zmijewski model aims to deliver a more reliable measure of financial distress compared to its predecessors. In contrast, the Springate method, developed in 1978, refines Altman's approach by selecting four specific financial ratios that are particularly effective in differentiating between distressed and non-distressed firms. This enhancement of Altman's model aims to improve prediction accuracy, making it a valuable tool for identifying companies at risk of financial trouble. The Grover method, which evolved between 1982 and 1996, further extends the Altman Z-Score model by integrating 13 financial ratios to enhance the precision of financial distress predictions. This method places particular emphasis on ratios such as Working Capital to Total Assets, Earnings Before Interest and Taxes to Total Assets, and Net Income to Total Assets. By incorporating a broader range of financial indicators, the Grover method provides a more nuanced and accurate assessment of a company's financial distress, as noted by Eka & Indra (2022). This comprehensive approach enables a more detailed evaluation of a company's financial stability, making it a significant tool in financial analysis.

Financial reports

Financial statements, according to Kasmir (2013), are crucial documents that showcase a company's financial condition and are key for evaluating its performance and resource management. These statements include four main types: the income statement, which outlines the company's revenues and expenses; the statement of changes in equity, which monitors transactions with owners and alterations in equity; the balance sheet, which displays the company's financial status by listing its assets, liabilities, and equity at a specific moment; and the cash flow statement, which details the cash inflows and outflows resulting from operational, investing, and financing activities. The Indonesian Institute of Accountants (2009) underscores that these financial statements are crucial for informed decision-making and reflect the management's accountability for the resources under their stewardship.

Methods

Population and sampling techniques

The population for this study consists of retail sub-sector companies listed on the Indonesia Stock Exchange (IDX). The sampling process was conducted using purposive sampling, which was guided by two specific criteria: (1) the companies must belong to the retail sub-sector and have been listed on the IDX during the period from 2019 to 2021, and (2) they must have complete and accessible financial statements for this period. By applying these criteria, the study was able to narrow down its focus, resulting in a final sample of 18 companies. This targeted sampling approach ensures that the selected companies are relevant to the study's objectives and that sufficient financial data is available for analysis. By adhering to these criteria, the study ensures that the sample is representative of the research objectives, concentrating on relevant and well-documented companies within the specified timeframe.

Data collection methods

This study employs the documentation method as its primary approach for data collection, utilizing secondary data obtained from annual financial statements of the companies being analyzed. These financial statements are sourced directly from the Indonesia Stock Exchange (IDX), which provides an authoritative and reliable repository of financial information. By leveraging these official records, the study ensures that the data used is not only pertinent but also accurately represents the financial condition of the selected companies.

The reliance on financial statements from the IDX is instrumental in maintaining the integrity and validity of the data. These statements offer a comprehensive view of the companies' financial performance and health, encompassing critical metrics such as revenues, expenses, assets, liabilities, and equity. This method ensures that the analysis is grounded in verifiable and standardized financial information, which is essential for an accurate assessment of financial distress within the retail sub-sector.

By using this documentation method, the study aims to achieve a high level of data reliability and consistency. The financial statements provided by IDX serve as a robust foundation for analyzing the financial health of the companies, enabling the research to draw well-supported conclusions regarding their financial stability. This approach not only enhances the credibility of the findings but also ensures that the assessment of financial distress is based on objective and rigorously verified data.

Research variables

The Altman Z-Score methodology, first introduced by Edward I. Altman in 1968 and later revised in 1995, aims to minimize the impact of industry-specific variables by omitting the asset turnover ratio (X5). This revised model, applicable across both manufacturing and non-manufacturing sectors, evaluates bankruptcy risk. According to Winarso and Edison (2020), the revised Altman Z-Score formula is expressed as: Z''-Score = 6.56(X1) + 3.26(X2) + 6.72(X3) + 1.05(X4). This adjusted formula is intended to lessen the influence of industry-specific factors by excluding the asset turnover variable. The categorization of the Z''-Score is as follows: a score exceeding 2.6 indicates a financially sound company, a score ranging between 1.1 and 2.6 denotes a grey area, and a score below 1.1 suggests potential financial distress (Acep, 2018).

