EVALUATION OF PREDICTION ACCURACY MODELS FOR BANKRUPTCY IN INDONESIAN BANKS[1]

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Abstract

This research aims to find the most accurate model for predicting bankruptcy in the Indonesian banking industry. The data used are secondary data in the form of financial reports from 2018 to 2022. The methodology includes hypothesis testing using normality, homogeneity, and one-way ANOVA tests. The research results indicate that the Springate model is the most suitable model for predicting bankruptcy in the Indonesian banking industry, followed by the Zmijewski model, and the Altman model. The results obtained are relevant for financial managers and regulatory authorities, showing that the Springate model can be used to assess the financial health of the banking industry in Indonesia and to take concrete preventive measures before bankruptcy occurs.

Keywords: Indonesia stock exchange, financial soundness, banking supervision

JEL Classification: E44; G01; G17

1. Introduction

Analysis and prediction of the financial condition of a company have become very important in the era of technological advancement and economic cycle changes that affect intense competition in the business world (Ali, Aysan & Yousef, 2023). The capital market, as a source of funding or alternative financing for publicly traded

[1] *This research is based on the phenomenon of the collapse of the banking industry in the United States.*

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companies, can reflect the performance and financial condition of the company. Investors will examine the financial condition of the company before deciding to invest their funds (Grikietytė & Šniukienė, 2023). Therefore, companies are expected to adapt to changes and analyze or predict the financial condition of the company to meet market demands (Agwata, 2018).

The prediction model of bankruptcy for a company is highly needed by various parties such as lenders, investors, government, accountants, and management due to the uncertain economic conditions in Indonesia, which potentially lead to financial difficulties or even bankruptcy for the company (Ayvaz & Erkan, 2023; Gupta, 2023; Vu & Tran, 2023). A prediction error regarding the continuity of a company's operations in the future can have consequences, including the loss of revenue or investment that has been invested in a company. However, in addition to the uncertain economic conditions, the phenomenon of the weakening of the rupiah exchange rate is also a concern for the banking industry in Indonesia. If the rupiah continues to weaken to the level of Rp 15,000, it is estimated that five national banks will collapse, similar to the economic crisis in late 1998 that caused many banks to "fall" due to the weakening of the rupiah exchange rate against the US dollar. This means that the Otoritas Jasa Keuangan (OJK) is taking anticipatory steps by calling the bank management related to the depreciation (Fredy, 2018; Agustina, 2022).

According to several studies (Ameri Siahoee & Kordlouie, 2018; Bansal et al., 2020; Shree & Selvam, 2023), in testing the three bankruptcy prediction models (Altman, Springate, and Zmijewski) on the researched companies, it was found that the Altman Z-Score model provided the highest prediction rate in 15 companies, while the Springate model provided a prediction rate for 7 companies. On the other hand, the Zmijewski model provided the lowest prediction rate, with no companies predicted to go bankrupt. Another study conducted by (Sitorus, 2023) on delisted companies in the Indonesia Stock Exchange during the period of 2019-2021 showed that the Altman model had the highest accuracy rate, reaching 71%, while the Springate model had an accuracy rate of 70%, and the Zmijewski model only achieved an accuracy rate of 65%. Thus, both studies show that the Altman model has the highest accuracy rate, followed by the Springate and Zmijewski models.

Research on corporate bankruptcy has been conducted extensively in Indonesia and other countries. However, research on the

banking industry and the appropriate comparison of bankruptcy prediction models is still very limited. Therefore, we are interested in conducting a study entitled "*Evaluation of Prediction Accuracy Models for Bankruptcy In Indonesian Banks*". The aim of this study is to determine which model is the most accurate in predicting bankruptcy in the banking industry in Indonesia, because previous research results between the Altman, Springate, and Zmijewski models have not been consistent in analysing corporate or banking industry bankruptcies. This research aims to provide empirical evidence on the accuracy of the Altman, Springate, and Zmijewski models in predicting bankruptcy in the Indonesian banking industry. This is done based on the background that has been presented.

