Turnitin_FINANCIAL DISTRESS PREDICTION MODELS: CASE STUDY OF TEXTILE INDUSTRY IN INDONESIA

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FINANCIAL DISTRESS PREDICTION MODELS: CASE STUDY OF TEXTILE INDUSTRY IN INDONESIA

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ABSTRACT

Financial distress is company's inability in completing financial obligation. Preventive action should be applied to maintain financial performance and to avoid any financial issues. This study aims to find the statistically significant difference and to compare the accuracy level of accounting-based financial distress prediction models by focusing on the research objects of 13 textile firms listed on the Indonesia Stock Exchange (IDX) during 2014-2018. The analyzed four prediction models are: Altman (Z-Score), Springate (S-Score), Grover (G-Score), and Zmijewski (X- Score). By employing a non-parametric approach, this study adopts Kruskal-Wallis and Mann Whitney Post Hoc as the difference tests, along with accuracy rate formulation. Type I Error and Type II Error are used to examine the accuracy level of each model. The Kruskal-Wallis test reveals that these models are statistically significantly different with the p-value of .000. Meanwhile, in pairs, Mann Whitney Post Hoc results prove that there is no significant difference between Springate's and Grover's models where the result is greater than 5%. Additionally, the result also designates that the most accurate prediction model to predict financial distress of textile firms is Zmijewski's which has the accuracy level of 66.15%, while the accuracy rate of Grover's and Altman's models are 63.08% and 53.85%, respectively. Therefore, Springate's model becomes the lowest accuracy level at 52.31%.

Keywords: Financial Distress, Altman, Springate, Grover, Zmijewski

INTRODUCTION

Economic growth is undoubtedly important for country development to continuously become stronger and grow independently. Manufacturing industry is one of the pillars of Indonesia economy which has contributed significantly to the country's national economic growth. In this case, it can be seen from the source of Indonesia Gross Domestic Product (GDP) where the GDP growth rate of manufacturing industry in 2018 was 0.91% which was the highest contribution among the other industries (Ministry of Industry of the Republic of Indonesia, 2019). Hence, it implies that manufacturing industry has an important role upon Indonesia economic growth in which it should be improved and/or maintained.

As the highest contributor to Indonesia's GDP, manufacturing industry is supported by the other subsectors that each has a different percentage of growth seen from each respective production growth. However, not all sectors perform well. For instance, the textile industry had a relatively small production growth compared to the other upper 12 industries by only 5.03% in 2018 (BPS-Statistics Indonesia, 2018). Therefore, although the performance of manufacturing industry in a whole can be indicated as a good industry with positive prospect, each supporting subsector needs to be considered to avoid any possible issue. One of the subsectors that requires more attention is the textile industry, because it has some issues in the following aspects: the export and import activities, domestic investment and foreign investment, and also the total number of bankrupt companies.

Table 1
TOTAL NUMBER OF TEXTILE INDUSTRY EXPORT AND IMPORT DURING 2012 – 2016

Year	Export	Import
	(USD Thousand)	(USD Thousand)
2012	5,286,810.07	6,426,743.90
2013	5,295,374.10	6,647,723.50
2014	5,378,798.30	6,744,119.30
2015	4,999,603.10	6,512,973.10
2016	4,660,023.30	6,705,393.20
Source: Ministry of Industry of the Republic of Indonesia		

International trade is one of the key factors that might increase the economic growth. It can be seen from the balance of exports and imports that tend to stimulate the investment activities and increase the income of community (Farina & Husaini, 2017). Therefore, the government needs to regulate strategical exports and imports movements of both goods and services to meet the desired result. In Indonesia, exports and imports from many sectors of industry are being developed by the Indonesia's government. However, the development of exports and imports from textile industry deserves more attention. As revealed by Table 1, the total number of textile industry's import still exceeded the total number of its export. Moreover, there was a negative trend of textile industry exported from 2014–2016. To overcome these challenges, a powerful collaboration among government and entrepreneurs are exactly needed.

