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COMPARATIVE ANALYSIS OF FINANCIAL DISTRESS MODELS IN INDONESIAN MULTI-INDUSTRIAL MANUFACTURING DURING COVID-19

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ABSTRACT

Financial distress is a critical financial condition characterized by a company's financial performance decline, resulting in reduced net income and challenges in meeting short- and long-term financial obligations. Left unaddressed, financial distress can ultimately lead to bankruptcy. Various predictive models, including the Altman Z-Score, Springate, Grover, Zmijweski, and Zavgren methods, are employed to forecast such distress. This study aims to assess the predictive accuracy of these models in analyzing financial distress and predicting bankruptcy across a diverse spectrum of manufacturing companies. Employing a quantitative and descriptive methodology, the research focuses on manufacturing firms listed on the IDX for 2016-2020, encompassing the impact of the COVID-19 pandemic. Data collection employs a purposive sampling method, with statistical analysis involving the computation of financial ratios from each bankruptcy prediction model. The study assesses the accuracy levels and error types of these models. Results indicate that Altman Z-Score, Springate, Grover, and Zmijweski demonstrated accuracy rates of 46.15%, 35.90%, 82.05%, and 69.23%, respectively. These models exhibit various error types and rates. In contrast, the Zavgren method displayed a remarkable accuracy rate of 100%, with no identified errors, establishing it as the most reliable predictor of bankruptcy, particularly within the Multi-Industrial Manufacturing Sector.

Keywords: Financial Distress, Bankruptcy, Altman Z-Score, Springate, Grover, Zmijweski, Zavgren, COVID-19.

ABSTRAK

Kesulitan keuangan merupakan kondisi keuangan yang kritis yang ditandai oleh penurunan kinerja keuangan perusahaan, yang mengakibatkan penurunan pendapatan bersih dan tantangan dalam memenuhi kewajiban keuangan jangka pendek dan panjang. Jika tidak ditangani, kesulitan keuangan pada akhirnya dapat mengakibatkan kebangkrutan. Berbagai model prediksi, termasuk metode Altman Z-Score, Springate, Grover, Zmijweski, dan Zavgren, digunakan untuk memprediksi kesulitan ini. Penelitian ini bertujuan untuk menilai akurasi prediksi dari model-model ini dalam menganalisis kesulitan keuangan dan memprediksi kebangkrutan di berbagai perusahaan manufaktur. Dengan mengadopsi metodologi kuantitatif dan deskriptif, penelitian ini berfokus pada perusahaan manufaktur yang terdaftar di IDX selama periode 2016-2020, termasuk dampak pandemi COVID-19. Pengumpulan data menggunakan metode purposive sampling, dengan analisis statistik yang melibatkan perhitungan rasio keuangan dari masing-masing model prediksi kebangkrutan. Penelitian ini menilai tingkat akurasi dan jenis kesalahan dari model-model tersebut. Hasil penelitian menunjukkan bahwa Altman Z-Score, Springate, Grover, dan Zmijweski menunjukkan tingkat akurasi masing-masing sebesar 46,15%, 35,90%, 82,05%, dan 69,23%. Model-model ini menunjukkan berbagai jenis dan tingkat kesalahan. Sebaliknya, metode Zavgren menampilkan tingkat akurasi yang luar biasa sebesar 100%, tanpa kesalahan yang teridentifikasi, menjadikannya sebagai prediktor kebangkrutan yang paling andal, terutama dalam sektor Manufaktur Multi-Industri.

Kata Kunci: *Financial Distress, Kebangkrutan, Altman Z-Score, Springate, Grover, Zmijweski, Zavgren, COVID-19.*

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INTRODUCTION

The current global economic conditions and the evolution of businesses in the era of globalization are influencing increased competition in the business world. This necessitates that business entities enhance their operations' quality and quantity. Pursuing goals and profit expansion compels companies to strengthen foundational management practices, ensuring survival and avoiding financial difficulties that could potentially result in bankruptcy or insolvency. In 2020, the international world experienced an epidemic, commonly referred to as the COVID-19 pandemic, caused by a dangerous virus with potentially fatal consequences. The Indonesian government responded by implementing social distancing and large-scale social restriction (PSBB) policies. According to Masrul et al. (2020), the implementation of social distancing is believed by some to constitute an effective measure in mitigating and decelerating the transmission of COVID-19. The current global economic conditions and the evolution of businesses in the era of globalization are driving heightened competition in the business world. This necessitates that business entities enhance their operations' quality and scale. Pursuing goals and profit expansion compels companies to fortify their foundational management practices, ensuring their survival and guarding against financial difficulties that could potentially result in bankruptcy or insolvency (Aritonang & Rahardja, 2022).