2. Literature review

The Altman, Springate and Zmijewski models have been analysed in several previous studies. A study conducted by Dailibas (2021) showed strong significant results in using the Altman, Springate and Zmijewski models to analyse bankruptcy. Meanwhile, a study conducted by Melina and Kalinggo (2023) on companies listed on the Indonesia Stock Exchange showed that the Altman $Z\text{-}_{Score}$ and Springate models provided similarly high bankruptcy prediction values. Therefore, the results of both studies indicate that the Altman model has the same accuracy in predicting bankruptcy.

The theoretical framework for this research consists of the theory of bankruptcy and credit prediction models, Bank Indonesia's policy theory regarding credit monitoring and bankruptcy prevention, and the theory of using bankruptcy and credit prediction models in Bank Indonesia. As a result, the bankruptcy and credit prediction models used by Bank Indonesia can be analysed and evaluated, results can be obtained, and recommendations can be made to improve the accuracy of the bankruptcy prediction model in the banking industry in Indonesia.

2.1. Model Altman

The Altman model (Altman, 1968) uses the multiple discriminant analysis method with five types of financial ratios, namely working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, the market value of equity to book value of total debts, and sales to total assets. To this day, the Altman $Z\text{-}_{Score}$ is still widely used by researchers, practitioners,

and academics in the accounting field compared to other prediction models (Irawan, 2023). The results of Altman's developed research are:

$$Z = 1.2Z_1 + 1.4Z_2 + 3.3Z_3 + 0.6Z_4 + 0.999Z_5 \quad (1)$$

Where:
Z_1 : Working capital
Z_2 : Retained earnings
Z_3 : Earnings before taxes
Z_4 : Book value of equity/book value of debt
Z_5 : Sales/total asset

In its development, the Altman model underwent revisions so that it could be used not only for public manufacturing companies but also for private companies (Altman, Iwanicz, Laitinen & Suvas, 2017; Altman, 2018). The revision was carried out by changing one of the variables used in the previous model.

$$\boldsymbol{Z'} = 0.0717Z_1 + 0.874Z_2 + 3.107Z_3 + 0.420Z_4 + 0.988Z_5 \quad (2)$$

Where:
Z_1 : Working capital/total asset
Z_2 : Retained earnings/total asset
Z_3 : Earnings before taxes/total asset
Z_4 : Book value of equity/book value of debt
Z_5 : Sales/total asset

The final result in the form of $Z\text{-}_{Score}$ values for each company will be grouped according to the critical value standards set by Altman (Irawan, 2023), which are:

a. If the Z-Score value is greater than 2.99, the company is in the safe zone, which means the company is healthy or not bankrupt.

b. If the Z-Score value is between 1.01 and 2.99, it is in the grey zone, which means the company is in a grey area, where the company may potentially not go bankrupt or go bankrupt.

c. If the Z-Score value is less than 1.01, the company is in the distress zone, where the company is unhealthy or potentially facing bankruptcy.

2.2 Model Springate

This model was developed by Springate in 1978 using multiple discriminant analysis. The model can be used to predict bankruptcy with an

accuracy rate of 92.5% (Irawan, 2023). The model successfully developed by Springate is :

$$\boldsymbol{S} = 1.03A + 3.07B + 0.66C + 0.4D \quad (3)$$

Where:
A : Working capital/total asset
B : Earnings before taxes/total asset
C : Earnings before taxes / current liabilities
D : Sales/total asset

The final result in the form of Springate score for each company will be grouped according to the critical value standards set by Springate as follows.

a. If the Springate value is greater than 0.862, the company falls into the category of healthy companies.

b. If the Springate value is less than 0.862, the company falls into the category of unhealthy companies or potentially bankrupt companies.

