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The Potential Financial Distress in Special Notation Companies on the Indonesia Stock Exchange: Prediction Model Approach

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ABSTRACT: This research aims to predict the potential financial distress in companies with special notation on the Indonesia Stock Exchange during the period from January 1, 2021, to December 2022, using the Modified Altman Model (Z-Score) and the Springate Model (S-Score) approaches. Data for the study were obtained from the official website of the Indonesia Stock Exchange, employing purposive sampling as the sampling technique. Based on the criteria, a total of 280 research observations were obtained. The results indicate that both models can predict the potential financial distress of companies using financial ratios. Furthermore, the research findings reveal differences in the accuracy level of predicting potential financial distress between the Modified Altman Z-Score and Springate models. The Modified Altman Z-Score model demonstrates higher accuracy compared to the Springate model in predicting the potential financial distress of companies with special notation. This research provides important information for companies with special notation codes that experience financial distress, to immediately improve financial conditions, and provides a basis for strategic decision making to ensure the sustainability of the company and for investors and other interested parties can be used as a basis for investment decision making.

Keywords: Potential Financial Distress, Special Notation Companies, Altman Z-Score, and Springate

INTRODUCTION

Improving the welfare of shareholders and maintaining the continuity of business operations are the main objectives of the company. To achieve this goal, companies must maintain their financial performance in order to remain competitive and avoid potential bankruptcy (Kisman & Krisandi, 2019). A company can go bankrupt for various reasons, one of which is financial distress (Cındık & Armutlulu, 2021; Dudley et al., 2022). Financial distress can be caused by internal factors, such as ineffective management of assets and liabilities, and external factors such as inflation, tax regulations, laws, and changes in foreign currencies (Kisman & Krisandi, 2019b)

Financial distress is something that must be anticipated immediately because it can hamper the smooth running of a company's operational activities (Eliu, 2014; Kartika et al., 2020; López-Gutiérrez et al., 2015; Nuswantara et al., 2023) A strategy that can be used to increase anticipation of financial distress is the Financial distress Prediction (FDP) approach. The FDP approach can help company management control financial risk, and help them modify investment plans to minimize risk as well as help investors understand the profitability of the company, (Li & Wang, 2023a). Financial distress conditions faced by a company can be a signal to investors that the company is experiencing serious problems that if allowed to continue can lead to bankruptcy. In December 2018, the Indonesia Stock Exchange has introduced a "Special Notation" feature that can be utilized by potential investors to find out the state of a company. This notation can provide clues about the initial condition of a company based on evaluations conducted by the Indonesia Stock Exchange.

Research on the potential for financial distress has been conducted with varied results but is more focused on companies in certain industrial sectors in general (Lestari et al., 2021) (Munira et al., 2021)(Martini et al., 2023)(Effendi, 2018); (Pulungan & Hartini, 2018); (Suidarma et al., 2022) (Zhu et al., 2023); (Tan & Wibisana, 2020). This study differs from previous studies as it predicts the potential for financial distress in companies included in the group of companies with a 'special notation' that have been evaluated by the Indonesia Stock Exchange, and the evaluation results indicate that the company is in trouble. The FDP approach in this study uses two models, namely the Modified Altman model (Z-Score) and the Springate model (S-Score). The main objectives of this study are (1) predicting the potential for companies with special notations on the Indonesia Stock Exchange to experience financial distress; (2) compare the two models to determine which model is more accurate in predicting financial distress.

Signalling Theory

Signalling theory was first introduced by (Spence michael, 1973) in his research entitled Job Market Signaling. The information that the company discloses signals to investors about the condition of the company and can reduce information asymmetry. Quality and integrated financial reporting information will reduce information asymmetry for principals, agents, and third parties. (Suranta et al., 2023) Outsiders will also react positively to good signals because market reaction depends heavily on the fundamental signals of the company. Investors will only invest in a company if they believe that it can generate more value for their money than if they put it elsewhere. Therefore, investors' focus will be on the company's performance presented in the company's financial statements. Signal theory that explains how companies provide positive and negative signals from financial statements (Gandhy & Fardinal, 2019). Based on signal theory, financial distress conditions experienced by companies can be a signal to investors that the company is experiencing serious problems that if allowed to continue can lead to bankruptcy.

Financial distress

Financial distress is generally understood to be the state in which a business is unable to pay its creditors and satisfy its own requirements(Friedl & Drescher, 2013) Financial distress occurs when a company faces financial problems and faces financial risks (Li & Wang, 2023b). Financial distress has a different meaning from bankruptcy, where financial distress conditions in companies occur before bankruptcy and become the cause of bankruptcy. So not all companies that experience financial distress will end in bankruptcy (Nikmah & Sulestari, 2021).

Financial distress can be caused by internal and external factors, such as long-term losses in the company's operational activities and government policies that can increase business expenses (Purwaningsih & Aziza, 2019). (Sari et al., 2021) claimed that financial hardship may arise from a company's inability to control and sustain stable financial performance and that financial crisis and bankruptcy scenarios can be anticipated from the company's financial statements by producing financial ratio analysis that is pertinent to the business. Research (Widarjo & Setiawan, 2009) proves that a business is in financial distress if it experiences losses in two consecutive fiscal years (periods). Information about financial distress is used by companies to accelerate management actions in preventing problems before bankruptcy such as mergers or takeovers so that companies can pay off debts and improve company performance, as well as early warnings before bankruptcy (Piatt & Piatt, 2002).

Altman Model *(Z-Score)*

Edward I. Altman originally presented the Altman model in 1968. This model is designed to assess a company's bankruptcy risk and can also be used to measure its overall financial performance. (Sari, 2016). Altman's Z-Score is a multivariate formula utilized to gauge financial distress and evaluate a company's financial well-being. To make his model applicable to all types of firms, including both manufacturing and non-manufacturing ones, Altman made modifications to it. The formula of the modified Altman Z-Score model (Altman,1995) is called the Modified Altman (Z-Score):

$$\boxed{Z'' = 6{,}56X1 + 3{,}26X2 + 6{,}72X3 + 1.05X4}$$

Information:
X1 = Working Capital / Total Assets
X2 = Retained Earning / Total Assets
X3 = Earnings Before Interest and Taxes / Total Assets
X4 = Book Value of Equity / Total Liabilities

Springate Model *(S-Score)*

According to (Denhas & Subroto, 2014) Gorgon L.V. Springate created this model for the first time in 1978. In its formulation, by employing four out of the 19 financial parameters and the Multiple Discriminant Analysis formulation approach, Springate assessed the company's level of financial distress (MDA). The model can predict financial distress with an accuracy rate of 92.5%, with the formula:

$$\boxed{\textit{S-score} = 1.03\ X1 + 3.07\ X2 + 0.66\ X3 + 0.4X4}$$

Information:
X1 = Working Capital / Total Assets

X2 = Profit Before Interest and Tax / Total Assets
X3 = Profit Before Tax / Current Debt
X4 = Sales / Total Assets

(Lestari et al., 2021) analyzed financial distress in tourism, hospitality and restaurant sub-sector companies with Altman (Z-Score), Springate (S-Score), Zmijewski (X-Score), and Grover (GScore) analysis methods, the results of the study proved that several companies experienced financial distress and the Springate (S-Score) model has the highest accuracy rate, reaching 68.75%. In line with (Effendi, 2018b) research on issuers in the transportation service sector using the Altman, Springate, Zmijewski, Foster, and Grover methods, and proved that the majority of issuers experienced financial distress and the Springate model showed the highest prediction model accuracy results.
(Munira et al., 2021b) measured the potential for bankruptcy in mining companies using the Altman Modified Z-Score and Springate methods, and the results proved that there were several companies that experienced financial distress, and overall the Altman Z-Score method had a higher accuracy rate of 66.49%. (Martini et al., 2023b) examined the comparison of financial distress predictions using Altman, Springate, Zmijewski, and Grover models at PT Garuda Indonesia (Persero) Tbk, and the results indicated that PT Garuda Indonesia (Persero) experienced financial distress, and prediction models gave varying results. Previous research has produced a variety of findings and levels of accuracy, depending on a number of specific factors and variables used in each industry or company studied.

