The Accuracy of Financial Distress Prediction During the COVID-19 Pandemic on Healthcare Sub-Sector Companies

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Abstract: - During the recent COVID-19 pandemic, most countries are in a phase of slowing economic growth that causes long-term financial distress and leads to bankruptcy. This paper describes the accuracy of financial distress prediction of the healthcare sub-sector companies using the Altman Modified Z-Score, Springate, and Zmijewski methods. The level of accuracy is determined based on the suitability of the calculation results of the three models with the company's bankruptcy data published on the Indonesia Stock Exchange and strengthened by the analysis based on the calculation of the type error I and II. Based on the level of accuracy and error types I and II, the Springate is the most accurate method in analyzing the financial distress prediction of the healthcare sub-sector companies with an accuracy rate of 91.4275. Comparing financial performance before and after the COVID-19 pandemic, the mean difference test shows that there is no significant difference in financial performance before and after the COVID-19 pandemic.

Key-Words: - bankruptcy, COVID-19 pandemic, economic crisis, financial distress

Received: October 4, 2021. Revised: July 21, 2022. Accepted: August 12, 2022. Published: September 6, 2022.

1 Introduction

The world's concern over the systemic impact of the coronavirus disease (COVID-19) pandemic is a reality. Since its presence on December 1, 2019, in Wuhan City, Hubei Province, China has changed the life system [1]. Even the virus that attacks the respiratory system, which has entered Indonesia since March 2, 2020, has devastated all aspects of human life. The COVID-19 pandemic has hampered the development to target economic growth and efforts to resolve socio-economic problems of the community [2]. One of the most prominent economic impacts of the COVID-19 pandemic is on the occurrence of recession on economies. Based on the Central Statistics Agency (BPS), the Government of Indonesia officially announced that the COVID-19 pandemic resulted in a decline in Indonesia's economic growth in 2020 [3]. Based on the Central Statistics Agency (BPS), the Government of Indonesia officially announced that the COVID-19 pandemic resulted in a decline in Indonesia's economic growth in 2020 as a result of limited economic activity and the decrease in company production caused by low public demand due to the weakening of people's purchasing power. The decrease in people's purchasing power causes firm financial difficulties due to the decline in production levels [4].

The decrease in the fundamental value of the firm will be reflected in the weakening of stock price movements in the capital market. [4]. Capital markets provide an early indication of the potential impact of economic shocks. Although signals from capital market prices are not always accurate, economic shocks hitting the economy can be seen in the capital markets before they manifest in the data, such as GDP or unemployment rates [5]. The decline in the composite stock price index experienced a very sharp decline to almost 20% in June 2020 due to investors' sentiment toward withdrawing their funds from the capital market [6] and also because of an uncertainty economic that is full of risk and unclear when this pandemic will end [7]. The COVID-19 pandemic has changed the perspective of investors in making decisions [8]. They have responded to the volatility of the capital market and the economic conjuncture by reducing equity and leverage which has an impact on decreasing market capitalization. The declining performance of the capital market is a response to the decline in economic growth and the various consequences that accompany it [4].

Besides the impact on the economic crisis, the COVID-19 pandemic has also greatly affected public health problems [9]. Compared with other industries, the margins of the healthcare industry are generally very low. Even before the COVID-19 pandemic, several hospitals were operating at negative margins. After the COVID pandemic emerged, hospitals had to stop all but very urgent non-covid treatments. This causes a decrease in revenue while costs remain high It is interesting to analyze the financial performance of the healthcare companies sector during the COVID-19 pandemic through the calculation of financial distress [10]. Financial distress is related to the company's ability to meet all obligations such as paying salaries, obligations to creditors, and others [12].

This study aims to measure the best model to predict the financial distress of healthcare sub-sector companies listed on the Indonesia Stock Exchange using the Modified Altman Z Score, Springate, and Zmijewski. The best estimation model is a model that can predict with a high level of accuracy and low type errors I and II by comparing the results of model calculations with company calculation data published on the Indonesian Stock Exchange. This study also compares differences in financial performance before and after the COVID-19 pandemic. The ability to predict financial distress aims to anticipate the consequences if it occurs [13]. The main focus of this research is on the analysis of financial distress in the healthcare sub-sector company during the COVID-19 pandemic in emerging markets, such as Indonesia and it will be the novelty and originality of this paper.