The implementation of (PSBB) policies during the COVID-19 pandemic significantly disrupted the community's economy, affecting companies and the nation at large. The instability in the economic sector affected both micro and macroeconomic variables, leading to instability. According to kompas.com, manufacturing companies experienced a sharp decline. The Indonesian Statistics (BPS) reported contractions in all components, resulting in a -5.32% Gross Domestic Product (GDP) in 2020. A sustained negative GDP signifies an economic recession for the country. According to the National Bureau of Economic Research, a recession is a significant decline in economic activity that spreads widely and lasts for several months (Iqbal, 2019). The indicators include significant job losses, diminished company sales, and companies generating lower sales. Furthermore, the recession during the pandemic triggered symptoms of financial distress in several companies.

Several indicators show the occurrence of an economic recession, such as the increase in job losses and a decline in sales of companies sales. During the COVID-19 pandemic, Indonesia experienced negative impacts, with many factories operating at low production capacities or not at all and many workers facing layoffs. These circumstances have predisposed companies to financial distress, often stemming from sustained losses, loan payment delinquencies, and poor financial management. Financial distress is evidenced by diminished liquidity (low current ratio) and compromised solvency (difficulties in meeting financial obligations in both the short and long term) (Irfani, 2020). While some companies, including the manufacturing sector, have experienced this condition during the pandemic, others remained relatively unaffected.

According to Bisnis Indonesia, which derives its information from the Indonesia Stock Exchange (IDX), manufacturing companies faced challenges during the pandemic. In the second quarter of 2020, the textile, leather goods, and footwear subsector experienced the most significant decline, recording a decrease of only 19.1%. On the contrary, the automotive sector experienced the most significant decline among the ten other manufacturing sectors. With this report, the focus was on companies spanning various industries listed on IDX. Certain companies have exhibited negative growth, and when this trend persists, it prompts concerns that they could face financial strain or potential bankruptcy amid the ongoing pandemic. In order to avert a scenario where the shift from negative to positive growth becomes unattainable, early prediction measures should be implemented. According to Kristanti (2019), financial distress reflects liquidity problems that can only be addressed or resolved through operational adjustment or company-wide restructuring. Inadequate short-term financial management can lead to more significant issues, eventually resulting in insolvency and bankruptcy. Irfani (2020) reported on the importance of companies evaluating financial performance against specific benchmarks, serving as indicators or an early warning system to signal the potential onset of financial distress.

Several challenges arising from the COVID-19 pandemic can lead companies in the manufacturing sector to experience negative growth. When these companies cannot withstand or recover from this downturn, they risk encountering financial difficulties or even bankruptcy. Firstly, issues related to the availability of raw materials and supplies can disrupt the supply and delivery of necessary goods during production, potentially leading to interruption in manufacturing. Secondly, due to social distancing policies, companies may need to reduce staff and implement distancing measures, decreasing production efficiency. This decline can lead to reduced product sales, potentially causing companies to fall short of their revenue targets. Another challenge faced during the COVID-19 pandemic was a drop in demand, both domestically and internationally, compelling businesses to scale down production, consequently reducing revenue. These three challenges can result in low income, financial difficulties, and struggles in meeting obligations and operational costs. Consequently, manufacturing companies must take appropriate actions to address these issues and maintain financial sustainability. Because of this, companies encounter financial crises when they fail to accurately predict their financial conditions on time and are unprepared to face shocks, both within and outside the company. This situation can have significant impacts, leading to difficulties in obtaining sufficient funding sources, challenges with debt repayment, and ultimately pushing them into a critical state.