Conceptual Framework and Hypothesis

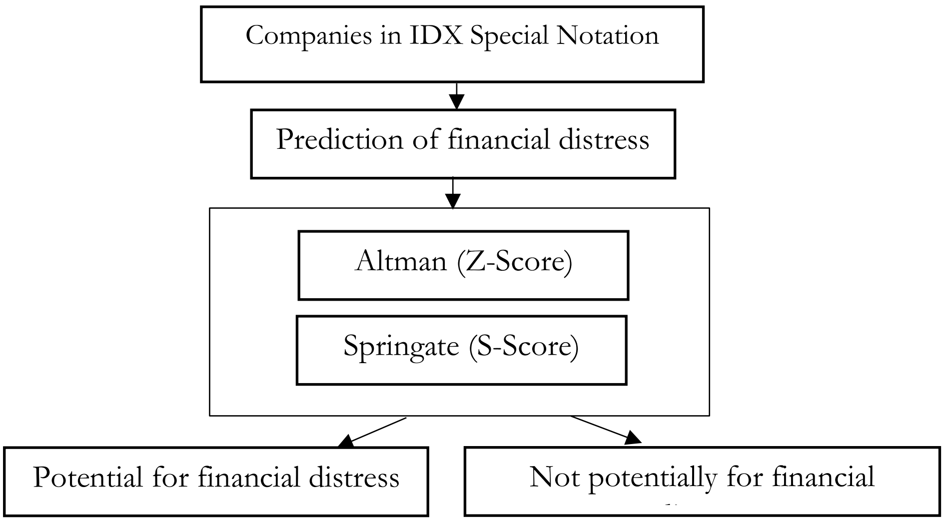

Figure.1 Conceptual Framework

Based on the conceptual framework and research objectives that have been described earlier, hypotheses can be developed from this study as follows:

H1: Altman model modified by Z-Score is able to predict the potential for financial distress in companies in a special notation of the Indonesia Stock Exchange

H2 : Springate S-Score model is able to predict potential financial distress in companies in a special notation of the Indonesia Stock Exchange

H3: There is a difference in the accuracy of financial distress prediction models between Altman prediction models modified Z-Score and Springate S-Score

METHOD

This research uses secondary data in the form of company financial statements obtained from through www.idx.co.id website. Sampling using purposive sampling techniques, namely: companies are listed in the special notation of the Indonesia Stock Exchange during the year from January 1, 2021 to December 2022; the company obtains special notation codes except with L and S codes; Have complete financial statements that have been audited and published during the 2018-2022 observation period and can be accessed and financial statements are presented in rupiah.

This research uses secondary data in the form of company financial statements with special notation codes obtained through www.idx.co.id website. Companies with special notation are companies that receive warnings from the Indonesia Stock Exchange because they have problems that are not in accordance with existing regulations. Special notation is marked by several codes in the form of letters totaling 17 codes that have different meanings according to the company's problems.

Sampling using purposive sampling techniques, with the following criteria:

1. The company is listed in the special notation of the Indonesia Stock Exchange during 2021-2022
2. The company gets special notation codes except with L and S codes (they cannot be used as samples because they do not meet the requirements of both analysis models to be used)
3. Have complete financial statements that have been audited and published during the observation period 2018-2022 and can be accessed
4. Financial statements using rupiah currency
5. Have all the data needed for each prediction model.

The analysis method involves the application of the Modified Altman Z-Score model and the Springate model, with the analysis process conducted in the following stages:

1) Z-Score calculation using Altman Modified Z-Score method :

$$Z'' = 6{,}56X1 + 3{,}26X2 + 6{,}72X3 + 1.05X4$$

Table 1. Altman Model Modified *Z-Score*

Altman Modifikasi *Z-Score*	Keterangan
> 2,6	*Non Distress*
1,1 - 2,6	*Grey area*
<1,1	*Distress*

2) S-Score calculation using Springate model :

$$S\text{-}score = 1.03\ X1 + 3.07\ X2 + 0.66\ X3 + 0.4X4$$

Table 2. Model Springate *S-Score*

Springate *S-Score*	**Keterangan**
> 1,062	*Non Distress*
0,862 – 1,062	*Grey area*
<0,862	*Distress*

3) Accuracy testing of the prediction mode

Testing the accuracy of prediction models is used to determine valid estimates and errors in the results of calculating the score of each prediction model, this stage is a way to determine which model is more precise in forecasting financial trouble for businesses listed on the IDX with specific note between 2018-2022, the accuracy level is calculated as follows (Munira et al., 2021b):

$$\text{Accuracy Rate} = \frac{\text{Number of Correct Predictions}}{\text{Number of Samples}} \times 100\%$$

Information:

a. The number of correct predictions is the number of companies in the special notation of the Indonesia Stock Exchange that are predicted to experience financial distress and indeed experience financial distress, and if calculated using the modified Altman model (Z-Score), and the Springate model states the same thing as the statement of the Indonesia Stock Exchange.
b. The number of samples is the number of companies sampled multiplied by the length of the year of observation.

4) Calculate the error rate of a prediction model

After calculating the accuracy rate, the prediction error rate for each model used is calculated. Error types are divided into two types, namely Type I and Type II errors. The error rate is calculated as follows, (Munira et al., 2021)

$$\text{Error Type I} = \frac{\text{Number of Errors I}}{\text{Number of Samples}} \times 100\%$$

$$\text{Error Type II} = \frac{\text{Number of Errors II}}{\text{Number of Samples}} \times 100\%$$

Information:

a. Type I error is an error that occurs when a model predicts that the sample studied is not experiencing financial difficulties, but in fact the sample is recorded as a company experiencing financial difficulties.

b. Type II error is an error that occurs when a prediction model estimates that the sample studied has financial difficulties, but in fact the sample is recorded as a company that does not experience financial difficulties.

RESULT AND DISCUSSION

There are 125 companies included in the special notation of the Indonesia Stock Exchange (IDX) from January 1, 2021 to December 2022, and based on the criteria, 56 sample companies or 280 observations were obtained. There were 125 companies included in the special notation of the Indonesia Stock Exchange (IDX) from January 1, 2021 to December 2022, and only 56 companies met the criteria sampled during the 5-year observation period or as many as 280 observations.

Descriptive Statistics

The results of descriptive statistical tests in this study can be seen in the following table:

a. Modified Altman Model (*Z-Score*)

Table 3. Altman Descriptive Statistics Modification (*Z-Score*)

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Working Capital to Total Assets (X1)	280	-73.91	.95	-.8356	604.904
Retained Earnings to Total Assets (X2)	280	-126.68	.76	-37.102	1.591.732
Earnings Before Interest and Tax to Total Assets (X3)	280	-15.19	3.82	-.2766	140.954
Book Value of Equity to Book Value of Total Debt (X4)	280	-.99	431.53	5.422	2.910.697
Valid N (listwise)	280				

Source : Data processed by the author (2023)

b. Springate Model

Table 4. Springate Descriptive Statistics

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Working Capital to Total Assets (X1)	280	-73.91	.95	-.8356	604.904
Earnings Before Interest and Tax to Total Assets (X2)	280	-15.19	3.82	-.2766	140.954
Net Profit Before Taxes to Current Liabilities (X3)	280	-71.04	15.89	-.7178	549.840
Sales to Total Assets (X4)	280	-1.03	28.82	.8795	225.790
Valid N (listwise)	280				

Source : Data processed by the author (2023)

Working Capital to Total Assets (WCTA) is a ratio that reflects a company's net working capital to total assets. The minimum value range from -73.91 to a maximum of 0.95 showed a significant variation of 604.9 in the study sample. The average WCTA ratio of -0.83 indicates an unfavorable value distribution. This indicates that the likelihood of financial distress increases with an average that is close to the minimum value.