Zmijewski's X-Score model utilizes Return on Assets (ROA), leverage ratio, and current asset ratio as predictors through a multiple regression framework. As reported by Winarso and Edison (2020), the X-Score model is formulated as: X-Score = -4.3 – 4.5(X1) + 5.7(X2) – 0.004(X3). In this model, a negative X-Score indicates financial stability, whereas a positive score suggests the presence of financial distress or imminent bankruptcy.

Springate's bankruptcy prediction model employs Multiple Discriminant Analysis (MDA), akin to Altman's methodology. Originally encompassing 19 financial ratios, Springate's model was subsequently refined to focus on four key ratios that are deemed effective in differentiating between bankrupt and non-bankrupt firms. The model, as delineated by Winarso and Edison (2020), is: S-Score = 1.03(X1) + 3.07(X2) + 0.66(X3) + 0.4(X4). A company is classified as bankrupt if its S-Score is below 0.862, while a score of 0.862 or higher indicates financial stability.

The Grover model, as described by Winarso and Edison (2020), is expressed through the formula: G-Score = 1.650(X1) + 3.404(X2) – 0.016(X3) + 0.057. The classification criteria for the Grover model are: a G-Score of ≤ -0.02 signifies bankruptcy, a G-Score of ≥ 0.01 indicates financial stability, and scores falling between these values are considered to be in a grey area.

Data analysis techniques

This study employs a comprehensive array of data analysis techniques to assess the efficacy of various financial distress prediction models. The initial phase involves the use of descriptive statistics, which are essential for identifying the fundamental characteristics of the dataset. Specifically, the minimum and maximum values are calculated to define the range of the data, while the mean provides an indication of the central tendency. Additionally, the standard deviation is computed to evaluate the dispersion or variability within the dataset.

Subsequent to this descriptive analysis, the study conducts normality testing to determine whether the data adheres to a normal distribution. Sugiyanto, as referenced in Winarso and Edison (2020), posits that data is considered to be normally distributed if the probability value exceeds 0.05. This criterion indicates that the data distribution approximates a normal curve. Conversely, a probability value below 0.05 suggests that the data deviates from a normal distribution. The Kolmogorov-Smirnov test is commonly utilized for this purpose, as it assesses how well the data aligns with a normal distribution.

When the data does not conform to a normal distribution, further statistical procedures are necessary. In such instances, a t-test is employed to evaluate differences in means between groups or conditions. The t-test facilitates the determination of whether observed differences are statistically significant, allowing for a more nuanced analysis even in the presence of non-normal data. This methodological approach ensures that deviations from normal distribution are accommodated, thereby providing valid and reliable results in the study's analysis.

Hypothesis testing

This study employs several key methods for hypothesis testing. Initially, it utilizes mean comparison techniques to evaluate differences between average values from independent or paired samples by calculating the t-student statistic and determining the two-tailed probability of mean differences. To compare the effectiveness of various financial distress prediction methods, including Altman, Zmijewski, Springate, and Grover, a one-sample t-test is used to analyze mean differences among these datasets. Additionally, prediction accuracy is measured by calculating the percentage of correct predictions made by each method relative to the total sample size, using the formula: Accuracy = (Number of Correct Predictions / Total Sample Size) × 100% (Hastuti, 2015). This involves comparing the number of companies predicted to be in financial distress by each method against the actual number of distressed companies, as determined by indicators like declines in sales or revenue, reduced profitability, and asset decreases over three years. Following the accuracy assessment, the error rates are evaluated, including Type I errors (false negatives, where a model fails to identify distressed companies) and Type II errors (false positives, where a model incorrectly predicts distress). The error rates are calculated as follows: Type I Error = (Number of Type I Errors / Total Sample Size) × 100% and Type II Error = (Number of Type II Errors / Total Sample Size) × 100%. The most effective prediction method is identified by the highest accuracy percentage and the lowest error rates, according to Hastuti (2015).