In addition, domestic and foreign investments should also be considered as the first step to carry out development. Focusing on domestic and foreign investments of textile industry, it performs a slow and fluctuated growth during 2012–2016. Figure 1 indicates that investors are not attracted enough to put their money on this industry. It is exhibited from an extreme decline of domestic investment from 2015 to 2016 which reached a half from that of 2015. Furthermore, the foreign investment also indicates unstable trend from 2012-2016. Thus, it becomes natural that the growth of textile industry is not too rapid, since there is a relatively low investment in this sector.

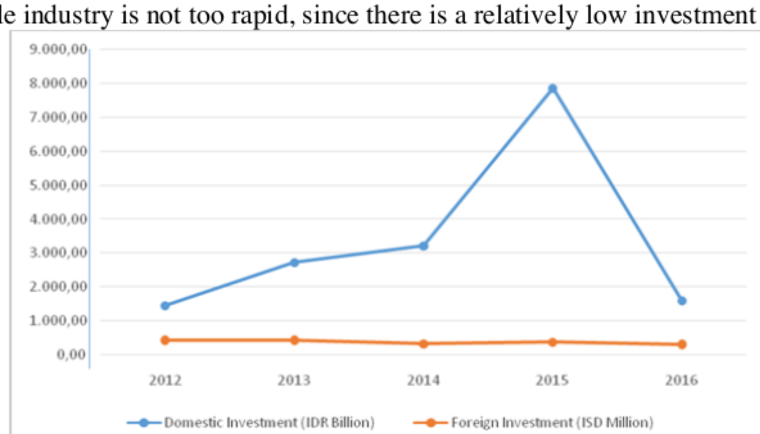

FIGURE 1
TOTAL NUMBER OF DOMESTIC INVESTMENT AND FOREIGN INVESTMENT OF TEXTILE INDUSTRY FROM 2012 – 2016

Source: Investment Coordinating Board

Heading to the two concerns on investments, it indicates that there is a negative impact of those concerns toward the performance of each firm in textile industry. For instance, the Section of Manpower and Transmigration of the West Java Province recorded that from January 2018 to September 2019, 188 textile and textile products firms in West Java were closed and moved to the Province of Central Java. Therefore, about 68 thousand workers lost their jobs due to the layoffs (The Section of Manpower and Transmigration of the West Java Province, 2019). Thus, to prevent the negative impact of these current phenomenon, it is important for every company to have the best operation management to achieve better performance ahead. Otherwise, lack of preparation and inability of the company to compete may cause financial problems. If the company cannot survive, it will lead to financial distress where the company is unable to cover its liabilities because of insufficient cash (Badu, 2017). Moreover, the company can go bankrupt.

According to the previous studies, various models can be implemented by the company as the consideration to predict financial distress during the time period in order to prevent unhealthy conditions, which may lead to company bankruptcy. It also can be used as a reference for the internal management and investors in making a decision. Some of the models are Altman, Springate, Grover & Zmijewski, in which these models can be used for financial distress prediction (Hantono, 2019). However, based on the findings of the previous studies, the researchers of this study found some gaps in terms of the accuracy level and the best models that should be implemented by the industry. Thus, it triggers the researchers of this study to become more curious to prove the best bankruptcy prediction model by focusing on the accuracy model of Altman, Springate, Grover & Zmijewski. This study is aimed to provide further information for the company to avoid financial distress condition. In addition, the population sample of this study is textile industry firms that were listed on Indonesia Stock Exchange with a specific focus on the period of 2014 to 2018.

LITERATURE REVIEW

Bankruptcy is designated as a condition where the firm's debt is exceeding the firm's asset (Mahmood, 2015) or a firm is declared to be bankrupt by the court when the condition of its cash balances totally fall to zero, in which it will not be able to pay its due obligation (Olotu & Onakoya, 2017). Bankruptcy is closely related to the firm's debt with certain period of time, level of solvency, and also the firm's cash and assets that are used for its operation. It can be highlighted that a firm can be interpreted as bankrupt if it cannot solve or find an alternative solution when it is on financial distress condition (Camacho-Minano & Lukason, 2019). Financial distress is the condition when a company is not able to complete its financial obligations to the debt holder, since the amount of its liabilities are exceeding the total equity which causes insufficient cash balance to cover it (Szpulak, 2016). In order to determine the parameter of predicting financial distress condition on a firm, there have been many previous researchers who attempted to find the best indicators. The parameters are various, and there are two more often used parameters: net loss and cash flow patterns.