Retained Earnings to Total Assets is a ratio that describes a company's ability to generate retained earnings from total assets. The minimum range from -126.68 to a maximum of 0.76 showed a significant variation of 1.59 in the study sample. The average of this ratio of -37.1 indicates an unfavorable distribution of profitability. Companies tend to be less efficient in generating enough revenue to cover their costs.

Earnings Before Interest and Tax to Total Assets is a productivity indicator that shows the distribution of earnings before interest and tax to total assets. The minimum value range from -15.19 to a maximum of 3.82 showed a significant variation of 140.9 in the study sample. This average ratio of -0.27 indicates that most companies in the sample have low levels of productivity, indicating inefficiencies in managing their assets.

Book Value of Equity to Book Value of Total Debt, this ratio indicates the maximum amount of asset loss that can occur before total liabilities exceed the book value of equity. The minimum value range of -0.99 to a maximum of 431.53 shows a significant variation of 2.91 in the research sample. The average of this ratio of 5.42 indicates a poor distribution value, as there is quite a lot of debt compared to the company's capital..

Earnings Before Interest and Tax to Total Assets is a productivity indicator that shows the distribution of earnings before interest and tax to total assets. The minimum value range from -15.19 to a maximum of 3.82 showed a significant variation of 140.9 in the study sample. This average ratio of -0.27 indicates that most companies in the sample have low levels of productivity, indicating inefficiencies in managing their assets.

Sales to Total Assets is a ratio that describes the efficiency of using assets to generate sales. The minimum value range from -1.03 to a maximum of 28.82 showed a significant variation of 225.7 in the study sample. An average of 0.87 indicates an under-distribution of value, indicating potential financial distress due to low sales compared to asset usage.

Data Testing and Hypothesis Testing

The following are the results of calculations (Z-Score) and S-Score as well as predictions of financial distress using both the modified Altman model and the Springate model in companies included in special notation from January 1, 2021 to December 2022 with a period of 5 years (2018-2022).

a. Modified Altman model (*Z-Score*)

Table 5. Altman Calculation Results modification (*Z-Score*)

No	Company Code	Altman (Z-Score)									
		2018		2019		2020		2021		2022	
		Z-score	Kategori	Z-score	Kategori	Z-score	Kategori	Z-score	Kategori	Z-score	Kategori
1	KIAS	4,12	*Non-FD*	-1,72	*FD*	2,09	*Grey Area*	3,40	*Non-FD*	1,99	*Grey Area*
2	RMBA	1,21	*Grey Area*	1,74	*Grey Area*	4,20	*Non-FD*	-0,06	*FD*	2,74	*Non-FD*
3	AKKU	3,88	*Non-FD*	-0,54	*FD*	3,30	*Non-FD*	-3,19	*FD*	-2,49	*FD*
4	HDTX	-19,13	*FD*	-18,84	*FD*	-21,16	*FD*	-23,89	*FD*	-32,31	*FD*
5	WSBP	3,17	*Non-FD*	2,90	*Non-FD*	-4,86	*FD*	-12,32	*FD*	-9,36	*FD*
6	BIMA	-8,31	*FD*	-1,68	*FD*	-4,66	*FD*	-5,43	*FD*	-3,19	*FD*
7	TALF	7,89	*Non-FD*	5,67	*Non-FD*	4,15	*Non-FD*	3,95	*Non-FD*	3,80	*Non-FD*
8	LMSH	10,81	*Non-FD*	7,47	*Non-FD*	7,68	*Non-FD*	9,56	*Non-FD*	11,04	*Non-FD*
9	ARKA	-2,05	*FD*	0,47	*FD*	-0,95	*FD*	-0,09	*FD*	0,54	*FD*
10	IKAI	0,28	*FD*	0,31	*FD*	-0,41	*FD*	-0,39	*FD*	0,54	*FD*
11	INTA	-0,72	*FD*	-1,68	*FD*	-11,02	*FD*	-12,68	*FD*	-5,37	*FD*
12	TIRT	-0,48	*FD*	-1,15	*FD*	-17,35	*FD*	-15,93	*FD*	-16,31	*FD*
13	JGLE	2,81	*Non-FD*	2,93	*Non-FD*	2,69	*Non-FD*	2,83	*Non-FD*	0,76	*FD*
14	JSPT	4,36	*Non-FD*	3,23	*Non-FD*	2,16	*Grey Area*	1,69	*Grey Area*	2,18	*Grey Area*
15	MIRA	-8,79	*FD*	-9,55	*FD*	-11,66	*FD*	-12,52	*FD*	-16,58	*FD*
16	MKNT	1,68	*Grey Area*	3,07	*Non-FD*	2,58	*Grey Area*	2,32	*Grey Area*	1,06	*FD*
17	MDIA	4,91	*Non-FD*	3,57	*Non-FD*	3,36	*Non-FD*	4,35	*Non-FD*	2,58	*Grey Area*
18	MDRN	-12,26	*FD*	-11,85	*FD*	-32,45	*FD*	-26,33	*FD*	-25,32	*FD*
19	LCKM	14,57	*Non-FD*	15,13	*Non-FD*	17,04	*Non-FD*	17,83	*Non-FD*	20,54	*Non-FD*
20	SAFE	-11,88	*FD*	-10,82	*FD*	-12,78	*FD*	-16,19	*FD*	-14,38	*FD*
21	POSA	-4,45	*FD*	-4,89	*FD*	-6,73	*FD*	-9,71	*FD*	-11,77	*FD*
22	PNSE	2,22	*Grey Area*	1,91	*Grey Area*	0,41	*FD*	-0,20	*FD*	0,03	*FD*
23	ANDI	0,42	*FD*	1,63	*Grey Area*	0,68	*FD*	1,21	*Grey Area*	1,19	*Grey Area*
24	BIKA	3,83	*Non-FD*	3,40	*Non-FD*	0,13	*FD*	0,95	*FD*	-0,96	*FD*
25	CMPP	-15,52	*FD*	-10,96	*FD*	-14,15	*FD*	-18,93	*FD*	-19,89	*FD*
26	CNKO	-11,10	*FD*	-11,03	*FD*	-22,19	*FD*	-18,48	*FD*	-24,56	*FD*
27	CTTH	0,74	*FD*	0,01	*FD*	-1,33	*FD*	-1,51	*FD*	-2,20	*FD*
28	DADA	4,15	*Non-FD*	2,45	*Grey Area*	2,96	*Non-FD*	4,68	*Non-FD*	4,07	*Non-FD*
29	DPUM	3,74	*Non-FD*	1,79	*Grey Area*	-2,76	*FD*	0,59	*FD*	0,46	*FD*
30	DEAL	1,72	*Grey Area*	0,87	*FD*	-2,76	*FD*	-7,06	*FD*	-6,07	*FD*
31	BTEK	1,52	*Grey Area*	0,99	*FD*	-1,04	*FD*	-0,55	*FD*	-0,76	*FD*
32	BUVA	0,30	*FD*	-0,56	*FD*	-9,30	*FD*	-9,93	*FD*	-10,66	*FD*
33	GMTD	4,47	*Non-FD*	4,20	*Non-FD*	3,39	*Non-FD*	3,60	*Non-FD*	3,03	*Non-FD*
34	IIKP	10,63	*Non-FD*	18,11	*Non-FD*	13,74	*Non-FD*	11,30	*Non-FD*	7,84	*Non-FD*