Results

Descriptive statistics

According to Hastuti (2015), descriptive statistics aim to analyze data by depicting the characteristics of the sample without making generalizations. In this study, measurements were conducted for the scores of Altman Z-Score, Grover (G-Score), Springate (S-Score), and Zmijewski (X-Score) methods. As presented in Table 1, the dataset comprises 54 entries, derived from 18 companies over three years. The minimum values indicate the poorest financial conditions, with the Altman Z-Score recording a minimum of -2.81 from Midi Utama Indonesia Tbk (MIDI) in 2021. Similarly, Grover's minimum value is -0.46 for MIDI in 2021, Springate's minimum is -2.18 from Hero Supermarket Tbk (HERO) in 2021, and Zmijewski's minimum is -3.72 from Mitra Adiperkasa Tbk (MAPI) in 2021.

The maximum values reflect the best financial conditions, with Altman Z-Score reaching 9.32522 from MAPI in 2019, Grover achieving 1.11551 from PT Omni Inovasi Indonesia Tbk (TELE) in 2019, Springate recording 2.19703 from MAPI in 2019, and Zmijewski reaching 1.12575 from Matahari Department Store Tbk (LPPF) in 2021. The mean values suggest financial conditions where Altman's score averages 2.6695381, placing companies in the Grey area, whereas scores above 2.6 indicate non-financial distress. Grover's mean of 0.2649591 suggests non-financial distress, with scores ≥0.01, while Springate's mean of 0.4492581 indicates financial distress, with scores >0.861 denoting better conditions. Zmijewski's mean of -1.4414091 indicates non-financial distress with scores <0. Standard deviations closer to zero indicate higher accuracy; Altman's standard deviation is 2.88312401, Grover's is 0.35861249, Springate's is 0.77982252, and Zmijewski's is 1.19880569, reflecting varying levels of precision in the predictions (Hastuti, 2015).

Table 1. Descriptive statistics

Descriptive Statistics					
	N	Minimum	Maximum	*Mean*	Std. Deviation
ALTMAN	54	-2.81220	9.32522	2.6695381	2.88312401
GROVER	54	-.46488	1.11551	0.2649591	0.35861249
SPRINGATE	54	-2.17520	2.19703	0.4492581	0.77982252
Zmijewski	54	-3.71848	1.12575	-1.4414091	1.19880569

Results of normality test

Normality testing is conducted to ascertain whether the data conforms to a normal distribution. As detailed in the Research Methodology section of Chapter 3, when data is normally distributed, the One Sample Kolmogorov-Smirnov Test is utilized. Conversely, if the data fails to meet the normality assumption, the Kruskal-Wallis Test is employed instead. For this study, the data was found to meet the criteria for normal distribution, prompting the use of the One Sample Kolmogorov-Smirnov Test.

The results, as summarized in Table 2, confirm that the data adheres to a normal distribution for all evaluated methods. Specifically, the Asymp. Sig (2-tailed) values for the Altman, Grover, Springate, and Zmijewski methods were 0.200, 0.200, 0.090, and 0.200, respectively, all exceeding the significance level threshold of 0.05. These results affirm that the data for each method—Altman, Grover, Springate, and Zmijewski—follows a normal distribution, consistent with Hastuti's (2015) criterion, which asserts that data is considered normally distributed if the significance level surpasses 0.05.