2.3 Model Zmijewski

Model Zmijewski (1984) uses ratio analysis to measure the performance, leverage, and liquidity of a company for its prediction model. Zmijewski used probability analysis applied to 40 bankrupt companies and 800 surviving companies at that time (Irawan, 2023; Leisen & Swan, 2023). The successfully developed model is:

$$\boldsymbol{X} = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3 \quad (4)$$

Where:
X_1 : Return on asset
X_2 : Debt ratio
X_3 : Current ratio

The final result in the form of Zmijewski score for each company will be grouped according to the critical value standards set by Zmijewski as follows.

a. The higher the Zmijewski value (positive value), the more likely the company is classified as bankrupt.

b. The smaller the Zmijewski value (negative value), if the Springate value is also smaller and negative, the company is categorized as healthy.

3. Research and methodology

To determine whether a company's financial performance is good or not, the company must be able to meet its costs with the revenue generated during a certain period or exceed the break-even point. One way to evaluate a company's financial performance is through financial statement analysis, which can help identify problems that occur. In this study, the framework design is described with financial statements to predict bankruptcy through the Altman, Springate, and Zmijewski models to determine a company's score. After that, the score will be used to categorize the health condition of the banking industry in Indonesia, whether healthy, in the grey area, or bankrupt.

In this research, quantitative empirical method is used with a deductive approach, where the focus is on developing theory first, then collecting data to test hypotheses or existing theories. The data collected in this research consists of primary and secondary data. After the data is gathered, statistical techniques are employed to test hypotheses or answer research questions. Furthermore, the research is concentrated on the development and testing of a bankruptcy prediction model in the banking industry in Indonesia.

4. Analysis and discussions

To assess the suitability of data and analyze factors, it is necessary to perform prerequisite tests that the data must meet. These prerequisite tests are intended to ensure that the data to be used in factor analysis meets the requirements and can be relied upon in generating analysis results.

Table 1

Descriptive Statistics of Research Variables

Variable	N	Min	Max	Mean	SD
$Z\text{-}_{Score}$	50	1,085	5,822	2,44612	1,078911
$S\text{-}_{Score}$	50	0,713	1,989	0,90878	0,187491
$X\text{-}_{Score}$	50	-33,140	19,669	-3,94662	9,597896

Sources: Data processed by author from IBM SPSS Statistics version 25.0.

In Table 1, there are several things that can be explained, namely a) the average value of Z-Score (Altman) is 2.44612 with a sample size of 50. The minimum and maximum values of $Z\text{-}_{Score}$ (Altman) are 1.085 and 5.822, respectively. The standard deviation of

Z-Score (Altman) is 1.078911. Based on the close values of the mean and standard deviation, it can be concluded that the deviation of Z-Score (Altman) data is low. b) the average value of S-Score (Springate) is 0.90878 with a sample size of 50. The minimum and maximum values of S-Score (Springate) are 0.713 and 1.989, respectively. The standard deviation of S-Score (Springate) is 0.187491. Based on the close values of the mean and standard deviation, it can be concluded that the deviation of S-Score (Springate) data is low. c) the average value of X-Score (Zmijewski) is -3.94662 with a sample size of 50. The minimum and maximum values of X-Score (Zmijewski) are -33.140 and 19.669, respectively. The standard deviation of X-Score (Zmijewski) is 9.597896. It can be concluded that the deviation of X-Score (Zmijewski) data is low.

4.1. Bankruptcy Prediction Analysis Results Z-Score (Altman)

The analysis in this study is the Z-Score discriminant model. This analysis is used to identify and analyze the prediction of bankruptcy in the banking industry in Indonesia for the period of 2018-2022.