35	GLOB	-133,62	*FD*	-687,79	*FD*	-630,13	*FD*	-583,35	*FD*	-1000,88	*FD*
36	HADE	39,76	*Non-FD*	-48,97	*FD*	-34,32	*FD*	-34,52	*FD*	-35,02	*FD*
37	TOPS	2,55	*Grey Area*	3,07	*Non-FD*	2,08	*Grey Area*	2,36	*Grey Area*	1,30	*Grey Area*
38	TRIO	-157,46	*FD*	-233,44	*FD*	-323,41	*FD*	-383,69	*FD*	-395,95	*FD*
39	VIVA	-1,07	*FD*	-3,36	*FD*	-5,18	*FD*	-6,39	*FD*	-9,00	*FD*
40	SMRU	0,56	*FD*	-1,44	*FD*	-5,15	*FD*	-9,33	*FD*	-8,60	*FD*
41	SONA	7,03	*Non-FD*	9,59	*Non-FD*	10,20	*Non-FD*	13,39	*Non-FD*	5,58	*Non-FD*
42	TARA	15,87	*Non-FD*	15,28	*Non-FD*	23,81	*Non-FD*	49,79	*Non-FD*	54,10	*Non-FD*
43	TAXI	-13,54	*FD*	-22,00	*FD*	-33,85	*FD*	-21,74	*FD*	-47,83	*FD*
44	DIGI	20,67	*Non-FD*	12,37	*Non-FD*	1,48	*Grey Area*	-4,30	*FD*	-14,83	*FD*
45	TAMA	-0,62	*FD*	-1,96	*FD*	-2,28	*FD*	-2,29	*FD*	-1,36	*FD*
46	TIRA	2,06	*Grey Area*	2,21	*Grey Area*	1,73	*Grey Area*	1,32	*Grey Area*	1,53	*Grey Area*
47	WOWS	-0,57	*FD*	5,16	*Non-FD*	5,86	*Non-FD*	5,69	*Non-FD*	5,30	*Non-FD*
48	NASA	13,83	*Non-FD*	19,25	*Non-FD*	19,24	*Non-FD*	18,53	*Non-FD*	19,76	*Non-FD*
49	REAL	6,31	*Non-FD*	102,25	*Non-FD*	144,17	*Non-FD*	151,33	*Non-FD*	456,48	*Non-FD*
50	PPRO	2,92	*Non-FD*	1,57	*Grey Area*	1,19	*Grey Area*	2,06	*Grey Area*	2,09	*Grey Area*
51	KBAG	-1,57	*FD*	3,63	*Non-FD*	8,68	*Non-FD*	8,87	*Non-FD*	11,79	*Non-FD*
52	KREN	9,20	*Non-FD*	9,60	*Non-FD*	8,89	*Non-FD*	6,73	*Non-FD*	6,40	*Non-FD*
53	KOTA	3,11	*Non-FD*	7,64	*Non-FD*	4,23	*Non-FD*	4,18	*Non-FD*	4,29	*Non-FD*
54	AGAR	2,43	*Grey Area*	3,60	*Non-FD*	4,33	*Non-FD*	4,21	*Non-FD*	3,16	*Non-FD*
55	SBAT	0,35	*FD*	-0,48	*FD*	-1,25	*FD*	-0,80	*FD*	-3,74	*FD*
56	SCPI	5,36	*Non-FD*	7,07	*Non-FD*	5,33	*Non-FD*	10,53	*Non-FD*	9,44	*Non-FD*

Source : Data processed by the author (2023)

Based on table 5. above shows that the results of the analysis using Altman Modified Z-Score in 2018 there were 24 companies experiencing Financial Distress, there were 8 companies in gray areas, and 24 other companies were included in the category of companies that were Non-Financial Distress. In 2019, there were 26 companies experiencing financial distress. Meanwhile, 7 companies are in the grey area stage, and 23 other companies are included in the category of healthy companies or Non-Financial Distress. In 2020, there were 29 companies experiencing Financial Distress. There are 7 companies that are in the grey area stage. While 20 other companies are included in the category of healthy companies (Non Financial Distress). In 2021, there were 31 companies experiencing Financial Distress, and there were 6 companies that were in the gray area. Meanwhile, as many as 19 companies are included in the category of healthy companies (Non Financial Distress). Furthermore, in 2022 there are 32 companies that are declared to be experiencing financial difficulties, and 7 companies that are at the stage (gray area). While the other 17 companies are healthy companies (Non Financial Distress). These results show that the Altman model modified z-score is able to predict financial distress in companies with a special notation code of the Indonesia Stock Exchange, thus the first hypothesis (H1) is accepted.

b. Springate Model

Table 6. Springate Model Calculation Results

No	Company Code	Springate (S-Score)									
		2018		2019		2020		2021		2022	
		S-Score	Kategori	S-Score	Kategori	S-Score	Kategori	S-Score	Kategori	S-Score	Kategori
1	KIAS	-0,072	*FD*	-2,129	*FD*	-0,245	*FD*	0,405	*FD*	0,401	*FD*
2	RMBA	0,709	*FD*	0,780	*FD*	-0,354	*FD*	0,585	*FD*	1,045	*Grey Area*
3	AKKU	-1,670	*FD*	-1,817	*FD*	-0,354	*FD*	-2,452	*FD*	-0,971	*FD*
4	HDTX	-4,294	*FD*	-0,794	*FD*	-0,735	*FD*	-0,622	*FD*	-1,163	*FD*
5	WSBP	0,736	*FD*	0,648	*FD*	-2,241	*FD*	-2,009	*FD*	-0,418	*FD*
6	BIMA	0,244	*FD*	0,323	*FD*	-0,995	*FD*	-0,726	*FD*	-0,117	*FD*
7	TALF	1,015	*Grey area*	0,729	*FD*	0,543	*FD*	0,542	*FD*	0,610	*FD*
8	LMSH	1,352	*Non-FD*	-0,072	*FD*	0,374	*FD*	1,253	*Non-FD*	0,667	*FD*
9	ARKA	0,001	*FD*	0,259	*FD*	-0,267	*FD*	0,210	*FD*	0,451	*FD*
10	IKAI	0,319	*FD*	-0,487	*FD*	-0,537	*FD*	-0,291	*FD*	-0,288	*FD*
11	INTA	-0,076	*FD*	-0,487	*FD*	-2,179	*FD*	-1,793	*FD*	-0,248	*FD*
12	TIRT	0,258	*FD*	-0,024	*FD*	-4,469	*FD*	-2,506	*FD*	-1,950	*FD*
13	JGLE	0,258	*FD*	-0,134	*FD*	-0,154	*FD*	-0,064	*FD*	-2,638	*FD*
14	JSPT	1,001	*Grey area*	0,351	*FD*	-0,303	*FD*	-0,423	*FD*	0,071	*FD*
15	MIRA	0,374	*FD*	0,101	*FD*	-0,392	*FD*	-0,282	*FD*	-0,791	*FD*
16	MKNT	2,262	*Non-FD*	1,869	*Non-FD*	2,520	*Non-FD*	1,716	*Non-FD*	1,736	*Non-FD*
17	MDIA	0,459	*FD*	0,366	*FD*	0,366	*FD*	0,411	*FD*	0,147	*FD*
18	MDRN	-0,990	*FD*	-0,630	*FD*	-3,239	*FD*	1,324	*Non-FD*	1,004	*Grey Area*
19	LCKM	1,423	*Non-FD*	1,155	*Non-FD*	1,397	*Non-FD*	1,154	*Non-FD*	1,061	*Grey Area*
20	SAFE	-1,006	*FD*	-0,491	*FD*	-0,941	*FD*	-1,175	*FD*	-0,469	*FD*
21	POSA	-3,859	*FD*	-1,140	*FD*	-1,234	*FD*	-1,580	*FD*	-1,744	*FD*
22	PNSE	0,008	*FD*	-0,034	*FD*	-0,967	*FD*	-0,778	*FD*	-0,188	*FD*
23	ANDI	0,231	*FD*	0,421	*FD*	-0,132	*FD*	0,140	*FD*	0,007	*FD*
24	BIKA	0,438	*FD*	0,298	*FD*	-0,033	*FD*	0,409	*FD*	-0,364	*FD*
25	CMPP	-1,746	*FD*	0,439	*FD*	-2,798	*FD*	-2,740	*FD*	-2,371	*FD*
26	CNKO	-1,987	*FD*	-0,364	*FD*	-2,218	*FD*	-1,276	*FD*	-1,320	*FD*
27	CTTH	0,304	*FD*	0,086	*FD*	-0,105	*FD*	0,001	*FD*	-0,176	*FD*
28	DADA	0,792	*FD*	0,575	*FD*	0,318	*FD*	0,560	*FD*	0,430	*FD*
29	DPUM	0,792	*FD*	-2,243	*FD*	-5,765	*FD*	-1,034	*FD*	-0,250	*FD*
30	DEAL	0,470	*FD*	0,167	*FD*	-1,122	*FD*	-1,028	*FD*	-0,417	*FD*
31	BTEK	0,282	*FD*	-0,137	*FD*	-1,960	*FD*	-0,491	*FD*	-0,589	*FD*
32	BUVA	-0,157	*FD*	-0,387	*FD*	-2,896	*FD*	-1,878	*FD*	-1,718	*FD*
33	GMTD	0,447	*FD*	-0,127	*FD*	-0,347	*FD*	0,049	*FD*	0,181	*FD*
34	IIKP	-0,657	*FD*	3,321	*Non-FD*	-28,594	*FD*	-18,935	*FD*	-13,449	*FD*
35	GLOB	-4,881	*FD*	-55,772	*FD*	-67,513	*FD*	-66,375	*FD*	-119,959	*FD*
36	HADE	4,187	*Non-FD*	-56,085	*FD*	-2,168	*FD*	-0,111	*FD*	0,126	*FD*