Table 2. Normality Test

One-Sample Kolmogorov-Smirnov Test					
		ALTMAN	GROVER	SPRINGETE	ZMIJEWSKI
N		54	54	54	54
Normal Parameters[a,b]	Mean	2.6695	0.2650	0.4493	-1.4414
	Std. Deviation	2.88312	0.35861	0.77982	1.19881
Most Extreme Differences	Absolute	0.093	0.068	0.112	0.097
	Positive	0.093	0.056	0.112	0.097
	Negative	-0.073	-0.068	-0.100	-0.097
Test Statistic		0.093	0.068	0.112	0.097
Asymp. Sig. (2-tailed)		0.200[c,d]	0.200[c,d]	0.090[c]	0.200[c,d]

Altman z-score method

The analysis of 18 retail sector companies listed on the Indonesia Stock Exchange for the period 2019-2021 using the Altman Z-Score method reveals the following findings: The results indicate that 15 instances (27.8%) are classified as financial distress, 13 instances (24.1%) fall into the grey area, which represents a financial condition between distress and safety, and 26 instances (48.1%) are categorized as non-financial distress.

Table 3. Altman Z-Score Calculation

No.	Company Code	Year	*Z-Score*	Status
1	ACES	2019	5.27859	Non *Financial distress*
		2020	5.41661	
		2021	4.93752	
2	AMRT	2019	4.95207	
		2020	5.61048	
		2021	5.20275	
3	CSAP	2019	-0.34830	*Financial distress*
		2020	1.08830	
		2021	2.23758	*Grey area*
4	DAYA	2019	5.23854	Non *Financial distress*
		2020	3.93701	
		2021	3.68086	
5	ECII	2019	0.18775	*Financial distress*
		2020	-0.00855	
		2021	-0.58372	
6	ERAA	2019	8.60152	Non *Financial distress*
		2020	3.39215	
		2021	2.43307	*Grey area*
7	GLOB	2019	2.64815	Non *Financial distress*
		2020	1.82694	*Grey area*
		2021	1.49277	
8	HERO	2019	-0.14256	*Financial distress*
		2020	-1.61951	
		2021	-1.78437	
9	LPPF	2019	-1.69872	
		2020	-0.44425	

		2021	-0.98697	
		2019	9.32522	
10	MAPI	2020	8.73391	Non *Financial distress*
		2021	8.60669	
		2019	-0.57974	
11	MIDI	2020	-0.15484	*Financial distress*
		2021	-2.81220	
		2019	-0.08555	
12	MKNT	2020	3.53178	Non *Financial distress*
		2021	1.88822	*Grey area*
		2019	1.65697	
13	MPPA	2020	5.14952	
		2021	8.64917	Non *Financial distress*
		2019	2.66882	
14	RALS	2020	1.98414	*Grey area*
		2021	1.31790	
		2019	2.63249	Non *Financial distress*
15	SKYB	2020	2.09006	*Grey area*
		2021	1.65854	
		2019	2.92206	Non *Financial distress*
16	SONA	2020	3.10002	
		2021	2.09265	*Grey area*
		2019	4.89026	Non *Financial distress*
17	TELE	2020	4.38076	
		2021	2.52174	*Grey area*
		2019	1.82058	
18	TRIO	2020	2.93361	Non *Financial distress*
		2021	2.68657	

Grover method (g-score)

The analysis of 18 retail sector companies listed on the Indonesia Stock Exchange for the period 2019-2021 using the Grover method yields the following results: The findings show that 11 instances (20.4%) are classified as financial distress, 2 instances (3.7%) fall into the grey area, indicating a financial condition between distress and safety, and 41 instances (75.9%) are categorized as non-financial distress.