2 Literature Review

Financial distress is a bad financial condition and risk of going bankrupt, caused by the amount of debt [14]. The company's level of financial difficulty is determined by the ownership of liquid assets and access to credit facilities to save from these conditions [15]. Companies with a lower level of liquidity than total assets have a greater chance of bankruptcy[16]. The higher (lower) the level of liquidity, the lower (higher) the financial distress [17]. Liquidity is defined by the company's ability to meet its short-term and long-term obligations [18].

Financial distress is classified into four categories namely economic failure, business failure, insolvency, and legal bankruptcy [16]. Economic failure due to the instability of the company's financial condition. Most economic failures occur quickly and are unpredictable which leads to an economic crisis for the company [16]. Business Failure shows the company's inability to run its operations caused by the inability to generate profits [19]. Insolvency relates to the company's inability to meet all of its short-term and long-term obligations by the due date [20]. Insolvency consists of technical insolvency and insolvency in bankruptcy. Technical insolvency is related to the inability to fulfill its debt obligations or obligations at a predetermined time. Technical insolvency occurs when a company‘s assets are higher than its total debt [21]. Technical insolvency is the forerunner of the company's economic failure initiated by illiquid conditions [22]. Insolvency in bankruptcy is a company's financial condition that is very severe, experiencing a financial crisis beyond technical insolvency. The debt owned exceeds the assets owned [23] or the market value is lower than the book value of the debt [24]. Legal bankruptcy is a legal statement regarding the bankruptcy of an institution that has the authority to state whether the company is truly in a state of bankruptcy or not.

Endogenous and exogenous are factors that cause business financial difficulties [16]. Endogenous factors include high expenses working capital management, inappropriate financial and marketing control, inaccuracy in selecting projects, production exceeding financing capacity, and improper company policy. The exogenous factors include market demand for a firm's products, local, national, and international competition, price supply commodity, macroeconomic factors and government key sector regulations, and technology change.

The potential internal factor may be causes of financial distress divided into financial and non-financial factors [25]. Financial factors include the problem of capital structure, the inappropriate debt to asset ratio, long-term accounts receivable payment firm's policy, undercapitalization of a business, and incorrect price calculation. Non-financial factors include business strategy and mismanagement in taking risks and firm decisions, low product promotion and competitiveness, low employee productivity, and late mitigating problems [26]. Platt and Platt [27] several problems that cause financial distress include mismanagement, low level of equity, inappropriate good business plan, goals, and marketing strategy, excessive optimism, and company's weaknesses.

Žiković [28] distinguishes failure, insolvency, or "bankruptcy. Failure is the inability to generate a return on investment, insolvency is the inability of a company to pay its maturing obligations, while bankruptcy is a legal meaning. The two most common factors in bankruptcy are the company having more debt than assets and the inability to pay the debt [29]. A decrease in sales revenue due to reduced consumer confidence in the quality of the company's products [30] and the decrease in sales revenue due to reduced consumer confidence in the quality of the company's products [31]. A decline in sales, a decrease in profit, and suffer a loss. Losses that occur continuously can reduce liquidity and increase leverage. Leverage shows the company's debts and represents a risk to the firm [32]. High financial leverage tends to be illiquid, insolvable, and bankrupt. The higher leverage, the higher risk, and the higher the cost of capital [23]. Accurately predictable bankruptcy can help companies to take action to minimize the risk of business losses and prevent bankruptcy [29].

The ratios used in predicting financial distress can be classified into two categories, namely, the ratio related to the company's ability to generate profits (profitability ratios) and the company's ability to meet short, medium, and long-term obligations (liquidity and solvency ratios) [33, 14, 34, 35]. In general, using the financial distress model to predict the company's financial condition, find out the factors that cause financial problems, and make problems solving. Based on empirical studies, size, risk of uncertainty, and company debt are the factors that cause the failure of the company's business [36].