37	TOPS	0,415	*FD*	0,105	*FD*	0,063	*FD*	0,396	*FD*	0,150	*FD*
38	TRIO	-1,126	*FD*	-7,166	*FD*	-20,633	*FD*	-20,669	*FD*	-4,592	*FD*
39	VIVA	-0,622	*FD*	-0,654	*FD*	-0,998	*FD*	-1,141	*FD*	-1,738	*FD*
40	SMRU	-0,169	*FD*	-0,809	*FD*	-1,657	*FD*	-1,487	*FD*	-0,647	*FD*
41	SONA	1,794	*Non-FD*	1,886	*Non-FD*	-0,890	*FD*	-0,758	*FD*	0,174	*FD*
42	TARA	-0,025	*FD*	-0,015	*FD*	-0,254	*FD*	0,732	*FD*	-0,100	*FD*
43	TAXI	-3,661	*FD*	-2,529	*FD*	-2,847	*FD*	17,387	*Non-FD*	-0,915	*FD*
44	DIGI	0,712	*FD*	0,726	*FD*	-2,217	*FD*	-2,660	*FD*	-3,573	*FD*
45	TAMA	0,060	*FD*	-0,323	*FD*	-0,562	*FD*	-0,418	*FD*	-0,450	*FD*
46	TIRA	0,476	*FD*	0,483	*FD*	0,376	*FD*	0,223	*FD*	0,398	*FD*
47	WOWS	0,012	*FD*	0,511	*FD*	0,351	*FD*	-0,116	*FD*	0,043	*FD*
48	NASA	0,048	*FD*	0,021	*FD*	-0,089	*FD*	-0,020	*FD*	0,049	*FD*
49	REAL	1,206	*Non-FD*	0,792	*FD*	0,829	*FD*	0,949	*Grey Area*	0,722	*FD*
50	PPRO	0,497	*FD*	0,319	*FD*	0,196	*FD*	0,286	*FD*	0,302	*FD*
51	KBAG	-0,162	*FD*	0,103	*FD*	0,609	*FD*	0,559	*FD*	0,896	*Grey Area*
52	KREN	2,701	*Non-FD*	2,117	*Non-FD*	1,335	*Non-FD*	1,336	*Non-FD*	1,932	*Non-FD*
53	KOTA	0,288	*FD*	0,026	*FD*	-0,182	*FD*	-0,100	*FD*	-0,174	*FD*
54	AGAR	1,419	*Non-FD*	1,042	*Grey Area*	1,093	*Non-FD*	1,261	*Non-FD*	1,306	*Non-FD*
55	SBAT	0,142	*FD*	-0,334	*FD*	-0,268	*FD*	-0,471	*FD*	-0,986	*FD*
56	SCPI	1,629	*Non-FD*	2,170	*Non-FD*	1,733	*Non-FD*	2,132	*Non-FD*	2,177	*Non-FD*

Source : Data processed by the author (2023)

Table 6. above is the result of calculations using the Springate method in 2018 there were 45 companies experiencing financial distress, and 2 companies were in gray areas. While 9 other companies are included in the category of Non-Financial Distress companies. In 2019, there were 49 companies experiencing financial difficulties, with 1 company being in the grey area. While 6 other companies are included in the category of Non-Financial Distress companies. In 2020, there were 51 companies experiencing financial difficulties. While the other 5 companies are included in the category of Non-Financial Distress companies. In 2021, there were 47 companies experiencing financial difficulties, and 1 company was in the grey area stage. While 8 other companies are included in the category of Non-Financial Distress companies. Furthermore, in 2022, there are 48 companies experiencing financial difficulties, and 4 companies are in a gray area. While 4 other companies are included in the category of healthy companies (Non Financial Distress). These results show that the Springate model is able to predict financial distress in companies with a special notation code of the Indonesia Stock Exchange (H2: Accepted).

Comparison of Company Health Status Based on Prediction Results

The two models were then compared to the company's actual health status. The company's financial condition is actually seen from the main factors that can cause financial distress, namely liquidity crisis, negative retained earnings, negative equity and ongoing losses experienced by the company. The following is the result of a comparison of financial distress prediction models with the actual state of the company:

Table 7. Company Status Analysis Results

No	Company Code	Year	Altman Z-Score	Springate S-Score	Conclusion	No	Company Code	Year	Altman Z-Score	Springate S-Score	Conclusion
1	KIAS	2018	*Non-FD*	*FD*	*FD*	2	RMBA	2018	*Grey Area*	*FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*Grey Area*	*FD*	*FD*
		2020	*Grey Area*	*FD*	*FD*			2020	*Non-FD*	*FD*	*FD*
		2021	*Non-FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*Grey Area*	*FD*	*FD*			2022	*Non-FD*	*Grey Area*	*FD*
3	AKKU	2018	*Non-FD*	*FD*	*FD*	4	HDTX	2018	*FD*	*FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*FD*	*FD*	*FD*
		2020	*Non-FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
5	WSBP	2018	*Non-FD*	*FD*	*Non-FD*	6	BIMA	2018	*FD*	*FD*	*FD*
		2019	*Non-FD*	*FD*	*Non-FD*			2019	*FD*	*FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
7	TALF	2018	*Non-FD*	*Grey Area*	*Non-FD*	8	LMSH	2018	*Non-FD*	*Non-FD*	*Non-FD*
		2019	*Non-FD*	*FD*	*Non-FD*			2019	*Non-FD*	*FD*	*FD*
		2020	*Non-FD*	*FD*	*Non-FD*			2020	*Non-FD*	*FD*	*FD*
		2021	*Non-FD*	*FD*	*Non-FD*			2021	*Non-FD*	*Non-FD*	*Non-FD*
		2022	*Non-FD*	*FD*	*Non-FD*			2022	*Non-FD*	*FD*	*FD*
9	ARKA	2018	*FD*	*FD*	*FD*	10	IKAI	2018	*FD*	*FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*FD*	*FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*