Table 4. Grover Calculation Results (G-Score)

No.	Company Code	Year	G-Score	Status
		2019	0.66691	
1	ACES	2020	0.67890	
		2021	0.59525	Non *Financial distress*
		2019	0.32908	
2	AMRT	2020	0.50942	
		2021	0.41391	
		2019	-0.02401	*Financial distress*
3	CSAP	2020	0.24722	
		2021	0.41463	
		2019	0.55870	Non *Financial distress*
4	DAYA	2020	0.18775	
		2021	0.18746	
		2019	-0.00099	*Grey area*
5	ECII	2020	-0.02780	*Financial distress*
		2021	-0.15565	
		2019	0.87009	
6	ERAA	2020	0.58743	
		2021	0.30216	Non *Financial distress*
		2019	0.55255	
7	GLOB	2020	0.33744	
		2021	0.21743	
		2019	-0.00438	*Grey area*
8	HERO	2020	-0.31622	
		2021	-0.39920	
		2019	-0.46488	*Financial distress*
9	LPPF	2020	-0.07843	
		2021	-0.11596	
		2019	0.68348	
10	MAPI	2020	0.48718	Non *Financial distress*
		2021	0.43512	
		2019	-0.45115	*Financial distress*
11	MIDI	2020	0.04515	Non *Financial distress*
		2021	-0.45270	*Financial distress*
		2019	-0.06204	
12	MKNT	2020	0.67052	Non *Financial distress*

		2021	0.27002
		2019	0.16967
13	MPPA	2020	0.06077
		2021	0.01792
		2019	0.34248
14	RALS	2020	0.16357
		2021	0.01470
		2019	0.25904
15	SKYB	2020	0.11445
		2021	0.02282
		2019	0.43273
16	SONA	2020	0.47391
		2021	0.23579
		2019	1.11551
17	TELE	2020	0.96557
		2021	0.52964
		2019	0.41632
18	TRIO	2020	0.70231
		2021	0.57620

Springate method (s-score)

Based on the research using the Springate (S-Score) method, the results are as follows: The calculations indicate that 38 instances (70.4%) are classified as financial distress, while 16 instances (29.6%) are categorized as non-financial distress.

Table 5. Springate Calculation Results (S-Score)

No.	Company Code	Year	S	Status
		2019	0.93545	Non *Financial distress*
1	ACES	2020	0.91710	
		2021	0.77108	*Financial distress*
		2019	0.83379	
2	AMRT	2020	1.15236	Non *Financial distress*
		2021	0.80988	
		2019	0.16329	*Financial distress*
3	CSAP	2020	0.53602	
		2021	0.69693	
		2019	1.39848	Non *Financial distress*
4	DAYA	2020	0.26787	
		2021	0.33264	
		2019	0.00688	*Financial distress*
5	ECII	2020	-0.08988	
		2021	-0.49567	
		2019	2.16114	Non *Financial distress*
6	ERAA	2020	1.01519	
		2021	0.54791	*Financial distress*
		2019	1.04387	Non *Financial distress*
7	GLOB	2020	0.58653	
		2021	0.43756	
		2019	-0.60841	
8	HERO	2020	-1.05195	*Financial distress*
		2021	-2.17520	
		2019	-0.38661	
9	LPPF	2020	-0.57196	
		2021	-0.51178	
		2019	2.19703	
10	MAPI	2020	0.98553	Non *Financial distress*
		2021	0.90751	
		2019	-0.71469	
11	MIDI	2020	-0.12872	*Financial distress*
		2021	-0.34872	
		2019	0.77272	
12	MKNT	2020	1.62308	Non *Financial distress*
		2021	0.83192	
		2019	0.37645	
13	MPPA	2020	-0.47620	
		2021	-0.47553	
		2019	0.63398	*Financial distress*
14	RALS	2020	0.30007	
		2021	0.19659	
		2019	0.48277	
15	SKYB	2020	0.24208	
		2021	0.13741	
		2019	0.89956	Non *Financial distress*

16	SONA	2020	0.87655	
		2021	0.74164	*Financial distress*
		2019	1.57040	Non *Financial distress*
17	TELE	2020	0.94489	
		2021	0.55722	*Financial distress*
		2019	0.73602	
18	TRIO	2020	0.92074	Non *Financial distress*
		2021	0.74713	*Financial distress*

Zmijewski method (x-score)

Based on the research involving 18 retail sector companies listed on the Indonesia Stock Exchange during the 2019-2021 period using the Zmijewski (X-Score) method, the results are as follows: The calculations reveal that 5 instances (9.3%) are classified as financial distress, while 49 instances (90.7%) are categorized as non-financial distress.