Various studies have been conducted over the past three decades to predict corporate financial distress. The first study to predict corporate financial distress was conducted by Beaver [37]. Some years later, Altman (1968) developed a new financial distress model called Altman Z-Score including profitability ratio, activity ratio, liquidity ratio, solvency ratio, and leverage ratio. Altman Z-Score formula has several weaknesses and only can be applied in go public manufacturing companies and been updated (1983) for both manufacturing and non-manufacturing companies and private and public firms [38].

The Springate financial distress method [40] consists of 4 ratios to determine whether the company is in financial distress. Zmijewski [41] used to predict the possibility of a company's financial distress using accounting variables to measure the proportion of financial distress based on the probit regression model and random exogenous sampling. The accounting ratios are net income to total assets, total debts to total assets, and current assets to total liabilities. The research results of Kliestik et al. [42] conclude that the models often used in measuring financial distress in several groups of countries studied are the current ratio, total liabilities to total assets ratio, and total sales to total assets ratio. The empirical result of Zizi et al.[43] highlight that interest in sales and return on assets was a significant role in financial distress prediction. Grover, Altman, Springate, and Zmijewski's models better predict financial crises on the Tehran Stock Exchange [44, 45]. On the Indonesia Stock Exchange, the Zmijewski X-Score is the most accurate model for predicting financial distress [46]. The existence of a gap in the results of previous research regarding which model is the most accurate in predicting financial distress is one of the considerations for conducting this research, especially in the healthcare sub-sector during the COVID-19 period. Based on the literature review, the hypotheses that can be built are as follows:

Ha1: Springate is the highest accuracy model rate compared with Altman and Zmijewski's model in predicting bankruptcy of healthcare sub-sector companies delisting on the Indonesia Stock Exchange (IDX).

Ha2: There is a significant difference between the company's financial performance before and after the COVID-19 pandemic.

3 Research Methods

The data used in this study is quantitative data sourced from the company's financial statements published on the Indonesian Stock Exchange (IDX). The company's financial statements are the data source due to the coverage information of this report. In addition to describing the company's financial performance and as a basis for decision-making for investors, financial statements are also often used to predict future finances. The data of the selected companies are accessible on the IDX website at http://www.idx.co.id and from http://www.finance.yahoo.com. The data used is quarterly data starting from the 4th quarter of 2018, to the 1st quarter of 2021.

Healthcare companies play a role in dealing with exposure to the COVID-19 virus to support community healthcare needs, especially in Pandemic COVID-19. The collected data will be processed using modified Altman Z-Score, Springate, and Zmijewski to determine the presence of financial distress.

The Altman Z-Score Method

The first Altman formula called the Z-Score (bankruptcy index) is as follows [38] :

$$Z = 1{,}2X_1 + 1{,}4\,X_2 + 3{,}3X_3 + 0{,}6X_4 + 1{,}0X_5$$

The Altman Z-Score method consists of net working capital to total assets (X_1), retained earnings to total assets (X_2), earnings before interest and taxes to total assets (X_3), a book value of equity to book value of debt (X_4), and sales to the total asset (X_5). The weakness of the first Altman is only be applied to go public manufacturing companies. The following revised Z-score method of bankruptcy prediction can be applied no to public and private manufacturing companies. The formula used is as follows. The formula used is as follows [38]:

$$Z'=0.717X_1 +0.847X_2 +3.108X_3 +0.42\,X_4 +0.988X_5$$

The next Altman Z Score modification model is formulated by eliminating sales to the total asset (X_5). To calculate financial distress prediction, the modified Altman Z-Score method defined the distress function in the following formula [47]:

$$Z''=6.56X_1 +3.26X_2 + 6.72X_3 +1.05X_4$$

X1, X2, X3, X4, and X5 are calculated by the formula as shown in table 1. The classification of financial distress, grey area, and non-financial companies is based on the value of Modified Altman Z-Score, which is: Z-Score < 1.1, the company is financial distress category. If Z-Score 1.1 < Z < 2.6, the company is in the gray area category. If Z-score > 2.6, the company is in non-financial distress. The Altman Z Score cut-off value is shown in table 2.