		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
11	INTA	2018	*FD*	*FD*	*FD*	12	TIRT	2018	*FD*	*FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*FD*	*FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
13	JGLE	2018	*Non-FD*	*FD*	*FD*	14	JSPT	2018	*Non-FD*	*Grey Area*	*Non-FD*
		2019	*Non-FD*	*FD*	*FD*			2019	*Non-FD*	*FD*	*Non-FD*
		2020	*Non-FD*	*FD*	*FD*			2020	*Grey Area*	*FD*	*FD*
		2021	*Non-FD*	*FD*	*FD*			2021	*Grey Area*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*Grey Area*	*FD*	*FD*
15	MIRA	2018	*FD*	*FD*	*FD*	16	MKNT	2018	*Grey Area*	*Non-FD*	*Non-FD*
		2019	*FD*	*FD*	*FD*			2019	*Non-FD*	*Non-FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*Grey Area*	*Non-FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*Grey Area*	*Non-FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*Non-FD*	*FD*
17	MDIA	2018	*Non-FD*	*FD*	*FD*	18	MDRN	2018	*FD*	*FD*	*FD*
		2019	*Non-FD*	*FD*	*Non-FD*			2019	*FD*	*FD*	*FD*
		2020	*Non-FD*	*FD*	*Non-FD*			2020	*FD*	*FD*	*FD*
		2021	*Non-FD*	*FD*	*Non-FD*			2021	*FD*	*Non-FD*	*FD*
		2022	*Grey Area*	*FD*	*Non-FD*			2022	*FD*	*Grey Area*	*FD*
19	LCKM	2018	*Non-FD*	*Non-FD*	*Non-FD*	20	SAFE	2018	*FD*	*FD*	*FD*
		2019	*Non-FD*	*Non-FD*	*Non-FD*			2019	*FD*	*FD*	*FD*
		2020	*Non-FD*	*Non-FD*	*Non-FD*			2020	*FD*	*FD*	*FD*
		2021	*Non-FD*	*Non-FD*	*Non-FD*			2021	*FD*	*FD*	*FD*
		2022	*Non-FD*	*Grey Area*	*Non-FD*			2022	*FD*	*FD*	*FD*

21	POSA	2018	*FD*	*FD*	*FD*	22	PNSE	2018	*Grey Area*	*FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*Grey Area*	*FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
23	ANDI	2018	*FD*	*FD*	*FD*	24	BIKA	2018	*Non-FD*	*FD*	*FD*
		2019	*Grey Area*	*FD*	*Non-FD*			2019	*Non-FD*	*FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*Grey Area*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*Grey Area*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
25	CMPP	2018	*FD*	*FD*	*FD*	26	CNKO	2018	*FD*	*FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*FD*	*FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
27	CTTH	2018	*FD*	*FD*	*FD*	28	DADA	2018	*Non-FD*	*FD*	*Non-FD*
		2019	*FD*	*FD*	*FD*			2019	*Grey Area*	*FD*	*Non-FD*
		2020	*FD*	*FD*	*FD*			2020	*Non-FD*	*FD*	*Non-FD*
		2021	*FD*	*FD*	*FD*			2021	*Non-FD*	*FD*	*Non-FD*
		2022	*FD*	*FD*	*FD*			2022	*Non-FD*	*FD*	*Non-FD*
29	DPUM	2018	*Non-FD*	*FD*	*Non-FD*	30	DEAL	2018	*Grey Area*	*FD*	*Non-FD*
		2019	*Grey Area*	*FD*	*FD*			2019	*FD*	*FD*	*Non-FD*
		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
31	BTEK	2018	*Grey Area*	*FD*	*Non-FD*	32	BUVA	2018	*FD*	*FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*FD*	*FD*	*FD*

		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
33	GMTD	2018	*Non-FD*	*FD*	*Non-FD*	34	IIKP	2018	*Non-FD*	*FD*	*FD*
		2019	*Non-FD*	*FD*	*FD*			2019	*Non-FD*	*Non-FD*	*FD*
		2020	*Non-FD*	*FD*	*FD*			2020	*Non-FD*	*FD*	*FD*
		2021	*Non-FD*	*FD*	*FD*			2021	*Non-FD*	*FD*	*FD*
		2022	*Non-FD*	*FD*	*Non-FD*			2022	*Non-FD*	*FD*	*FD*
35	GLOB	2018	*FD*	*FD*	*FD*	36	HADE	2018	*Non-FD*	*Non-FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*FD*	*FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
37	TOPS	2018	*Grey Area*	*FD*	*Non-FD*	38	TRIO	2018	*FD*	*FD*	*FD*
		2019	*Non-FD*	*FD*	*FD*			2019	*FD*	*FD*	*FD*
		2020	*Grey Area*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*Grey Area*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*Grey Area*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
39	VIVA	2018	*FD*	*FD*	*FD*	40	SMRU	2018	*FD*	*FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*FD*	*FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*FD*	*FD*	*FD*
		2021	*FD*	*FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
41	SONA	2018	*Non-FD*	*Non-FD*	*Non-FD*	42	TARA	2018	*Non-FD*	*FD*	*FD*
		2019	*Non-FD*	*Non-FD*	*Non-FD*			2019	*Non-FD*	*FD*	*FD*
		2020	*Non-FD*	*FD*	*FD*			2020	*Non-FD*	*FD*	*FD*
		2021	*Non-FD*	*FD*	*FD*			2021	*Non-FD*	*FD*	*Non-FD*

		2022	*Non-FD*	*FD*	*FD*			2022	*Non-FD*	*FD*	*FD*
43	TAXI	2018	*FD*	*FD*	*FD*	44	DIGI	2018	*Non-FD*	*FD*	*FD*
		2019	*FD*	*FD*	*FD*			2019	*Non-FD*	*FD*	*FD*
		2020	*FD*	*FD*	*FD*			2020	*Grey Area*	*FD*	*FD*
		2021	*FD*	*Non-FD*	*FD*			2021	*FD*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*FD*	*FD*	*FD*
45	TAMA	2018	*FD*	*FD*	*FD*	46	TIRA	2018	*Grey Area*	*FD*	*Non-FD*
		2019	*FD*	*FD*	*FD*			2019	*Grey Area*	*FD*	*Non-FD*
		2020	*FD*	*FD*	*FD*			2020	*Grey Area*	*FD*	*Non-FD*
		2021	*FD*	*FD*	*FD*			2021	*Grey Area*	*FD*	*FD*
		2022	*FD*	*FD*	*FD*			2022	*Grey Area*	*FD*	*Non-FD*
47	WOWS	2018	*FD*	*FD*	*FD*	48	NASA	2018	*Non-FD*	*FD*	*FD*
		2019	*Non-FD*	*FD*	*Non-FD*			2019	*Non-FD*	*FD*	*FD*
		2020	*Non-FD*	*FD*	*Non-FD*			2020	*Non-FD*	*FD*	*FD*
		2021	*Non-FD*	*FD*	*FD*			2021	*Non-FD*	*FD*	*FD*
		2022	*Non-FD*	*FD*	*FD*			2022	*Non-FD*	*FD*	*FD*
49	REAL	2018	*Non-FD*	*Non-FD*	*FD*	50	PPRO	2018	*Non-FD*	*FD*	*Non-FD*
		2019	*Non-FD*	*FD*	*Non-FD*			2019	*Grey Area*	*FD*	*Non-FD*
		2020	*Non-FD*	*FD*	*Non-FD*			2020	*Grey Area*	*FD*	*Non-FD*
		2021	*Non-FD*	*Grey Area*	*Non-FD*			2021	*Grey Area*	*FD*	*Non-FD*
		2022	*Non-FD*	*FD*	*Non-FD*			2022	*Grey Area*	*FD*	*Non-FD*
51	KBAG	2018	*FD*	*FD*	*FD*	52	KREN	2018	*Non-FD*	*Non-FD*	*Non-FD*
		2019	*Non-FD*	*FD*	*Non-FD*			2019	*Non-FD*	*Non-FD*	*Non-FD*
		2020	*Non-FD*	*FD*	*Non-FD*			2020	*Non-FD*	*Non-FD*	*FD*
		2021	*Non-FD*	*FD*	*Non-FD*			2021	*Non-FD*	*Non-FD*	*FD*
		2022	*Non-FD*	*Grey Area*	*Non-FD*			2022	*Non-FD*	*Non-FD*	*FD*
53	KOTA	2018	*Non-FD*	*FD*	*Non-FD*	54	AGAR	2018	*Grey Area*	*Non-FD*	*Non-FD*

		2019	*Non-FD*	*FD*	*FD*			2019	*Non-FD*	*Grey Area*	*Non-FD*
		2020	*Non-FD*	*FD*	*FD*			2020	*Non-FD*	*Non-FD*	*FD*
		2021	*Non-FD*	*FD*	*FD*			2021	*Non-FD*	*Non-FD*	*Non-FD*
		2022	*Non-FD*	*FD*	*FD*			2022	*Non-FD*	*Non-FD*	*FD*
55	SBAT	2018	*FD*	*FD*	*FD*	56	SCPI	2018	*Non-FD*	*Non-FD*	*Non-FD*
		2019	*FD*	*FD*	*FD*			2019	*Non-FD*	*Non-FD*	*Non-FD*
		2020	*FD*	*FD*	*FD*			2020	*Non-FD*	*Non-FD*	*Non-FD*
		2021	*FD*	*FD*	*FD*			2021	*Non-FD*	*Non-FD*	*Non-FD*
		2022	*FD*	*FD*	*FD*			2022	*Non-FD*	*Non-FD*	*Non-FD*

Source : Data processed by the author (2023)

Table 7. above presents information on the financial health of companies included in the special notation of the Indonesia Stock Exchange, the results of analysis using Altman approaches modified *by Z-Score* and Springate. The table also shows the real state of the company from 2018-2022.