The study of Oz & Yelkenci, (2017) stated that earnings components have a high-level of accuracy prediction based on analyzed theoretical model. Moreover, research which discussed the accuracy of financial distress prediction models from Arifin et al., (2018), Primasari et al., (2017), and Gunawan et al., (2017) were also concerned on net loss as the indicator to determine financial distress of the company. Arifin et al., (2018) claim that the indication of financial distress is shown by the net loss generated by the company because it signifies that the company cannot raise enough profit to maintain the company to be not liquidated. In line with the previous studies, the study of Primasari et al., (2017) mentions that the key factor to identify whether a company is on distress condition or not can be seen from its net income, if the company is not able to generate profit or it has negative net income for several years or more than one year, then it is indicated that the company is experiencing distress condition. In addition, Gunawan et al., (2017) also demonstrate that financial distress is a stage when a company is experiencing insolvency in which the profits cannot cover the due debts, or simply assume that the company has net loss for that period.

The other financial distress indicator is based on the cash flow pattern which consist of cash flow activities. According to Ward and Foster (as cited in Arlov et al., 2016), distress companies have a tendency of having negative cash flow from operating, investing, and also financing about one or two years before they are going to bankrupt. Furthermore, the study from Jantadej (as cited in Kamaluddin et al., 2015) claims that cash flow pattern is more reliable and relevant to predict financial distress than the information of earnings components. It is followed by further research carried by Kamaluddin et al., (2015) which finds four cash flow patterns that have significant relationship with financial distress incidence. The four cash flow patterns are positive cash inflow in operating activities and negative cash flow in both investing and financing activities (+, -, -); positive cash inflow in both operating and investing activities and negative cash flow in financing activities (+, +, -); positive cash inflow in both operating and financing and negative cash flow in investing (+, -, +); and negative cash flow for all components (-, -, -). Thus, the results suggest that these types of cash flow patterns can be considered in predicting financial distress, especially for a firm that has decreasing on financial performance.

Potential bankruptcy can be realized earlier by implementing various prediction models which are currently mentioned as early warning system (Husein & Pambekti, 2014). These models are developed as a tool to forecast the potential of bankruptcy which are then expected to give a right solution to fix the problem before going to the worst stage, financial crisis (Hayati & Munawarah, 2019). According to Gerritsen (2015), there are two major types of financial distress prediction models which are known as accounting-based and market-based prediction models. This study argues that accounting-based prediction models are employed to predict financial distress based on the empirical accounting data of companies, while market-based prediction models rely on both accounting data and current market information including stock price and macroeconomic variables. In existing literature, several accounting-based models for predicting financial distress have been established. These models include the findings from Grover in 2001, Springate in 1978, Zmijewski in 1984, and the oldest was developed by Altman in 1968 (Azizah & Parquinda, 2019).

Table 2
DETAILED INFORMATION ON ALTMAN, SPRINGATE, GROVER, AND ZMIJEWSKI MODELS

Model	Formula	Notes	Classification
Altman	Z=1.21X1+ 1.4X2 +3.3X3+0.6X4+0.999X5	X1=WorkingCapital/TotalAssets	Z<1.81=distress
		X2=Retained Earnings/Total Assets	1.81≤Z≤2.99=greyarea
		X3=EarningsbeforeInterestandTaxes (EBIT)/Total Assets	Z>2.99=non-distress
		X4=Market Value of Equity Book Value of Total Debt	
		X5=Sales/Total Assets	
		Z=Overall Index (Z-Score)	
Springate	S=1,03X1+ 3,07X2 +0,66X3+ 0,4X4	X1=Working Capital/Total Assets X2=Net Profit before Interest and Taxes/TotalAssets	S<0.862=distress
		X3=Net Profit before Taxes /Current Liabilities	S>0.862=non-distress
		X4=Sales/Total Assets	
		S=Overall Index (S-Score)	
Grover	G=1,650X1 +3,404X2 –	X1=Working Capital/Total Assets	G ≤ -0.02=distress