The Springate Method.

The Springate method consists of working capital to total assets (A), earnings before interest and taxes to total assets (B), net income before tax to current liabilities (C), and sales to total assets (D). The Springate method defined financial distress estimates with the following formula [40]:

$$S = 1.03A + 3.07B + 0.66C +0.4D$$

A, B, and C are calculated by the formula as shown in table 1.

The Springate cut-off value is as shown in table 2: Peter and Yoseph [48]. The cut-off value of Springate is shown in table 2. If S scores < 0.862, the company may experience financial distress. If an S score of 0.862 < S < 1.062, it means that the company is probably in a gray area. If the S score is while if the S score is higher than 0.861 then the company is Non-financial distressed. The Springate cut-off value is as shown in table 2 [40]

The Zmijewski Method.

The Zmijewski method consists of earning after tax to total assets (X_1), total debt to total assets (X_1), and current assets to current liabilities (X_3). X_1, X_2, X_3, and X_4 are calculated by the formula as shown in table 1.

Table 1. Explanatory Variable and Financial Ratio

Method	Financial Ratio	Notation	Variable	Formula
Modified Altman Z-Score	Liquidity	X_1	Net Working Capital to Total Assets	$\frac{\text{Working Capital}}{\text{Total Asset}}$
	Profitability	X_2	Retained Earnings to Total Assets	$\frac{\text{Retained Earning}}{\text{Total Asset}}$
	Profitability	X_3	Earnings before Interest and Taxes to Total Assets	$\frac{\text{Profit Before Interest and Tax}}{\text{Total Asset}}$
	Solvency	X_4	Book Value of Equity to Book Value of Debt	$\frac{\text{Book value of Equity}}{\text{Book Value of Total Debt}}$
Springate	Liquidity	A	Working Capital to Total Assets	$\frac{\text{Working Capital}}{\text{Total Asset}}$
	Profitability	B	Earnings before Interest and Taxes to Total Assets	$\frac{\text{Earning Before Interest and Tax}}{\text{Total Asset}}$
	Liquidity	C	Net income before Tax to Current Liabilities	$\frac{\text{Net Profit before Tax}}{\text{Current Liabilities}}$

	Profitability	D	Sales to Total Assets	$\frac{\text{Sales}}{\text{Total asset}}$
Zmijewski	Profitability	X_1	Earning after Tax to Total Assets	$\frac{\text{Earning After-Tax}}{\text{Total Asset}}$
	Solvency	X_2	Total Debt to Total Assets	$\frac{\text{Total Debt}}{\text{Total Asset}}$
	Liquidity	X_3	Current Assets to Current Liabilities	$\frac{\text{Current Asset}}{\text{Current Liabilities}}$

The Zmijewski cut-off value is shown in table 2 [48]. The Zmijewski cut-off value is shown in table 2. If the X score is > 0, indicate that the company is in financial distress. If the X score is < 0, means the company is in non-financial distress. The research results conclude that the models often used in measuring financial distress in several groups of countries studied are the current ratio, total liabilities to total assets ratio, and the total-sales-to-total-assets ratio. The empirical results of Zizi et al. [43] conclude the significant financial ratio to predict financial distress are interest in sales and return on assets.

Table 2. The Financial Distress Cut-off Value

Financial Distress Method	Cut off	Condition
Modified Altman *Z-Score*	Z” < 1,1	Financial distress
	1,1 < Z”< 2,6	Gray area
	Z” > 2,6	Non-financial distress
Springate	S < 0,861	Financial Distress
	S > 0,861	Non-Financial Distress
Zmijewski	Z > 0	Financial distress
	Z < 0	Non-financial distress

The Accuracy Level in the Altman Z-Score, Springate, and Zmijewski Methods

To test the accuracy of the model, the steps taken are to measure the accuracy rate by comparing the correct prediction with the number of samples and calculate the type 1 error and type 2 error. The accuracy test of the model was used to answer the hypothesis (Ha1). The level of accuracy is calculated by the following formula:

$$\text{Accuracy Rate} = \frac{\text{Number of Correct Prediction}}{\text{Number of Sample}} \text{ x } 100\%$$