Table 8. Analysis Results

No	Methode	Year	Prediction		Result		Total
			Financial Distress	***Non Financial Distress***	***Financial Distress***	***Non Financial Distress***	
1	**Altman Modified *Z-Score***	2018	32	24	37	19	56
		2019	33	23	39	17	56
		2020	36	20	46	10	56
		2021	37	19	45	11	56
		2022	39	17	46	10	56
2	**Sprinagte**	2018	47	9	37	19	56
		2019	50	6	39	17	56
		2020	51	5	46	10	56
		2021	48	8	45	11	56
		2022	52	4	46	10	56

Source : Data processed by the author (2023)

Table 8. shows the results of comparative analysis between two methods namely Altman Modification *Z-Score* and Springate. The comparison results show that there are several differences between the results of the analysis using the two methods and the actual state of the company.

Accuracy of Prediction Models

Here's a comparison of the accuracy of the prediction model and the error rate:

Table 9. Comparison of the Accuracy of *Financial Distress Prediction Models*

Analysis Method	**Accuracy Calculation Method**	**Sample (total company x 5 years)**	**Total**	**Observation Year (2018-2022)**
Altman Modified *Z-Score*	Accuracy Level	280	213	70%
	Eror I Type	280	50	18%
	Eror II Type	280	16	6%
Springate	Accuracy Level	280	213	60%
	Eror I Type	280	14	5%
	Eror II Type	280	45	16%

Source : Data processed by the author (2023)

Based on the table. 9 it is seen that there is a difference in the accuracy of financial distress prediction models between the Altman and Springate models. The accuracy rate of both models is obtained from the number of samples that are predicted to be true to experience financial distress divided by the total sample and multiplied by one hundred percent, then reduced by the type two error rate. The results of the calculation of the accuracy level obtained the results of the accuracy rate of the Altman model of 70%, with error type 1 of 18% and error type 2 of 6%. While the Springate model has an accuracy rate of 60%, with error type 1 of 5% and error type 2 of 16%. Based on these calculations, it can be concluded that the model that has the highest level of accuracy in predicting financial distress in companies with a special notation of the Indonesia Stock Exchange (IDX), is Altman modified Z-Score with an accuracy rate of 70%. These results show that there is a difference in the level of accuracy between the modified Altman z-score model and the Springate model, so that the third hypothesis in this study (H3) is accepted.

Type 1 errors occur when the prediction model states the company does not experience financial dsitress but actually the company experiences financial distress and type 2 errors occur when the prediction model states the company experiences financial dsitress but it turns out that the company does not experience financial. Knowing the difference between Error type 1 and type 2 helps investors understand how well the model is at signaling a company's financial condition. The theoretical foundation of this research includes the principles of signal theory, where investors look for indicators or signals to make better investment decisions. By understanding the difference between Error type 1 and type 2, investors can optimize their investment decisions by considering the risk of errors that may occur in the interpretation of statistical models such as Altman Modified Z-Score and Springate. Based on these calculations, it can be concluded that the model that has the highest level of accuracy in predicting financial distress in companies with a special notation of the Indonesia Stock Exchange (IDX), is Altman modified Z-Score with an accuracy rate of 70%. These results show that there is a difference in the level of accuracy between the modified Altman z-score model and the Springate model, so that the third hypothesis in this study (H3) is accepted.

The statistical analysis with signal theory indicates that companies with specific notation codes can convey negative signals to management, investors, and other stakeholders through financial statement analysis using the Altman Modified Z-Score and Springate models. From the analysis results, it is found that the majority of companies in the sample are experiencing financial distress. The analysis was conducted over the past five years, providing a current overview of the financial condition of these companies. Positive signals, as detected by the statistical models, can serve as a serious warning for the company's management to promptly address the financial condition. These findings also provide a robust foundation for strategic decision-making that can help ensure the company's sustainability in the future

CONCLUSION

The results of this study indicate that companies with special notation codes on the Indonesia Stock Exchange may potentially experience financial distress based on the analysis methods of the modified Altman Z-Score and Springate S-Score models. Both models have proven to be capable of predicting the health condition of the company using established financial ratios. The results of these two models show significant differences in analyzing the potential financial distress of companies with special notation.

There are several predictions that are in accordance with the actual financial situation. But there are also those whose prediction results are not in accordance with the actual financial condition of a company. Although there are some prediction errors, the prediction results can still be used as indicators to see the sustainability of the company in the future and can be used as an indicator A signal for company management to immediately improve the company's financial condition, and can be used as a signal for investors and other interested parties in making decisions.

The results of the analysis predicting the potential financial distress using Altman Modified Z-Score and Springate indicate that both methods have different criteria and limitations in determining the financial condition of a company. Indicated by the results of different levels of accuracy of the two models. The Altman model has an accuracy rate of 70%, with error type 1 at 18% and error type 2 at 6%. While the Springate model has an accuracy rate of 60%, with error type 1 of 5% and error type 2 of 16%. From these results, it can be concluded that the model with a higher level of accuracy is the Altman model modified z-score with an accuracy rate of 70%, which means the Altman model has better performance in predicting financial distress of a company. This result is in line with research (Munira et al., 2021), (Ridhawati & Suryantara, 2023) which found that the accuracy of the Altman Z-Score model is higher than the Springate method.

This research provides important information for companies with special notation codes that experience financial distress, to immediately improve financial conditions, and provides a basis for strategic decision making to ensure the sustainability of the company and for investors and other interested parties can be used as a basis for investment decision making.

This study has several limitations such as the analysis in this study considers more internal company factors. The analysis method of this research still uses two commonly used methods, namely the Altman Z-score model and Springte.

Future research is expected to be able to make a wider scope such as adding external factors of the company in predicting financial distress and using other precondition models such as Deep Learning Models or Deep Neural Networks (DNN).

REFERENCE

Annafi, G. D., & Yudowati, S. P. (2021). Analisis Financial Distress, Profitabilitas, dan Materialitas Terhadap Kecurangan Laporan Keuangan. *Jurnal Akuntansi Kompetif*, *4*(3), 255–262.

Cındık, Z., & Armutlulu, I. H. (2021). A revision of Altman Z-Score model and a comparative analysis of Turkish companies' financial distress prediction. *National Accounting Review*, *3*(2), 237–255. https://doi.org/10.3934/nar.2021012

Denhas, Y., & Subroto, B. (2014). Penggunaan Model Springate untuk Memprediksi Potensi Kebangkrutan Perusahaan (Studi Pada Perusahaan Sektor Food and Beverages yang Terdaftar di Bursa Efek Indonesia Pada Tahun 2011-2013). *Jurnal Unviersitas Brawijaya Malang*, 1–23.

Dudley, E., Andrén, N., & Jankensgård, H. (2022). How do firms hedge in financial distress? *Journal of Futures Markets*, *42*(7), 1324–1351. https://doi.org/10.1002/fut.22336

Effendi, R. (2018a). Analisis Prediksi Kebangkrutan Dengan Metode Altman, Springate, Zmijewski, Foster, Dan Grover Pada Emiten Jasa Transportasi. *Jurnal Parsimonia*, *4*(3), 307–318.