Table 6. Zmijewski Calculation Results (X-Score)

No.	Company Code	Year	X	Status
		2019	-2.94480	
1	ACES	2020	-2.94703	
		2021	-2.71151	
		2019	-3.21935	
2	AMRT	2020	-2.94310	
		2021	-2.66248	
		2019	-0.02728	Non *Financial distress*
3	CSAP	2020	-1.34517	
		2021	-1.75212	
		2019	-2.93100	
4	DAYA	2020	-2.26032	
		2021	-2.11640	
		2019	-0.74025	
5	ECII	2020	-0.51854	
		2021	0.06531	*Financial distress*
		2019	-1.12215	
6	ERAA	2020	-0.66404	
		2021	-0.63683	
		2019	-1.14717	Non *Financial distress*
7	GLOB	2020	-0.54458	
		2021	-0.50261	
		2019	-0.87137	
8	HERO	2020	-0.15332	
		2021	0.34196	
		2019	0.21844	*Financial distress*
9	LPPF	2020	0.67434	
		2021	1.12575	
		2019	-3.71848	
10	MAPI	2020	-3.49798	
		2021	-3.46737	
		2019	-1.36888	
11	MIDI	2020	-0.62153	
		2021	-0.09863	
		2019	-1.13128	
12	MKNT	2020	-2.47862	
		2021	-1.62891	
		2019	-1.80799	
13	MPPA	2020	-2.96773	
		2021	-3.52417	
		2019	-1.52253	
14	RALS	2020	-1.18193	Non *Financial distress*
		2021	-1.12183	
		2019	-1.80931	
15	SKYB	2020	-1.58724	
		2021	-1.42350	
		2019	-1.20287	
16	SONA	2020	-1.07987	
		2021	-0.99272	
		2019	-1.42968	
17	TELE	2020	-0.70900	
		2021	-3.50177	
		2019	-0.60150	
18	TRIO	2020	-0.48674	
		2021	-0.53841	

4-average difference test

According to Table 7, the significance value is less than α (0.05), which indicates that there are significant differences among the Altman Z-Score, Zmijewski, Springate, and Grover methods in predicting bankruptcy for retail sector companies listed on the Indonesia Stock Exchange. This result confirms that Hypothesis 1 (H1) is accepted.

Table 7. Test of Differences of 4 Averages

One-Sample Test						
	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference Lower	Upper
ALTMAN	6.804	53	0.000	2.66954	1.8826	3.4565
GROVER	5.429	53	0.000	0.26496	0.1671	0.3628
SPRINGETE	4.233	53	0.000	0.44926	0.2364	0.6621
ZMIJEWSKI	-8.836	53	0.000	-1.44141	-1.7686	-1.1142

Accuracy level

The accuracy test for predictive methods is a critical process for evaluating the performance of various financial distress prediction models. This test calculates the accuracy rate, which is defined as the ratio of correct predictions to the total number of samples, and is expressed as a percentage. To determine this accuracy rate, the number of correct predictions is divided by the total number of companies in the sample, and the resulting quotient is then multiplied by 100%. Correct predictions are assessed by comparing the number of companies a model predicts as being in financial distress with the actual number of companies that are indeed in distress. This comparison is based on real-world indicators, such as reductions in sales, profits, or total assets over a specified period, typically three consecutive years. These financial indicators provide concrete evidence of a company's declining financial health and serve as reliable benchmarks for validating the accuracy of the predictive models. By correlating model predictions with these tangible indicators, the effectiveness of each model in forecasting financial distress can be rigorously evaluated and assessed.