	0,016X3 + 0,057	X2=Earnings before Interest and Taxes (EBIT)/TotalAssets	
		X3=Net Income/Total Assets	G ≥ 0.01= non-distress
		G=Overall Index (G-Score)	
Zmijewski	X=-4,3 – 4,5X1+5,7X2 – 0,004X3	X1=Net Income/Total Assets	X>0=distress
		X2=Total Debt/Total Assets	X<0= non-distress
		X3 =Current Assets /CurrentLiabilities	
		X=Overall Index (X-Score)	
Sources: Falahuddin, Heikal, Khaddafi, and Nandari (2017), Ashraf, Deo, and Rajasekar (2014), Primasari and Savitri (2017), Gerritsen (2015)			

To elaborate more, Table 2 has explained the details of each model. Altman conducted a research to find which integration of financial ratio estimation was considered as the best model to predict financial distress (Azizah & Parquinda, 2019). There are three discriminant functions constructed by Altman which were known as the original model (Z-Score), the first revision model (Z'-Score), and the second revision model (Z''-Score). Initially, the original model was intended only for public manufacturing companies, and then the revision models were adjusted for private companies (Altman, Iwaniez-Drozdowska, Laitinen & Suvas, 2017).

Springate (S-Score) Model was developed in 1978 by Gordon L. V. as the extension study of Altman in 1968 (Diyant, Sari & Januri, 2017). It was also introduced as the prediction model of company's financial condition. In line with Altman's model, this model also employed Multiple Discriminant Analysis (MDA) to test the variables (Husein & Pambekti, 2014).

In 2001, Jeffrey S. Grover established a prediction model of financial distress by designing and reassessing the prediction model developed by Altman in 1968 (Hantono, 2019). Initially, Grover conducted the analysis of the Altman's model by adding several new ratios which consisted of Total Assets Turnover, Current Ratio, Inventory Turnover, ROA, ROE, Fixed Assets Turnover, Financial Leverage Index, Fixed Assets/Total Equity, GPM, and also Working Capital Turnover (Thanjaya, 2016). Afterwards, three variables from Altman's model had been eliminated and there was one variable added as the difference. Then, the eliminated variables were analyzed by employing Canonical Discriminant Function Coefficients (Thanjaya, 2016). Finally, this model constructed a new formulation which generated an index called G- Score.

Another financial distress prediction model was introduced by Zmijewski in 1984. This model was a further research from Ohlson's work in 1980 as the probit model (Ashraf, Felix & Serrasqueiro, 2019). The probit model is a statistical method which is also similar to logistic regression. However, it can only use two values of dependent variables (in this case are bankrupt or non-bankrupt). This model aims to assess the probability whether the sample with specific characters will be classified into a predefined category (Gerritsen, 2015). Zmijewski model is also categorized into accounting-based model where there are two categories determined: bankrupt and non-bankrupt. There were three popular financial ratios chosen by Zmijewski to generate X-Score.

Based on the previous research and literature, theoretical framework and some hypotheses have been arranged as follows:

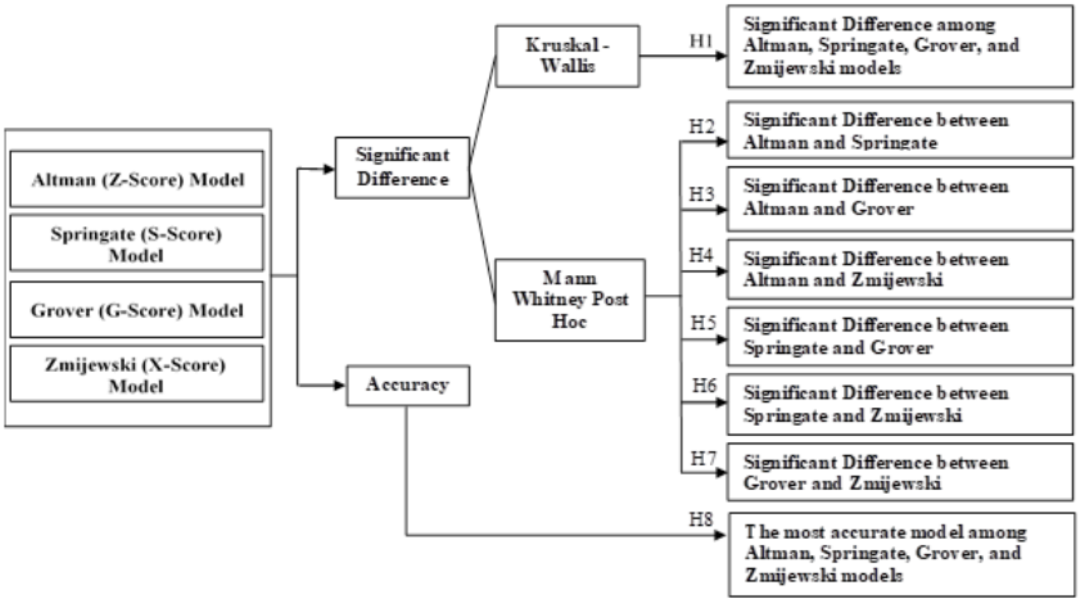

FIGURE 2
THEORETICAL FRAMEWORK

Source: Adjusted by Researcher, 2021

RESEARCH HYPOTHESES

H1 *There is statistically significant difference among Altman, Springate, Grover, and Zmijewski models when predicting financial distress in the textile companies listed on IDX for the period of 2014-2018.*

H2 *There is statistically significant difference between Altman and Springate models when predicting financial distress in the textile companies listed on IDX for the period of 2014-2018.*

H3 *There is statistically significant difference between Altman and Grover models when predicting financial distress in the textile companies listed on IDX for the period of 2014-2018.*

H4 *There is statistically significant difference between Altman and Zmijewski models when predicting financial distress in the textile companies listed on IDX for the period of 2014-2018.*

H5 *There is statistically significant difference between Springate and Grover models when predicting financial distress in the textile companies listed on IDX for the period of 2014-2018.*

H6 *There is statistically significant difference between Springate and Zmijewski models when predicting financial distress in the textile companies listed on IDX for the period of 2014-2018.*

H7 *There is statistically significant difference between Grover and Zmijewski models when predicting financial distress in the textile companies listed on IDX for the period of 2014- 2018.*

H8 *There is one financial distress prediction model that has the highest accuracy rate in predicting financial distress on the textile companies listed in IDX for the period of 2014-2018.*

RESEARCH METHOD

This research is quantitative and applying deductive process as the quantitative model, where the hypotheses development is according to the theories and previous research findings that include the explanation about the difference and accuracy of financial distress prediction models (Sekaran, 2014). In addition, in terms of the analysis method, this research is using nonparametric analysis. Regarding to the analysis model, Wolfowitz (as cited in Kvam et al., 2007) argued that nonparametric is implied as an analysis where the samples are not required to be normally distributed. By implementing purposive sampling, this research selects the population of companies listed in IDX which are categorized into textile industry that is limited by only 13 textile companies operated during 2014–2018.

Table 3
CATEGORY CLASSIFICATION FOR DETERMINING THE DEGREE OF FINANCIAL CONDITION

Category of Financial Condition	Description	Degree of Financial Condition
Category 0	If there is net income and the cash flow pattern of operating, investing as well as financing activity are none of the pattern mentioned in category 1.	Stable/Non-distress
	If there is net loss and positive cash inflow in operating, negative cash outflow in investing, as well as negative cash outflow in financing activity (pattern: +, -, -)	
Category 1	If there is net loss and positive cash inflow in operating, positive cash inflow in investing, as well as negative cash outflow in financing activity (pattern: +, +, -)	Distress
	If there is net loss and positive cash inflow in operating, negative cash outflow in investing, as well as positive cash inflow in financing activity (pattern: +, -, +)	
	If there is net loss and negative cash outflow in operating, investing, and financing activity (pattern:-, -, -)	