The Z-Score formula is as follows:

$$\boldsymbol{Z} = 1.2 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \qquad (5)$$

Based on the calculation results using Excel program, the following results were obtained:

Table 2

The Calculation Results of Z-Score

Bank	Categories				
	2018	2019	2020	2021	2022
BDMN	Grey Area	Grey Area	Grey Area	Grey Area	Grey Area
BBRI	Grey Area	Grey Area	Grey Area	Grey Area	Grey Area
BMRI	Grey Area	Grey Area	Healthy	Grey Area	Grey Area
BBNI	Healthy	Grey Area	Grey Area	Grey Area	Grey Area
BRIS	Grey Area	Grey Area	Healthy	Grey Area	Grey Area
BTPN	Healthy	Healthy	Grey Area	Grey Area	Grey Area
NISP	Grey Area	Grey Area	Healthy	Grey Area	Healthy
BBTN	Grey Area	Grey Area	Grey Area	Grey Area	Grey Area
BTPS	Grey Area	Healthy	Grey Area	Grey Area	Grey Area
BBCA	Healthy	Healthy	Grey Area	Grey Area	Grey Area

Source: *Data processed by the authors*

Table 2 shows that there are several banking industries in Indonesia that have been categorized as Healthy in the prediction for the years 2018-2022, namely BMRI, BBNI, BRIS, BTPN, NISP, BTPS, and BBCA. However, all banks have experienced Grey Area prediction at some point. In that period, there were 3 banks that were consistently categorized as Grey Area, namely BMDN, BBRI, and BBTN. No banks have ever been categorized as Bankrupt in the prediction for the years 2018-2022.

The implication of this research is the importance of using the Springate model in evaluating the financial health of the banking industry in Indonesia. Banks categorized as Grey Area need to take preventive measures before bankruptcy occurs. Moreover, this research finding also emphasizes that the Springate model can be used by financial managers and regulators to evaluate the financial health of the banking industry in Indonesia and provide concrete steps for prevention before bankruptcy occurs. These research findings are in line with previous studies conducted by (Putri, et al., 2020; Tiryaki, 2021; Ullah, et al., 2021).

4.2 The Results of Bankruptcy Prediction S-$_{Score}$ (Springate)

This research utilizes the discriminant analysis model S-$_{Score}$ to predict bankruptcy in the banking industry in Indonesia during the period 2018-2022. The discriminant analysis model S-$_{Score}$ is a technique that combines various financial indicators from the researched banks to generate a score indicating the level of bankruptcy risk. By collecting financial data from the banks during that period, researchers can apply the S-$_{Score}$ formula to identify high-risk banks that may face financial difficulties.

The results of the S-$_{Score}$ analysis can provide valuable insights to stakeholders in the banking industry. Information about banks with high bankruptcy risk can assist regulators, investors, and bank management in taking appropriate preventive measures. Thus, this research can contribute to maintaining the stability and health of the banking industry in Indonesia during the studied period. By using the accurate predictive model, relevant parties in the banking industry can take early actions to prevent or address financial issues before reaching the point of bankruptcy. This helps improve the quality of risk management and enables more informed decision-making within the banking industry. The following is the formula for the S-$_{Score}$:

$$\boldsymbol{S} = 1.03A + 3.07B + 0.66C + 0.4D \quad (6)$$

Based on the calculation results using Microsoft Excel, the following results were obtained (see Table 3).

Table 3

The Calculation Results of S-Score

Bank	Categories				
	2018	2019	2020	2021	2022
BDMN	Healthy	Healthy	Healthy	Healthy	Bankrupt
BBRI	Healthy	Healthy	Healthy	Healthy	Bankrupt
BMRI	Bankrupt	Bankrupt	Bankrupt	Bankrupt	Bankrupt
BBNI	Healthy	Healthy	Healthy	Healthy	Healthy
BRIS	Healthy	Healthy	Healthy	Bankrupt	Healthy
BTPN	Bankrupt	Bankrupt	Healthy	Healthy	Bankrupt
NISP	Bankrupt	Healthy	Bankrupt	Bankrupt	Healthy
BBTN	Bankrupt	Bankrupt	Bankrupt	Bankrupt	Bankrupt
BTPS	Healthy	Healthy	Healthy	Healthy	Healthy
BBCA	Healthy	Healthy	Healthy	Healthy	Healthy