The level of error is the error description on every model. Type I error is an error that occurs if the model predicts the sample does not experience financial distress, in fact, according to the Indonesia Stock Exchange data, the company is in financial distress. Type II error is an error that occurs if the model predicts the sample experienced financial distress, but according to the Indonesia Stock Exchange data, the sample is not included in the financial distress. Type I error and type II error is calculated as follows:

$$\text{Type I Error} = \frac{\text{The number of Types I error}}{\text{number of sample}} \text{ x } 100\%$$

$$\text{Type II Error} = \frac{\text{The number of Type II error}}{\text{number of sample}} \text{ s } 100\%$$

The Theoretical Framework of Financial Distress Method as shown in figure 1

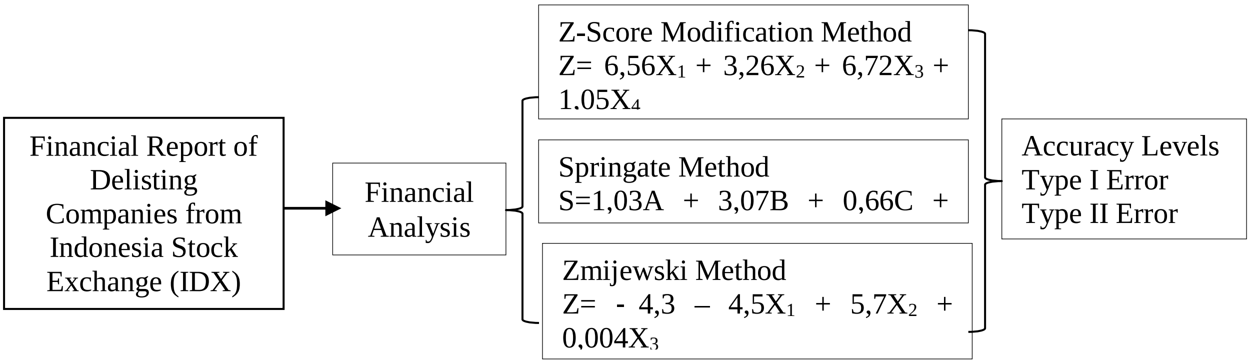

Fig. 1: Theoritical Framework of Financial Distress Method

4 Results and Discussion

The performance metrics of the financial distress prediction models at eight healthcare subsector companies in 2018-2021 using the modified Altman Z-Score, Springate, and Zmijewski methods are summarized in Table 3

Table 3. Firm Financial Distress Category According to Z-Score, Springate, and Zmijewski

Ticker Code	Year	Quarter	Z-Score	Springate	Zmijewski
MIKA	2018	IV	10.8690***	2.34458***	-4.071584***
	2019	I	9.94267***	4.02643***	-3.525729***
		II	9.94301***	2.61349***	-3.772433***
		III	9.60583***	2.18424***	-3.872325***
		IV	9.70832***	2.18444***	-4.02033***
	2020	I	9.85914***	4.10011***	-3.55002***
		II	9.24075***	2.69084***	-3.348282***
		III	9.70618***	2.29562***	-3.824573***
		IV	10.1292***	2.28472***	-4.074812***
	2021	I	10.33911***	3.59516***	-3.622004***
SAME	2018	IV	9.75835***	1.20877***	-1.231973***
	2019	I	8.89964***	1.79788***	-1.100677***
		II	9.91276***	1.34127***	-1.144458***
		III	-2.84919*	-1.05371*	-0.414575***
		IV	-5.85712*	-0.17274*	-0.304621***
	2020	I	-6.81728*	-1.1606*	-0.45637***
		II	-9.18992*	-0.77418*	-0.381743***
		III	0.95008*	-0.38558*	1.4835539*
		IV	3.00151***	-0.24226*	1.5332515*
	2021	I	-3.53945*	0.83763*	-1.473819***
SILO	2018	IV	11.0827***	1.38984***	-3.122585***
	2019	I	9.93260***	1.16313***	-2.992226***
		II	10.3950***	1.05631***	-3.026270***
		III	9.74340***	1.23748***	-2.984158***
		IV	18.7396***	1.6046***	-2.593768***
	2020	I	15.9144***	0.6853*	-2.098012***
		II	137.414***	1.86803***	-2.058522***
		III	38.4015***	1.05336***	-2.124109***
		IV	20.8760***	1.49752***	-2.457180***
	2021	I	12.9032***	0.96425***	-2.339203***
HEAL	2018	IV	5.27145***	2.06669***	-1.617150***
	2019	I	6.63647***	0.87145***	-1.573409***
		II	9.90268***	1.18344***	-1.554341***
		III	8.74882***	1.43099***	-1.573340***
		IV	9.81471***	1.70523***	-1.582245***
	2020	I	8.25423***	1.27195***	-1.393765***