Source: Adjusted by Researchers, 2020

As revealed on Table 3, the samples that have been eliminated are then divided into two groups: company in stable or non-distress condition (category 0) along with company in distress condition (category 1). The separation of each category is based on the combination of two theories about distress indicator which are earning information and cash flow pattern as explained on Table 3. The study from Oz & Yelkenci, (2017) stated that earnings components have a high-level of prediction accuracy based on analyzed theoretical model. On the other hand, the study from Jantadej, as cited in Kamaluddin et al., (2015) claimed that cash flow pattern is more reliable than the information of earnings as distress indicator. Therefore, in order to accomplish a better finding, this study adopted these two theories as the financial distress indicator by focusing on four patterns of cash flow and net loss as the representative of earnings components.

By choosing secondary data as the research design, the authors will obtain a valid and reliable data to be analyzed (Sugiyono, 2015). Different statistical tools also have a different function. Therefore, in this case the authors have chosen some statistical tools including SPSS version 25 and Microsoft Excel 2016 which are expected to meet this research's needs, especially for data processing. Some methods are applied in order to meet the research objectives: descriptive test, Kruskall-Wallis test, Mann-Whitney Post Hoc Test, and accuracy test. Descriptive test aims to describe the state of the data as it is and provide the basic information through the data used which consists of maximum, minimum, mean, and standard deviation. Kruskall-Wallis concerns as comparative test along with Mann-Whitney as its post hoc test to obtain more detail information. Accuracy test consist of accuracy rate estimation, Type I Error, and Type II Error which are detailed as follow:

$$Accuracy\ Rate = \frac{The\ number\ of\ correct\ Predition}{Total\ number\ of\ Samples} \times 100\% \quad (1)$$

Source: (Diyanti, Januri, & Sari, 2017)

Table 4 TYPE OF ERRORS		
Actual Position	**Model's Prediction**	
	Distress	**Non-distress**
Distress	Correctly Predicted	Type I Error
Non-distress	Type II Error	Correctly Predicted

Source: (Ashraf, Felix, & Serrasqueiro, 2019)

These following equations are the formula of Type I Error and Type II Error:

$$Type\ I\ Error = \frac{The\ number\ of\ Type\ I\ errors}{Total\ actual\ number\ of\ Distress\ Samples} \times 100\% \quad (2)$$

Source: (Ashraf, Felix, & Serrasqueiro, 2019)

$$Type\ II\ Error = \frac{The\ number\ of\ Type\ II\ errors}{Total\ actual\ number\ of\ Non-Distress\ Samples} \times 100\% \quad (3)$$

Source: (Ashraf, Felix, & Serrasqueiro, 2019)

In addition, to find out the percentage of the overall error, the researcher employed the overall error formula as shown below:

$$Overall\ Error = \frac{The\ number\ of\ Total\ Incorrect\ Prediction}{Total\ number\ of\ Samples} \times 100\% \quad (4)$$

Source: (Ashraf, Felix, & Serrasqueiro, 2019)

However, below are the equations to find out the accuracy rate of each model based on Type I Error and Type II Error:

$$Type\ I\ Error = \frac{The\ number\ of\ correct\ Prediction\ based\ on\ Type\ I\ errors}{Total\ actual\ number\ of\ Distress\ Samples} \times 100\% \quad (5)$$

Source: (Ashraf, Felix, & Serrasqueiro, 2019)

$$Type\ I\ Error = \frac{The\ number\ of\ correct\ Prediction\ based\ on\ Type\ II\ errors}{Total\ actual\ number\ of\ Non-Distress\ Samples} \times 100\% \quad (6)$$

Source: (Ashraf, Felix, & Serrasqueiro, 2019)

RESULTS AND DISCUSSION

Table 5 DESCRIPTIVE STATISTIC RESULT: WCTA, RETA, EBITTA, MCTL, STA, EBTCL, ROA, TDTA, CACL					
Model	**N**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
WCTA	65	-4.2859	0.6582	-0.24	1.1568

RETA	65	-9.5145	0.2361	-1.004	2.4628
EBITTA	65	-0.2959	0.1339	-0.003	0.0796
MCTL	65	0.0085	11.9989	1.2185	2.4523
STA	65	0.1863	2.0113	0.856	0.387
EBTCL	65	-0.5003	1.0224	0.017	0.2691
ROA	65	-0.2898	0.0994	-0.022	0.0771
TDTA	65	0.085	5.0733	0.9795	1.1911
CACL	65	0.1064	6.4569	1.8031	1.4923
Source: Proceed by researchers using SPSS 25, 2021					

Table 5 shows the descriptive statistics of the variables used in this study. This table is intended to provide a description in the form of minimum, maximum, mean, and standard deviation.