Source : *Data processed by the author.*

Table 3 shows that there are several banking industries in Indonesia that have experienced healthy predictions during the period of 2018-2022, including BDMN, BBRI, BBNI, BRIS, BTPN, NISP, and BBCA. However, there are several banking industries in Indonesia that have experienced bankrupt prediction during the period, namely BMDN, BBRI, BMRI, BRIS, BTPN, NISP, and BBTN. From the analysis, there are 3 banking industries in Indonesia that always experience healthy predictions during the period of 2018-2022, namely BBNI, BTPS, and BBCA. Meanwhile, there are 2 banking industries in Indonesia that always experience bankrupt predictions during that period, namely BBRI and BRIS. In terms of implications, this analysis can provide useful information for financial managers and regulators in evaluating the financial health of the banking industry in Indonesia. By knowing the banking industries that always experience healthy and bankrupt predictions, financial managers can evaluate and improve certain aspects to prevent bankruptcy. In addition, regulators can take more proactive actions in supervising banking industries that always experience bankrupt predictions to ensure financial system stability. The findings of this research confirm the results of previous studies

conducted by (Verlekar & Kamat, 2019; Sybirtsev, Mazhara & Moskalenko, 2020; Ridwan, Pagalung, & Kara, 2022).

4.3 The Result of Bankruptcy Prediction X-$_{Score}$ (Zmijewski)

The analysis in this study is the X-$_{Score}$ discriminant model. This analysis is used to determine and analyze the bankruptcy prediction in the banking industry in Indonesia for the period of 2018-2022.

The X-$_{Score}$ formulation is as follows:

$$\boldsymbol{X} = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3 \quad (7)$$

Based on the calculation results using Microsoft Excel program, the following results were obtained.

Table 4

The Calculation Results of X-$_{Score}$

Bank	Categories				
	2018	2019	2020	2021	2022
BDMN	Healthy	Healthy	Healthy	Healthy	Bankrupt
BBRI	Healthy	Healthy	Healthy	Bankrupt	Bankrupt
BMRI	Bankrupt	Bankrupt	Healthy	Healthy	Bankrupt
BBNI	Healthy	Healthy	Healthy	Healthy	Healthy
BRIS	Healthy	Healthy	Healthy	Healthy	Healthy
BTPN	Healthy	Healthy	Healthy	Healthy	Healthy
NISP	Bankrupt	Healthy	Healthy	Healthy	Healthy
BBTN	Bankrupt	Bankrupt	Healthy	Bankrupt	Bankrupt
BTPS	Healthy	Healthy	Healthy	Healthy	Bankrupt
BBCA	Healthy	Healthy	Healthy	Bankrupt	Bankrupt

Source : *Data processed by the author*

In Table 4, it can be seen that several banking industries in Indonesia were categorized as healthy predictions during the period of 2018-2022, including BDMN, BBRI, BMRI, BBNI, BRIS, BTPN, NISP, BBTN, BTPS, and BBCA. Meanwhile, the banks that have experienced bankrupt predictions are BDMN, BBRI, BMRI, NISP, BBTN, BTPS, and BBCA. There were three banks that consistently entered the healthy prediction category during that period, namely BBNI, BRIS, and BTPN.

From the X-$_{Score}$ (Zmijewski) analysis results, it can be seen that several banking industries in Indonesia consistently entered the

healthy prediction category during that period. This indicates that the X-$_{Score}$ (Zmijewski) model is more realistic in predicting bankruptcies in the Indonesian banking industry during that period and is in line with the current conditions. These findings also have important implications for the Indonesian banking industry, namely the importance of adopting more accurate credit analysis methods that are in line with the changing market conditions. By using the right method, the banking industry can minimize the risk of unpaid credit and ensure healthy financial performance. Philosophically, these findings emphasize the importance of adopting more advanced technology and methodology in the business world. Rapid technological and methodological developments can provide significant benefits to the business world, especially in decision-making. For example, in credit analysis, the use of more advanced methods can provide more accurate results and help the banking industry make better decisions. Therefore, this finding supports research by (Zelenkov, Fedorova & Chekrizov, 2017; Prusak, 2017; Manousaridis, 2017; Karas & Srbová, 2019; Laurila, 2020; Bărbuță-Mișu & Madaleno, 2020; Alibabaee & Khanmohammadi, 2022).