		II	7.07593***	1.07221***	-1.571599***
		III	10.3412***	1.44571***	-1.463042***
		IV	7.19202***	1.7664***	-1.628895***
	2021	I	7.00563***	1.28444***	-1.461654***
PRIM	2018	IV	1.85306**	0.53678*	-3.924140***
	2019	I	2.39863**	0.70472*	-3.888701***
		II	2.31002**	0.44371*	-3.891543***
		III	2.30945**	0.42371*	-3.781726***
		IV	3.33572***	0.52554*	-3.872552***
	2020	I	4.00882***	1.2466***	-3.909879***
		II	4.46936***	0.87436***	-3.994306***
		III	5.69221***	0.82765*	-4.089326***
		IV	7.52189***	1.03787***	-4.061103***
	2021	I	7.94346***	2.22089***	-3.796787***
PRDA	2018	IV	27.7929***	2.95714***	-3.460261***
	2019	I	24.3739***	3.85728***	-3.225030***
		II	28.9852***	2.7682***	-3.271596***
		III	27.0208***	2.7641***	-3.353484***
		IV	23.4460***	3.05648***	-3.634795***
	2020	I	21.7862***	4.11035***	-3.088542***
		II	26.2007***	2.78981***	-2.958513***
		III	21.3457***	2.60464***	-3.295978***
		IV	19.132***	2.86557***	-3.535678***
	2021	I	17.8466***	3.35173***	-3.376197***
SRAJ	2018	IV	1.47631**	-0.69437*	-1.953515***
	2019	I	1.83210**	-2.0714*	-1.919421***
		II	2.11245**	-1.23981*	-1.875704***
		III	2.71292**	-0.78718*	-1.657645***
		IV	3.55949***	-0.98338*	-1.320620***
	2020	I	5.66359***	-5.17701*	-1.000758***
		II	3.19113***	-2.16035*	-0.275503***
		III	-10.6166*	3.45442***	-5.542824***
		IV	7.16210***	-1.17566*	-0.292128***
	2021	I	7.23084***	-2.54985*	-0.488890***

*Financial Distress, **Grey Area, ***Non-Financial Distress

Based on the Altman Z-Score modification method analysis, SAME in the third and fourth quarters of 2019, the first, second, and third quarters of 2020, and the first quarter of 2021 are in financial distress. PRIM and SRAJ in the fourth quarter of 2018 and the first - third quarter of 2019 are in the gray area. SRAJ is in financial distress in the third quarter of 2021. While in other periods, all companies are in non-financial distress.

The analysis of financial distress predictions using Springate found that SAME in the third-fourth quarter of 2019, the first - fourth quarter of 2020, and the first quarter of 2021 are in financial distress. SILO in the first quarter of 2020 is in financial distress. PRIM and SRAJ in the fourth quarter of 2018, the first - fourth quarter of 2019, SRAJ in the first, second, and fourth quarter of 2020, and the first quarter of 2021 are in financial distress. PRIM in the third of 2020 is in financial distress. All companies in other periods are in non-financial distress.