Table 6
KRUSKAL-WALLIS TEST STATISTICS

Item Name	Model
Kruskal-Wallis H	22.642
Df	3
Asymp. Sig	0
Source: Processed by researchers using SPSS 25, 2021	

The financial distress prediction models of Altman, Springate, Grover, and Zmijewski are statistically significant different. Reflecting on the result of Kruskal-Wallis test, the p-value is less than 0.05 which is equal to 0.000 as revealed in the Table 6. This means that there is at least one interpolated median that is different than the other. This result is in line with the finding of Al-Kaff (2016) who argued that based on Kruskal-Wallis test, there were statistically significant difference among Altman, Springate, Grover, and Zmijewski models. However, to define specifically which groups are significantly different, a more comprehensive test as a post hoc test is required. Mann Whitney U test is one of the commonly used tests.

The results of Mann Whitney U Test as exhibited in the Table 7 show that there are statistically significant differences among the pairs of Altman and Springate, Altman and Grover, Altman and Zmijewski, Springate and Zmijewski, and Grover, and Zmijewski. It interprets that these pairs developed dissimilar formulation index along with diverse combination of variables and proxies to build a complex model. However, there might be a similarity between Springate and Grover regarding the combination of variables' components where these two models use both working capital to total assets as well as earnings before interest and taxes. Moreover, Grover only added one diverse variable which is return on assets where it implies that the other two are remain the same. Thus, the discrepancy of the interpolated median between Springate and Grover will not be as much as the other groups. This outcome is consistent with the findings of Fredy (2018), Hastuti (2015), and Sembiring et al. (2015).

Table 7
MANN-WHITNEY U TEST RESULT

No.	Paired Model	Mann-Whitney U	Z	Asymp. Sig (2-tailed)
Pair 1	Altman – Springate	1362	-3.495	0
Pair 2	Altman - Grover	1240	-4.063	0

Pair 3	Altman - Zmijewski	1579	-2.484	0.013
Pair 4	Springate – Grover	1769	-1.599	0.11
Pair 5	Springate – Zmijewski	1428	-3.187	0.001
Pair 6	Grover – Zmijewski	1551	-2.615	0.009
Source: Proceed by researcher using SPSS 25, 2021				

Table 8
THE OVERALL ACCURACY RATE OF ALTMAN, SPRINGATE, GROVER, AND ZMIJEWSKI MODELS IN PREDICTING FINANCIAL DISTRESS

Model	Total Sample	Number of Correct Prediction			Accuracy Rate
		Distress	Non-distress	Total	
Altman (Z-Score)	65	17	18	35	53.85%
Springate (S-Score)	65	21	13	34	52.31%
Grover (G-Score)	65	8	33	41	63.08%
Zmijewski (X-Score)	65	8	35	43	66.15%
Source: Adjusted by researcher using Microsoft Excel 2016					

Table 8 reports the accuracy test which interprets that the highest overall accurateness rate has been performed by Zmijewski, which also has the highest total number of correct prediction models. However, the lowest level of overall accuracy is performed by Springate model. The characteristic of textile industry might be the cause of these findings. Other than non-manufacturing industry, manufacturing industry manages the product starting from raw materials processing until becoming a finished good, it is including textile sector as a part of manufacturing industry. Hence, it needs a huge amount of funding to capitalize the production process.