The analysis conducted in this study identifies several companies as being in financial distress based on specific financial indicators. As detailed in Table 8, the companies confirmed to be experiencing significant financial distress include PT Sumber Alfaria Trijaya Tbk (AMRT), Catur Sentosa Adiprana Tbk (CSAP), PT Globe Kita Terang Tbk (GLOB), Midi Utama Indonesia Tbk (MIDI), Sona Topas Tourism Industry Tbk (SONA), and Trikomsel Oke Tbk (TRIO). These companies have shown notable declines in key financial metrics—such as sales, profits, and total assets—over a period of three consecutive years. The pronounced reductions in these critical financial indicators strongly suggest that these firms are facing severe financial difficulties, highlighting their distressed financial state.

Table 8. Results Accuracy Level and Error Type

No.	Method	Correct Prediction	Number of Samples	Accuracy Level	Type Error I	Type Error II
1	Altman	32	54	59,3%	22,22%	18,52%
2	Grover	31	54	57,4%	27,78%	14,81%
3	Springate	24	54	44,4%	9,26%	46,30%
4	Zmijewski	31	54	57,4%	33,33%	9,26%

Table 8 demonstrates that the Altman Z-Score method outperforms other models in predicting financial distress, as indicated by its highest accuracy and lowest error rate. Therefore, Hypothesis 2 (H2), which posits that the Grover (G-Score) model is the most effective predictor of bankruptcy for retail sector companies listed on the Indonesia Stock Exchange, is not supported by the data. The findings indicate that the Altman Z-Score method is more reliable for this purpose compared to the Grover (G-Score) model.

Discussion

The analysis reveals that the Altman Z-Score method is the most accurate model for predicting financial distress among retail sector firms listed on the Indonesia Stock Exchange for the period from 2019 to 2021. The superior performance of this method is attributable to its comprehensive and integrative approach, which incorporates a range of critical financial ratios. By evaluating these ratios collectively, the Altman Z-Score provides a detailed and reliable assessment of a company's financial health and its risk of bankruptcy. Its effectiveness is particularly notable due to the model's sophisticated application of weighted coefficients for each financial ratio. This methodology allows the model to assign appropriate significance to each ratio based on its relevance in forecasting financial distress, thus ensuring that the model accurately reflects the impact of different financial metrics on a company's overall financial stability. Consequently, this enhances the model's capacity to deliver precise predictions regarding the likelihood of financial distress.

Research by Aryo and Trisnaningsih (2021) supports the efficacy of the Altman Z-Score model, demonstrating its precision in forecasting financial distress compared to the Grover model (G-Score). The Grover model, which integrates 13 financial ratios, is subject to potential manipulation through accounting practices and financial engineering, and its effectiveness diminishes for companies with lower financial stability or those experiencing financial losses. Contrastingly, the Altman Z-Score model exhibits a high degree of accuracy, achieving an accuracy rate of 86% one year prior to a company's delisting from the stock exchange and a perfect accuracy rate of 100% two years before such an event, as reported by Damayanti et al. (2019). These findings underscore the model's capability for early detection and prediction of financial instability, making it an invaluable tool for stakeholders seeking to mitigate financial risk.

While the Altman Z-Score provides immediate predictions, the Zmijewski model excels in offering forecasts over a longer time horizon. According to research, the Zmijewski model is proficient in predicting bankruptcy up to three years before a company's delisting, achieving an accuracy rate of 71%. This extended predictive capability allows for additional time to address potential financial distress and implement necessary interventions. The Grover method ranks second in predictive accuracy for the retail sector during the 2019-2021 period. This model has demonstrated strong predictive capabilities, especially in sectors with distinctive financial profiles. Research by Prasetianingtias and Kusumowati (2019) reveals that the Grover model has an accuracy rate of 85.29%, and surpasses other predictive models, including Altman, Zmijewski, and Springate, in the agricultural sector. This suggests that while the Grover model may not be the top performer in all contexts, it is particularly valuable in specific industries where its approach aligns well with the financial conditions faced by companies. In the retail sector, its near-top ranking highlights its robustness and applicability across different business environments. However, the Grover model's effectiveness may be somewhat limited compared to the Altman method due to its exclusion of the sales-to-assets ratio, as noted by Sudrajat and Wijayanti (2019). Additionally, the model's accuracy can vary significantly depending on the industry, with an accuracy rate of 85.14% in manufacturing sectors reported by Wulandari and Fauzi (2022). This indicates that while the Grover model is effective in certain contexts, its performance is not universally superior.