Companies that overlook the timely assessment of their financial status and the forecasting of potential crises may face adverse consequences in the future. However, some enterprises successfully navigated financial hardships during the COVID-19 pandemic. Firstly, these companies tackled challenges and impediments by implementing strong financial control measures. Secondly, they harnessed innovation and maximized technological resources. The companies that steered through the pandemic without financial strain were those skilled at accurately foreseeing their financial position early on, thereby positioning for resilience against internal and external shocks. This early anticipation of financial difficulties empowers company leadership to take preemptive measures to enhance the organization's financial well-being—enterprises capable of such foresight stand to reap future benefits (Irfani, 2020). Analysis was conducted among the predictive methods for financial distress, such as Altman Z-Score, Springate, Grover, Zmijewski, and Zavgren, to determine the prediction accuracy. The results deviate from previous studies covering diverse sectors, showing that Zavgren was the most precise tool for predicting financial distress.

LITERATURE REVIEW

According to Kristanti (2019), financial distress is a condition of financial difficulties related to the ability of companies to generate profits. A noticeable decline in overall performance characterizes this phase, typically manifested through reduced sales and significant shifts in operating profit. Concurrently, an increase in customer complaints about product quality, delivery, and overall services was observed. It is important to note that, during this phase, companies might grapple with financial challenges while still fulfilling their obligations to creditors. The trajectory toward continued default or recovery depends significantly on negotiations with lenders. Access to information regarding financial distress is crucial for companies because it helps detect potential difficulties that could lead to bankruptcy when left unattended, allowing companies to take necessary measures. Furthermore, this information is vital for prospective investors looking to invest capital in companies.