Moreover, most textile firms in Indonesia still lack of technology awareness, so they are still stuck at the old process. This would impact to the effectiveness of operational cost. This is also consistent with the problem of the industry, where there is a prodigious invasion of imported goods. It might contribute a negative outcome to its sales, earnings, debts, and assets. The most obvious effect is on the earnings in which more than a half of textile firms have experienced negative net income, and even three companies are still struggling with negative income since the late five years.

Other than that, total debt of some companies is exceeding its total assets which are countered by the unappropriated earnings that have been negative for a long time and it also causes a negative equity or capital deficiency. Consequently, the gap between total debt and total equity is relatively significant, while the total asset is not as much as total debt. It is allegedly due to an attempt of company to cover the interest payment in which indicates that the company is not capable to pay the debts at all. Therefore, Zmijewski might be ideal for textile companies since the variables are focused on net income, total debt, total assets, current assets, and current liabilities. This finding is consistent with the other findings by Ashraf et al. (2019).

Table 9
LEVEL OF ERROR OCCURRED BY ALTMAN, SPRINGATE, GROVER, AND ZMIJEWSKI MODELS BASED ON TYPE I AND TYPE II ERROR

Model	Type I Error	Type II Error	Overall Error
Altman (Z-Score)	19.05%	59.09%	46.15%
Springate (S-Score)	0.00%	70.45%	47.69%
Grover (G-Score)	61.90%	25.00%	36.92%
Zmijewski (X-Score)	61.90%	20.45%	33.85%
Source: Adjusted by researcher using Microsoft Excel 2016			

Table 10
ACCURACY RATE OF ALTMAN, SPRINGATE, GROVER, AND ZMIJEWSKI MODELS BASED ON TYPE I ERROR AND TYPE II ERROR

Model	Type I	Type II	Overall Accuracy
Altman (Z-Score)	80.95%	40.91%	53.85%
Springate (S-Score)	100.00%	29.55%	52.31%
Grover (G-Score)	38.10%	75%	63.08%
Zmijewski (X-Score)	38.10%	79.55%	66.15%
Source: Adjusted by researcher using Microsoft Excel 2016			

CONCLUSION AND IMPLICATIONS

After executing several statistical tests and examinations, there are some conclusions that have met the study's objectives. First, according to the Kruskal-Wallis test result, there are statistically significant difference among the prediction models of Altman, Springate, Grover, and Zmijewski. The difference is because there are obvious differences of population median among these prediction models. However, in order to find specifically which group that is significantly different, the Mann Whitney Post Hoc is conducted as the comprehensive difference test. It is found that in pairs, there are no statistically significant difference between Springate and Grover. Meanwhile, the other pairs have significant difference. The inconsistent result between Kruskal-Wallis test and Mann Whitney Post Hoc occurred because of the total significant different groups. Basically, how these tests work are identically the same. However, Kruskal Wallis test cannot mention the specific groups that are statistically significant difference. Therefore, a comprehensive test like Mann Whitney test is required to specify which groups that have statistically significant difference.

In addition, the result of accuracy test indicates that the most ideal prediction model of financial distress is Zmijewski's model which combined three financial ratios, return on asset, total debt to total assets, and current assets to current liabilities ratios. Referring to the components of variables, Zmijewski tends to focus on the income, debt, and assets which are relatable to the characters and condition of Indonesia textile companies. The characteristics are referred to the industry condition such as production process, sales, operational cost, earnings, the awareness of technology, and the opportunities of import activities. Production process has a strong linkage with company's debt where it needs an intense capitalization to achieve a positive progress in a long term. Operational cost and the awareness of technology also relate to the company's efficiency. If there is a lack attention on the new technology, then the operational cost would increase, the efficiency will not be maximized, and also there is higher possibility of assets depreciation. In addition, the increase of imported goods in Indonesia is giving a negative effect in some cases which also has an impact on the company's income. Thus, the condition and the characteristic of Indonesia textile companies are considered fit to the prediction model developed by Zmijewski. It can be used as an early warning or simple predictor to determine the financial condition of companies engaged on textile sector. However, the weakness of Zmijewski's model is it is not too strict when predicting financial distress accurately, even though it is great in determining a stable or healthy condition. Thus, more combination between this model and market-based prediction model would be recommended.

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