The analysis of financial distress predictions using Zmijewski found that only SAME in the third and fourth quarter of 2019 are experiencing financial distress. All companies in other periods are in non-financial distress.

Level of Accuracy and Error Rate

The accuracy level of financial distress prediction was based on the correct number of predictions divided by the total data and multiplied by 100%. The correctness predictions are measured by comparing the output of the model in the study period (t) with the debt to equity ratio (DER) in the following year (t + 1).

The debt to Equity Ratio (DER) is the ratio used to assess debt to equity [49]. This ratio is found by comparing all debt, including current debt, and total equity. Debt to equity ratio (DER) is a financial ratio to measure the level of solvency of a company's ability to meet all of its obligations. There is a significant relationship between the solvency ratio and the level of financial difficulty, indicating that a cash flow ratio is reliable for predicting financial distress [14, 50]. DER is a reference for categorizing a company in financial distress or not. The company is in financial distress if it is not balanced with the availability of sufficient funds to pay off its debts. The higher the financial risk, the higher the company is in financial distress [51]. A higher ratio, especially above 1.0, indicates that a company is significantly funded by debt and may have difficulty meetings its obligations. Generally, DER below 1.0 is relatively safe, whereas ratios of 2.0 or higher would be considered risky.

Table 4 shows the level of accuracy model using the Altman Z-Score Modification, the Springate, and the Zmijewski method. The modification Altman Z-Score method produces the lowest accuracy rate which is 28.57% in the fourth quarter of 2020, the Zmijewski method produces the lowest accuracy rate which is 28.57% in the second quarter of 2020. The Springate method produces the lowest accuracy rate which is 57.14% in the second quarter of 2020.

Springate is a financial distress prediction model with the highest average accuracy of 91.427% with average type I error and the lowest type II error of 17.14%. Zmijewski is a financial distress prediction model with the lowest average accuracy of 65.714% with average type I error and the highest type II error of 34.29% and 40.00%, respectively. The level of accuracy of the Altman Z-Score modification method of 68.571% is better than Zmijewski in 65.714%. The average type I error and type II error of Zmijewski is about 34.29% and 40.00%.

Table 5 shows a different test of the average level of accuracy of the financial distress model. The accuracy of Springate in bankruptcy prediction is significantly different from Modified Altman's Z-score and Zmijewski at the 0.05 significance level. While although the Modified Altman Z-Score model performs better accuracy than Zmijewski, the statistical results in predicting bankrupt firms are insignificant. Thus, it cannot say one model is superior to other models for companies in the health care sub-sector during the COVID-19 pandemic.

The results of this study are not in line with the results of previous studies conducted by Salim and Ismudjoko [52] that concluded the Modified Altman is the most accurate predictive model with the highest accuracy rate. Springate is the lowest accuracy rate among the coal mining sector firms listed on Indonesia Stock Exchange (IDX) for 2015 – 2019.

Table 4. The Accuracy Level of Financial Distress (FD) and Non-Financial Distress (NFD) Prediction and Error Rate

Method	Year	Quarter	Prediction		Real		Level of Accuracy (%)	Type I Error (%)	Type II Error (%)
			FD	NFD	FD	NFD			
Altman Modifikasi Z-Score	2018	IV	0	7	2	5	71.43	28.57	28.57
	2019	I	0	7	2	5	71.43	28.57	28.57
		II	0	7	2	5	71.43	28.57	28.57
		III	1	6	3	4	71.43	28.57	28.57
		IV	1	6	4	3	57.14	28.57	42.86
	2020	I	1	6	2	5	85.71	14.28	14.28
		II	1	6	5	2	42.86	57.14	14.28
		III	2	5	3	4	85.71	14.28	14.28
		IV	7	0	2	5	28.57	71.43	71.43
	2021	I	1	6	1	6	100	0	0
	Average						68.571	17.14	17.24
Springate	2018	IV	2	5	2	5	100	0	0
	2019	I	2	5	2	5	100	0	0
		II	2	5	2	5	100	0	0
		III	3	4	3	4	100	0	0
		IV	3	4	4	3	85.71	14.28	14.28
	2020	I	3	4	2	5	85.71	14.28	14.28
		II	2	5	5	2	57.14	42.86	42.86
		III	3	4	3	4	100	0	0
		IV	2	5	2	5	100	0	0
	2021	I	2	5	1	6	85.71	14.28	14.28
	Average						91.427	17.14	17.14
Zmijewski	2018	IV	0	7	2	5	71.43	28.57	28.57