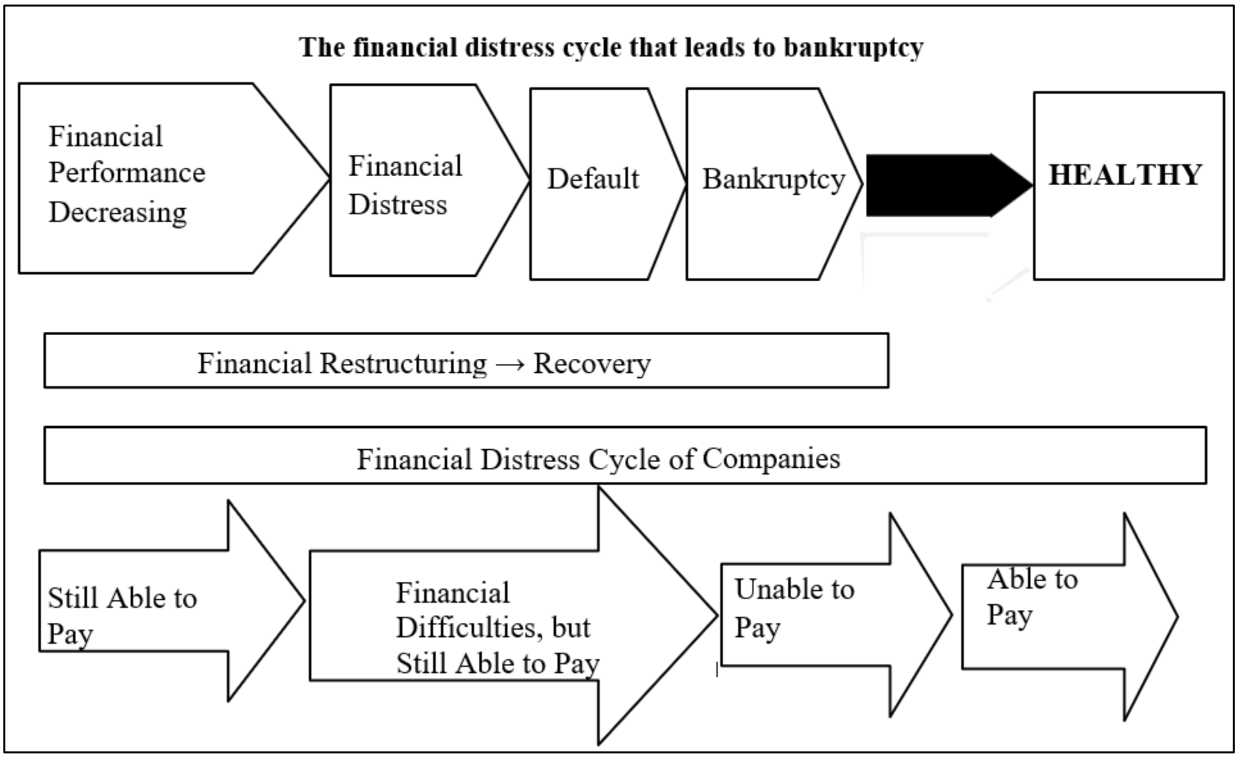

Figure 1: Financial Distress Cycle of Companies

Altman Z-Score Method

According to Edi & Tania (2018), Altman Z-Score was introduced by Edward I. Altman in 1983, who stated that companies with low profitability were highly vulnerable and had the potential for bankruptcy. This modified bankruptcy method can be applied to public and non-public companies of all sizes and across various companies (Rahardja, 2010). The following equation (Prihadi, 2019) represents Altman Z-Score:

$$\mathbf{Z = 6.56X_1 + 3.26X_2 + 6.72\ X_3 + 1.05X_4}$$

(Source: Altman Z-Score, 1983)

Where:

Z : Bankruptcy Index

X_1 : Working Capital/Total Assets

X_2 : Retained Earning/Total Assets

X_3 : Earnings Before Interest and Taxes/Total Assets

X_4 : Book Value of Equity/Book Value of Total Debt

Springate Method

Springate, developed in 1978, was an extension of the Altman Z-Score, incorporating Multiple Discriminant Analysis (MDA). Following the procedure established by Altman, Springate employs stepwise multiple discriminant analysis to select 4 out of 19 popular financial ratios that distinguish companies in the bankruptcy zone from those in a secure financial position. This method evaluated all 19 popular financial ratios. However, through rigorous testing, Springate narrowed it down to 4 ratios to determine classification of companies as either financially sound or potentially at risk of bankruptcy (Rudianto, 2013). The following represents the formula for this method.

$$\mathbf{S = 1.03A + 3.07B + 0.66C + 0.4D}$$

(Source: Springate, 1978)

Where:
S : Bankruptcy Index
A : Working Capital/Total Assets
B : Net Profit Before Interest and Taxes/Total Asset
C : Net Profit Before Taxes/Current Liabilities
D : Sales/Total Assets

Grover Method

Brigham and Weston (2005) explained that Jeffrey S. Grover developed and re-evaluated Altman Z-Score. The study comprised a sample of 70 companies, with 35 bankruptcies from 1982 to 1996. The following represent the Grover method:

$$\mathbf{G = 1.650X_1 + 3.404X_2 - 0.016X_3 + 0.057}$$

(Sourcer: Grover, 1982)

Where:
X_1 : Working Capital / Total Assets
X_2 : Earnings Before Interest and Taxes / Total Assets
X_3 : Net Income/Total Assets

Zmijewski Method

Brigham and Weston (2005) expounded on Zmijewski's (1984) contribution to the field of bankruptcy prediction. The study was extended by enhancing the validity of financial ratios as a tool for detecting corporate financial distress. This enhancement was achieved through an extensive review of previous bankruptcy reports spanning over two decades. The method yields the following formula (Rudianto, 2013):

$$\mathbf{X = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3}$$

(Source: Zmijweski, 1984)

Where:
X_1 : ROA (Return on Asset)
X_2 : Leverage (Debt Ratio)
X_3 : Liquidity (Current Ratio)

Zavgren Method

Zavgren (1985) studied predicting corporate bankruptcy from 1980 to the early 1990s using logistic analysis as a substitute for MDA. In the Zavgren method, Y was defined as follows:

$$\mathbf{Y = 0.23883 - 0.108X_1 - 1.583X_2 - 10.78X_3 + 3.074X_4 - 0.486X_5 - 4.35X_6 + 0.11X_7}$$

(Source: Zavgren, 1985)

Where:
Y : Multivariate Function
X_1 : Inventories/Sales
X_2 : Account Receivable/Inventories
X_3 : Cash/TotalAssets
X_4 : Current Assets/Current Liabilities
X_5 : Net Income/(Total Assets –Current Liabilities)
X_6 : LongTerm Liabilities/(Total Assets –Current Liabilities)
X_7 : Sales/(Working Capital+Fixed Assets)