The Zmijewski model ranks third in predictive accuracy, demonstrating significant effectiveness in forecasting financial distress. Listyarini (2020) reports that the Zmijewski model achieved a perfect accuracy rate of 100% in predicting financial distress within the manufacturing sector. Similarly, Nilasari and Haryanto (2018) highlight a high accuracy rate of 97.9% for retail companies, underscoring the model's reliability in specific contexts where its predictive framework aligns well with financial distress indicators. In contrast, the Springate model ranks lowest in terms of accuracy. Studies by Edi and Tania (2018) and Azizah (2017) indicate that while the Springate model is useful for financial distress prediction, it is less accurate compared to the Altman and Grover models. This discrepancy in predictive performance is particularly evident when compared to findings by Prihanthini (2013) and Wulandari (2022), which emphasize the superior accuracy of the Grover model in other sectors. Overall, the Altman Z-Score model remains a robust and versatile tool applicable across various sectors, while the Grover model's limitations, such as its omission of the sales-to-assets ratio, highlight the need for careful consideration of model strengths and weaknesses relative to the industry and financial indicators involved.

Conclusion

Based on the analysis and discussions presented in the preceding chapters, notable differences have emerged among the Altman Z-Score, Zmijewski, Springate, and Grover models in their efficacy for predicting bankruptcy among retail companies listed on the Indonesia Stock Exchange (IDX). Each model employs a unique methodology and demonstrates varying levels of predictive effectiveness. The Altman Z-Score method is identified as the most accurate model for forecasting financial distress. The Altman Z-Score's superior accuracy is attributed to its comprehensive approach, which integrates a diverse set of financial ratios encompassing liquidity, growth, profitability, and solvency. This model's strength lies in its holistic approach, which focuses on critical areas such as profitability and short-term debt management. By assessing these dimensions collectively, the Altman Z-Score provides early warning signals for companies at risk of financial instability. Its ability to offer a thorough evaluation of financial health and detect emerging issues well before they escalate underscores its reliability as a predictive tool. In contrast, the Grover model ranks second in predictive accuracy. This model employs liquidity ratios and two profitability ratios, making it a robust predictor of financial distress. However, its performance is slightly inferior to that of the Altman Z-Score, partly due to its less effective management of profitability. The Grover model's focus highlights the importance of operational performance in mitigating financial risks, suggesting that companies using this model should enhance their profitability management to improve predictive accuracy.

The Zmijewski model, ranked third, emphasizes debt ratios as its primary focus. While effective in forecasting financial distress associated with high debt levels, its narrow focus on debt ratios can result in an incomplete assessment of a company's overall financial health. The model's emphasis on high debt levels can reflect poor management practices and adversely affect investor perceptions, which can influence the model's predictive reliability. The Springate model ranks lowest among the models analyzed. Although it incorporates liquidity, two profitability ratios, and an activity ratio, its effectiveness in predicting financial distress is limited. The model's reliance on profitability as a principal indicator suggests effective management and reduced financial distress risk, but its exclusion of other critical factors contributes to its lower ranking. For companies, it is advisable to utilize the most accurate predictive models, such as the Altman Z-Score, to proactively analyze their financial conditions and mitigate bankruptcy risks. Continuous improvement in financial performance and innovation are crucial for sustaining financial health. Investors should diligently monitor financial indicators and employ reliable predictive models to identify potential distress early, facilitating more informed investment decisions. Academics are encouraged to use this study as a basis for further exploration of financial distress prediction methods and to guide future research in this domain.

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