2019	I	0	7	2	5	71.43	28.57	28.57
	II	0	7	2	5	71.43	28.57	28.57
	III	0	7	3	4	57.14	42.86	42.84
	IV	0	7	4	3	42.86	57.14	57.14
2020	I	0	7	2	5	71.43	28.57	28.57
	II	0	7	5	2	28.57	71.43	71.43
	III	1	6	3	4	71.43	28.57	57.14
	IV	1	6	2	5	85.71	14.28	42.84
2021	I	0	7	1	6	85.71	14.28	14.28
Average						65.714	34.29	40.00

Several factors that cause the accuracy differences are the differences in the sample or the comparison tools used, including the auditor's opinion and the company's income in the next period. With so many considerations in determining the level of model accuracy, it is difficult to say or claim that one model is more accurate than another. The results of this study can add insight and knowledge on how to predict financial distress in the period leading up to and during the COVID-19 pandemic in the healthcare sub-sector published on the Indonesia Stock Exchange, that Springate is a bankruptcy analysis tool that is better than other analytical tools.

Table 5. Average Difference Test Accuracy Level of Financial Distress Measurement

	Modified Altman Z-Score	Springate	Modified Altman Z-Score n	Zmijewski	Springate	Zmijewski
Mean	68.571	91.427	68.571	65.714	91.427	65.714
Variance	444.4191	190.5143	444.4191	326.50432	190.5143	326.5043
t Stat	-2.868377		0.32539		3.576018	
P(T<=t)	0.00511		0.374319		0.00108	
t Critical	1.734064		1.734064		1.734064	

To find out the financial distress difference before and after the pandemic, the difference test is carried out as presented in table 6. The average difference test shows that the financial distress difference after and before COVID-19 is insignificant, indicated by the p-value of 0.89 >alpha (5%) and t stat < t critical.

Table 6. The Average Difference Test of Financial Distress Before and After Pandemic COVID-19.

	Before COVID-19	After COVID-19
Mean	1.212723714	1.156332857
Variance	2.109884699	3.899942031
t Stat	0.136085465	
P-Value	0.892155792	
t Critical	1.995468931	

5 Conclusion

The lack of research on predicting financial distress in the period before and during COVID-19 at healthcare subsector companies in Indonesia has encouraged this research. The purpose of this study is to determine the most relevant predictor to identify the occurrence of financial distress and to find out the financial distress difference before and after the pandemic COVID-19.

To achieve this objective, three predictor models of financial distress were used. Empirical results on the test sample using the Altman Z-Score, Springate, and Zmijewski concluded the Springate method is the most accurate and appropriate method for measuring financial distress in healthcare sub-sector companies at the 0.05 significance level. While although the Modified Altman Z-Score model performs better accuracy than Zmijewski, the statistical results in predicting bankrupt firms are insignificant. Thus, it cannot say one model is superior to other models for companies in the health care sub-sector during the COVID-19 pandemic.

Based on the average difference test, there are no significant financial condition differences in the healthcare sub-sector before and after the COVID-19 pandemic. Although there is no significant difference between before and after the COVID-19 pandemic, the average score on the Springate shows a decreased value after COVID-19.

The results have practical implications for creditors and managers in making financing decisions to pay attention to the company's financial adequacy to avoid losses. In the interest of academics, this research provides the empirical result that Springate is significantly more accurate than the other models used.

Constrained by the weaknesses in this study, suggestions for further research can be developed by increasing the number of research samples, adding qualitative variables and other test models, and considering macroeconomic factors that affect the company's financial condition. Finally, relevant research in the future can use this research as a reference by comparing this research results with other relevant research.

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