Previous studies examined various models to predict bankruptcy for Food and Beverage companies listed on IDX. Prihantini and Sari (2013) used Grover, Altman Z-Score, Springate, and Zmijewski, indicating that only one company was bankrupt. The results established Grover with exceptional accuracy at 100%, Springate and Zmijewski at 90%, and Altman Z-Score at 80%. In a study focused on Bank Indonesia, Kusuma (2017) analyzed Financial Distress measurement with Altman and Springate as early warning systems. The results showed that the descriptive calculation of each financial ratio data was applied to all five analysis models. In terms of accuracy, there were differences in the accuracy levels in measuring financial distress. Based on observations, Springate had the highest accuracy, making it the best for an early warning system. Furthermore, Prasandri (2018) evaluated financial distress using Altman Z-Score, Springate, and Zmijewski to predict cigarette companies' bankruptcy on IDX from 2013 to 2016. The results showed that Zmijewski had an accuracy rate of 18.75%, while the other 2 had an equal value of 25%. Anggraini (2020) analyzed Altman Z-Score, Springate, and Zmijewski to predict financial distress in textile and garment companies listed on IDX from 2014-2016. Altman Z-Score predicted that, out of 7 sampled companies, 1 was healthy, 3 were in a grey area, and the remaining were bankrupt. For Springate, 3 were healthy, with the remaining being unhealthy. Subsequently, Wulandari (2020) studied the use of Springate, Ohlson, Altman Z-Score, and Grover Score to predict financial distress during the COVID-19 pandemic. The results showed variations in accuracy levels among these methods, with the Grover Score demonstrating the highest precision. Due to the inconsistent results from previous investigations, this study aimed to reevaluate the prediction of financial distress using the Altman Z-Score, Springate, Grover, Zmijewski, and Zavgren for manufacturing companies listed on IDX from 2016 to 2020.

Based on the theoretical foundation, the results of previous studies, and the issues raised, a thinking framework was presented as a reference for formulating hypotheses.

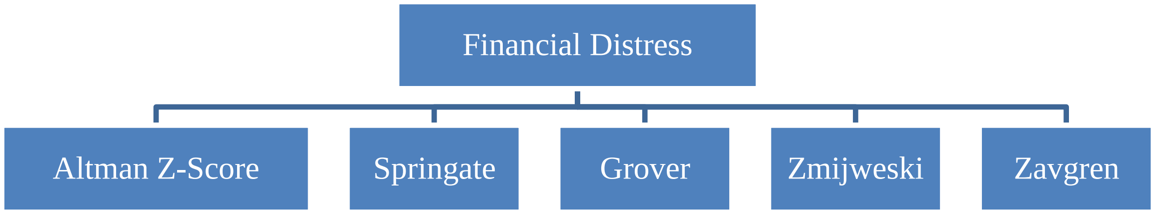

Figure 2: Conceptual Framework

METHODS

The population for this study encompasses all manufacturing companies listed on the IDX from 2016 to 2020, owing to their significant contribution to the Indonesian economy. This pool comprises 50 companies, with 39 chosen as the study's sample. Sample selection was carried out using the purposive sampling method, wherein specific criteria predefined to align with the study's objectives were established. The inclusion criteria encompassed manufacturing companies listed on the IDX from 2016 to 2020, with published financial reports spanning from 2016 to 2020 for four consecutive years. Adhering to these criteria, a sample of 39 companies was selected from 50 manufacturing companies, as detailed in Table 1. Consequently, 39 x 5 years = 195 data observations were collected. The names of the selected companies are presented in Table 1.

Table 1: Sample Selection

No	Criteria	Not Qualified	Number of Samples
1	Manufacturing companies listed on IDX from 2016 to 2020.	0	50
2	Manufacturing companies that published financial reports for 4 (four) consecutive years from 2016 to 2020.	-11	39
		Total Sampling	39
		Period: 2016-2020	5
		Total Samples for the Study Period (39 x 5 Years)	195

The prediction accuracy of each method is crucial for assessing its ability to distinguish between financially distressed companies and those in stable condition. This evaluation entails comparing the predicted outcomes with the actual status of the sample companies in 2020. The formula below outlines the process for determining the prediction result:

$$\textbf{Prediction Result} = \frac{\textbf{Score2016+Score 2017+Score 2018+Score2019+Score2020}}{\textbf{5}}$$

In this study, a sample comprising 39 companies was utilized. The accuracy level represents the percentage of correctly predicted samples out of the total size. This measure was calculated using the following formula:

$$\textbf{Accuracy Level} = \frac{\textbf{Number of Correct Predictions}}{\textbf{Number of Samples}} \textbf{ x 100\%}$$