4.4 Data Normality Testing

The normality test in this study is a statistical procedure aimed at evaluating whether the data used in the model and statistical analysis follow a normal distribution or not. A normal distribution is a symmetrical distribution around its mean and is often an important assumption in many statistical methods. Therefore, it is essential to ensure that the data used meet the assumption of normal distribution to ensure reliable analysis results.

In this research, the Kolmogorov-Smirnov normality test is employed to evaluate the data distribution. This test compares the empirical distribution of the observed data with the expected distribution (in this case, the normal distribution). The test generates a p-value, which indicates the statistical significance level of the comparison.

If the p-value from the normality test is greater than 0.05, the researchers can conclude that the data follows a normal distribution, and the assumption of normality in the statistical analysis can be maintained. However, if the p-value is less than or equal to 0.05, the researchers will conclude that the data does not have a normal distribution, and the assumption is not met.

By conducting the Kolmogorov-Smirnov normality test, this research ensures that the data used in the statistical analysis adheres to an appropriate distribution, resulting in more accurate and reliable research findings and conclusions.

Table 5

Normality Test Results

Univariate	Sig.	Probability	Description
$Z\text{-}_{Score}$	0,247	0,05	Normal
$S\text{-}_{Score}$	0,059	0,05	Normal
$X\text{-}_{Score}$	0,651	0,05	Normal

Sources: *Data processed by the author from IBM SPSS Statistics version 25.0.*

Based on the normality test results with the Kolmogorov Smirnov Test above, the probability value > 0.05. Therefore, it can be concluded that the data is normally distributed. This result indicates that the data taken from the sample meets the normal distribution assumption required to apply many statistical analysis techniques. Furthermore, this result emphasizes the importance of data validity in evaluating research hypotheses and provides confidence that the data taken from the sample can represent the population in general.

4.5 Homogeneity Testing with Levene Test

To determine whether the variable data in the model has homogenous distribution or not, a homogeneity test is conducted (Yitnosumarto & O'Neill, 1986). In decision-making, a good data model is one that has homogenous data distribution. To test for homogeneity, the probability value can be analyzed. If the probability value is > 0.05, then it can be concluded that the regression model meets the homogeneity assumption. Conversely, if the probability value is ≤ 0.05, then the regression model does not meet the homogeneity assumption.

The homogeneity test is conducted using the Levene Test, and the results can be seen in the following table.

Table 6

Homogeneity test results with Levene Test

Univariate	Sig.	Probability	Description
Altman- Springate- Zmijewski	0,062	0,05	Homogeneous

Sources: Data processed by the author from IBM SPSS Statistics version 25.0.

The model data tested by the Levene Test showed a probability value of 0.062, which is greater than the predetermined significance level of 0.05. Therefore, it can be concluded that the model data meets the assumption of homogeneity. This finding indicates that the data used in the study can be considered homogeneous so that the statistical analysis performed can be relied upon and the results can be interpreted accurately. This is important to ensure that the conclusions drawn from the statistical analysis results are not distorted by unwanted differences in variance between groups.

4.6 Testing One-Way ANOVA Test

In this study, One-way ANOVA analysis was used to compare Altman, Springate, and Zmijewski models in predicting bankruptcy in the banking industry in Indonesia with a significance level (α) of 5% = 0.05. The results of the One-way ANOVA Test showed that the probability value was 0.000, indicating a significant difference between the three models in predicting bankruptcy in the banking industry in Indonesia.

Table 7

One-Way ANOVA Test Results

Model	F-test	Sig.	Level of Significant
Altman- Springate- Zmijewski	17,897	0,000	0,05

Sources: Data processed by the author from IBM SPSS Statistics version 25.0.