Effendi, R. (2018b). Analisis Prediksi Kebangkrutan Dengan Metode Altman, Springate, Zmijewski, Foster, Dan Grover Pada Emiten Jasa Transportasi. *Jurnal Parsimonia*, *4*(3), 307–318.

Eliu, V. (2014). Pengaruh Financial Leverage dan Firm Growth terhadap Financial Distress. *Finesta*, *2*.

Friedl, G., & Drescher, F. (2013). Insolvency timing and managerial decision-making. *Insolvency Timing and Managerial Decision-Making*, *2004*, 1–191. https://doi.org/10.1007/978-3-658-02819-0

Gandhy, & Fardinal. (2019). Analysis of Financial Ratio to Predict Financial Distress Conditions (Empirical Study on Manufacturing Companies listed on the Indonesia Stock Exchange for 2014-2017). *International Journal of Business and Management Invention (IJBMI)*, *8*(06), 27–34.

Kartika, A., Abdul Rozak, H., Nurhayat, I., Daniel Bagana, B., Studi Manajemen, P., Bisnis, F., Stikubank, U., & Studi Akuntansi, P. (2020). *Rasio Keuangan Sebagai Prediksi Financial Distress*. Prosiding Sendi.

Kisman, Z., & Krisandi, D. (2019a). How to Predict Financial Distress in the Wholesale Sector: Lesson from Indonesian Stock Exchange. *Journal of Economics and Business*, *2*(3), 569–585. https://doi.org/10.31014/aior.1992.02.03.109

Kisman, Z., & Krisandi, D. (2019b). How to Predict Financial Distress in the Wholesale Sector: Lesson from Indonesian Stock Exchange. *Journal of Economics and Business*, *2*(3), 569–585. https://doi.org/10.31014/aior.1992.02.03.109

Lestari, R. M. E., Situmorang, M., Pratama, M. I. P., & Bon, A. T. (2021a). Financial distress analysis using altman (Z-score), springate (S-Score), zmijewski (X-Score), and grover (G-Score) models in the tourism, hospitality and restaurant subsectors listed on the Indonesia stock exchange period 2015-2019. *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 4249–4259.

Lestari, R. M. E., Situmorang, M., Pratama, M. I. P., & Bon, A. T. (2021b). Financial distress analysis using altman (Z-score), springate (S-Score), zmijewski (X-Score), and grover (G-Score) models in the tourism, hospitality and restaurant subsectors listed on the Indonesia stock exchange period 2015-2019. *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 4249–4259.

Li, J., & Wang, C. (2023a). A deep learning approach of financial distress recognition combining text. In *Electronic Research Archive* (Vol. 31, Issue 8, pp. 4683–4707). aimspress.com. https://doi.org/10.3934/ERA.2023240

Li, J., & Wang, C. (2023b). A deep learning approach of financial distress recognition combining text. In *Electronic Research Archive* (Vol. 31, Issue 8, pp. 4683–4707). aimspress.com. https://doi.org/10.3934/ERA.2023240

López-Gutiérrez, C., Sanfilippo-Azofra, S., & Torre-Olmo, B. (2015). Investment decisions of companies in financial distress. *BRQ Business Research Quarterly*, *18*(3), 174–187. https://doi.org/10.1016/j.brq.2014.09.001

Martini, R., Raihana Aksara, R., Rachma Sari, K., Zulkifli, Z., & Hartati, S. (2023a). Comparison of Financial Distress Predictions With Altman, Springate, Zmijewski, and Grover Models. *Golden Ratio of Finance Management*, *3*(1), 11–21. https://doi.org/10.52970/grfm.v3i1.216

Martini, R., Raihana Aksara, R., Rachma Sari, K., Zulkifli, Z., & Hartati, S. (2023b). Comparison of Financial Distress Predictions With Altman, Springate, Zmijewski, and Grover Models. *Golden Ratio of Finance Management*, *3*(1), 11–21. https://doi.org/10.52970/grfm.v3i1.216

Munira, M., Satria, I., & Ayun, I. Q. (2021a). The Effectiveness of The Altman Z-Score and Springate Methods in Analyzing The Potential for Company Bankruptcy. *International Journal of Business and Technology Management*, *3*(1), 63–78.

Munira, M., Satria, I., & Ayun, I. Q. (2021b). The Effectiveness of The Altman Z-Score and Springate Methods in Analyzing The Potential for Company Bankruptcy. *International Journal of Business and Technology Management*, *3*(1), 63–78.

Nikmah, N., & Sulestari, D. D. (2021). Prediksi Financial Distress Untuk Perusahaan Besar Dan Kecil Di Indonesia Perbandingan Ohlson Dan Altman. *Jurnal Fairness*, *4*(1), 37–60. https://doi.org/10.33369/fairness.v4i1.15299

Nuswantara, D. A., Fachruzzaman, D. A., Prameswari, R. D., Suyanto, R. D., Rusdiyanto, R., & Hendrati, I. M. (2023). The role of political connection to moderate board size, woman on boards on financial distress. *Cogent Business and Management*, *10*(1). https://doi.org/10.1080/23311975.2022.2156704

Piatt, H. D., & Piatt, M. B. (2002). Predicting corporate financial distress: Reflections on choice-based sample bias. *Journal of Economics and Finance*, *26*(2), 184–199. https://doi.org/10.1007/bf02755985

Pulungan, D. R., & Hartini, T. (2018). *METODE SPRINGATE DALAM ANALISA POTENSI KEBANGKRUTAN PERUSAHAAN PROPERTIDI INDONESIA*. *November*.

Purwaningsih, R. W., & Aziza, N. (2019). Pengaruh Corporate Social Responsbility Terhadap Financial Distress Dimoderasi Oleh Siklus Hidup Perusahaan Pada Tahap Mature. *Jurnal Akuntansi*, *9*(3), 173–186. https://doi.org/10.33369/j.akuntansi.9.3.173-186

Sari, D. W., Husaini, H., & Usman, D. (2021). Analisis Kinerja Keuangan Dan Financial Distress Perbankan Syariah Di Indonesia. *Jurnal Fairness*, *7*(2), 79–96. https://doi.org/10.33369/fairness.v7i2.15148

Spence michael. (1973). I shall argue that the paradigm case of the market with this type of informational structure is the job market and will therefore focus upon it . By the end I hope it will be clear (although space limitations will not permit an extended argument) that a. *The Quarterly Journal of Economics*, *87*(3), 355–374.

Studi, D. A. N. G., Mulyani, L., Luh, N., Erni, G., & Wahyuni, M. A. (2018). *ANALISIS PERBANDINGAN KETEPATAN PREDIKSI FINAN- PADA PERUSAHAAN RETAIL YANG TERDAFTAR DI BURSA EFEK INDONESIA PERIODE 2015-2017)*. 139–150.

Suidarma, I. M., Wayan, N., Widyari, T., Sudama, I. K., Arniti, N. K., & Marsudiana, I. D. N. (2022). *Analysis of the Determining Factors of Financial Distress (A Case Study at PT . Bank Rakyat Indonesia (Persero)*. *15*(5), 21–29. https://doi.org/10.5539/ibr.v15n5p21

Suranta, E., Satrio, M. A. B., & Midiastuty, P. P. (2023). Effect of Investment, Free Cash Flow, Earnings Management, Interest Coverage Ratio, Liquidity, and Leverage on Financial Distress. *Ilomata International Journal of Tax and Accounting*, *4*(2), 283–295. https://doi.org/10.52728/ijtc.v4i2.714

Tan, E., & Wibisana, T. A. (2020). *A comparative Analysis Altman (Z-Score) Revision and Springate (S-Score) Model in Predicting Financial Distress in the Manufacturing Company - Indonesia Stock Exchange*. *2*(4).

Widarjo, W., & Setiawan, D. (2009). Pengaruh Rasio Keuangan Terhadap Kondisi Financial Distress Perusahaan Otomotif. *Jurnal Bisnis Dan Akuntansi*, *11*(2), 107–119.

Zhu, J., Zhu, H., & Lin, N. (2023). *A Dynamic Prediction Model of Financial Distress in the Financial Sharing Environment*. *2023*.