In addition to the accuracy of each method, this study also considered the error rate, categorized into Type I and II. Type I error occurs when the model incorrectly predicts that a sample will not experience financial distress. Meanwhile, Type II arises when it incorrectly predicts a sample to financial distress. The following formula was used to calculate the error rate:

$$\textbf{Type I Error} = \frac{\textbf{Number of Type I Errors}}{\textbf{Number of Distress Samples}} \textbf{ x 100\%}$$

$$\textbf{Type II Error} = \frac{\textbf{Number of Type II Errors}}{\textbf{Number of Samples (Non-Distressed + Grey Area)}} \textbf{ x 100\%}$$

The combination of Type I and II error results in a weighted error rate, which was calculated as follows:

Weighted Error Rate = 100% - Accuracy Level

The following is an alternative formula:

$$\textbf{Type II Error} = \frac{\textbf{(Error I Type x Sampel Distress) + (Error II Type x Non-Distress Sample)}}{\textbf{Total Samples}} \textbf{ x 100\%}$$

RESULT AND DISCUSSION

This study was conducted to analyze the prediction of financial distress using Altman Z-Score, Springate, Grover, Zmijweski, and Zavgren. The aim was to determine the most accurate financial distress prediction method. A paired sample t-test analysis with Microsoft Excel was employed to achieve this. Table 2 presents the accuracy level and error rate calculation in predicting financial distress using Altman Z-Score.

Table 2: Accuracy Level and Error Rate of Altman Z-Score

Total Sample		**Correct Prediction**		**Wrong Prediction**		**Type of Error**	
Distress	11	Distress	7	Distress	4	Type I	36.36%
Non-Distress	24	Non-Distress	7	Non-Distress	17	Type II	60.71%
Grey Area	4	Grey Area	0	Grey Area	4		
Total	39	Total	14	Total	25		
Accuracy Level		**46.15%**		**Total Weighted Error**		**53.85%**	

Table 3 presents the calculation using Springate, and the results showed that the accuracy level was 46.15%, with a total weighted error of 53.85%.

Table 3: Accuracy Level and Error Rate of Springate

Total Sample		**Correct Prediction**		**Wrong Prediction**		**Type of Error**	
Distress	29	Distress	14	Distress	15	Type I	51.72%
Non-Distress	10	Non-Distress	0	Non-Distress	10	Type II	100%
Total	39	Total	14	Total	25		
Accuracy Level		**35.90%**		**Total Weighted Error**		**64.10%**	

Table 4 presents the calculation using Grover, and the results indicated that the accuracy level was 45.90%, with a total weighted error of 64.10%.

Table 4: Accuracy Level and Error Rate of Grover

Total Sample		**Correct Prediction**		**Wrong Prediction**		**Type of Error**	
Distress	9	Distress	5	Distress	4	Type I	44.44%
Non-Distress	30	Non-Distress	27	Non-Distress	3	Type II	9.52%
Total	39	Total	32	Total	7		
Accuracy Level		**82.05%**		**Total Weighted Error**		**17.95%**	

Table 5 presents the calculation using Zmijweski, and the results indicated that the accuracy level was 82.05%, with a total weighted error of 17.95%.

Table 5: Accuracy Level and Error Rate of Zmijweski

Total Sample		**Correct Prediction**		**Wrong Prediction**		**Type of Error**	
Distress	9	Distress	3	Distress	6	Type I	66.67%
Non-Distress	30	Non-Distress	24	Non-Distress	6	Type II	20%
Total	39	Total	27	Total	12		
Accuracy Level		**69.23%**		**Total Weighted Error**		**30.77%**	

Table 6 shows the calculation using Zavgren, and the results indicated that the accuracy level was 69.23%, with a total weighted error of 30.77%.

Table 6: Accuracy Level and Error Rate of Zavgren

Total Sample		**Correct Prediction**		**Wrong Prediction**		**Type of Error**	
Distress	0	Distress	0	Distress	0	Type I	0%
Non-Distress	39	Non-Distress	39	Non-Distress	0	Type II	0%
Total	39	Total	39	Total	0		
Accuracy Level		**100%**		**Total Weighted Error**		**0%**	

Table 7 summarizes the accuracy and error rate testing in predicting financial distress using Altman Z-Score, Springate, Grover, Zmijweski, and Zavgren.

Table 7: Analysis Results of Accuracy Level and Type of Error in Prediction Methods

Rank	**Method**	**Accuracy level**	**Total Weighted Error**	**Type I Error**	**Type II Error**
1	***Zavgren***	**100%**	**0%**	**0%**	**0%**
2	*Grover*	82.05%	17.95%	44.44%	9.52%
3	*Zmijweski*	69.23%	30.77%	66.67%	20%
4	*Altman Z-Score*	46.15%	53.85%	36.36%	60.71%
5	*Springate*	35.90%	64.10%	51.72%	100%

Grover and Zmijweski have different accuracy levels of 82.05% and 69.23%, respectively, while Altman Z-Score and Springate have lower scores of 46.15% and 35.90%. Based on observations, it was concluded that the most suitable method for analyzing financial distress to predict bankruptcy in manufacturing companies was Zavgren, with accuracy and error type rates of 100% and 0%, respectively.

When scrutinizing Type I errors, Zavgren had the lowest error rate of 0% compared to Altman Z-Score, Grover, Springate, and Zmijweski, with 36.36, 44.44, 51.72, and 66.67%, respectively. This showed that Zavgren tended to have no errors in predicting companies experiencing financial distress. Regarding Type II error, Zavgren has no errors compared to Grover, Zmijweski, Altman Z-Score, and Springate, with error rates of 9.52%, 20%, 60.71% and 100%, respectively. This explained that the model tended to have no errors in predicting companies experiencing financial distress of Type II.

The ranking of methods based on accuracy and type of error showed that Zavgren was the best, followed by Zmijweski, Grover, Altman Z-Score, and Springate. This study differs from the previous report by

Prihantini (2013), which examined the food and beverage companies and identified Grover as the best method for predicting financial distress, followed by Springate, Zmijewski, and Altman Z-Score. Wulandari (2020), which studied manufacturing companies, presented Grover as the best predictor of financial distress. Kusuma (2017), studying the coal companies, suggested that Ohlson was the best, followed by Smijewski, Grover, Springate, and Altman Z-Score. Prasadri (2020), focusing on cigarette companies, showed that Zmijewski was the best method for predicting financial distress, followed by Altman and Springate. These inconsistent results provided an opportunity for further comprehensive investigation.

CONCLUSION

In conclusion, this study assessed the variation in accuracy score among Altman Z-Score, Springate, Grover, Zmijewski, and Zavgren. Additionally, it determined the most accurate prediction model for predicting financial distress in manufacturing companies listed on IDX from 2016 to 2020. The results showed that (1) Altman Z-Score had an accuracy rate of 46.15%, with Type I and II errors of 36.36 and 60.71%, respectively. (2) Springate had an accuracy rate of 35.90%, with Type I and II errors of 51.72 and 100%. (3) Grover exhibited an accuracy rate of 82.05%, with Type I and II errors of 44.44 and 9.52%. (4) Zmijewski had an accuracy rate of 69.23%, with Type I and II errors of 66.67% and 20%. (5) Zavgren exhibited the best accuracy rate, at 100%, with Type I and II errors of 0%. The financial distress prediction methods were evaluated using Altman Z-Score, Springate, Grover, Zmijewski, and Zavgren methods. The analysis indicated that Zavgren demonstrated perfect accuracy at 100%, with zero Type I and II errors. This led to the conclusion that, in terms of precision and error types, the models ranked as follows: Zavgren, Zmijewski, Grover, Altman Z-Score, and Springate.

This study was expected to enrich knowledge about financial distress prediction methods. Given the inconsistencies in previous results across various companies, the results can serve as a reference for future studies. This study has a few limitations. Firstly, it examined five financial distress prediction methods: Altman Z-Score, Springate, Grover, Zmijewski, and Zavgren. Additionally, the observation period was from 2016 to 2020, and the sample companies exclusively belonged to the manufacturing sector and were listed on IDX. Several suggestions were provided to improve future studies. These included adding more than five prediction methods alongside other identified models, such as Ohlson and Fulmer, and second, studying the companies listed on IDX in different sectors and extending the observation period by continuing the study into the following years.

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