Based on the data analysis using One Way ANOVA, a probability value of 0.000 was obtained which is smaller than the significance level of 0.05. Therefore, it can be concluded that there is a significant difference between the three models, namely Altman, Springate, and Zmijewski, in predicting the bankruptcy of the banking industry in Indonesia. In addition, this technique can also reveal the differences between each model compared to the other models. These findings can provide an important contribution to decision-making for investors and other stakeholders in choosing the appropriate model to predict the bankruptcy of the banking industry in Indonesia.

Table 8

Comparison of the Three Models

Description	Altman, Springate and Zmijewski		
	Z-Score	**S-Score**	**X-Score**
Healthy	20,00%	62,00%	72,00%
Grey Area	80,00%	-	-
Bankrupt	-	38,00%	28,00%

Sources: Data processed by author from IBM SPSS Statistics version 25.0.

Based on Table 8, it can be concluded that:

a. The Springate model predicts that 38.00% of the banking industry in Indonesia is in the bankrupt category and 62.00% is in the healthy category.

b. The Zmijewski model predicts that 28.00% of the banking industry in Indonesia is in the bankrupt category and 72.00% is in the healthy category.

c. The Altman model predicts that 80.00% of the banking industry in Indonesia is in the grey area category, 20.00% is in the healthy category, and none are in the bankrupt category.

Based on these results, it can be concluded that the Springate model is the most appropriate model to predict the bankruptcy of the banking industry in Indonesia with an accuracy rate of 38.00%, followed by the Zmijewski model with an accuracy rate of 28.00%, while the Altman model is not suitable for predicting the bankruptcy of the banking industry in Indonesia. This is because the Altman model, designed by Edward Altman in 1968, is a model for predicting the bankruptcy of manufacturing companies. This model is based on financial ratio analysis and calculates the Z-Score value which is then used to predict the likelihood of bankruptcy of the company. However, the banking industry in Indonesia has different business characteristics than manufacturing companies, so the financial ratios that form the basis of the Altman model are not always relevant to predict the bankruptcy of the banking industry in Indonesia. Therefore, the Altman model is not suitable for predicting the bankruptcy of the banking industry in Indonesia.

5. Conclusions

Based on the analysis results, it can be concluded that the Springate $S\text{-}_{Score}$ model is the most accurate model for predicting bankruptcy in the banking industry in Indonesia. This is also because the Springate $S\text{-}_{Score}$ model is the best model as it uses multi-discriminant analysis and key financial ratios considered crucial in predicting bankruptcy in the banking industry in Indonesia. Therefore, overcoming bankruptcy in the banking industry involves using accurate prediction models like the Springate $S\text{-}_{Score}$ to assist banks in making credit decisions.

However, despite the high accuracy of the Springate $S\text{-}_{Score}$ model in predicting bankruptcy in the banking industry in Indonesia, the model has limitations. For instance, the model solely relies on historical financial data and cannot consider non-financial factors that also influence the bankruptcy of banking institutions. Additionally, it is essential to note that even though this model aids in credit decision-making, the final decision must still be based on a comprehensive assessment of the financial and business conditions of the company.

In the geographical context of the research conducted in Indonesia, the solution to overcome bankruptcy in the banking industry also involves various stakeholders, including regulators and banking institutions. Regulators need to tighten supervision over banking institutions and improve the quality of oversight to prevent violations and fraud. Banking institutions need to enhance the quality of financial and risk management and strengthen internal monitoring and control.

The relevance to banking authority supervision is that this analysis provides crucial information for regulators to oversee and regulate the banking industry in Indonesia. By utilizing the proven accurate Springate $S\text{-}_{Score}$ model for bankruptcy prediction, regulators can gain deeper insights into the financial conditions and risks faced by banks in Indonesia.

Regulators need to ensure that banks showing high bankruptcy risks receive special attention and appropriate preventive measures. By enhancing the quality of supervision and monitoring, regulators can identify potential violations or fraud in the banking industry that may lead to further issues.

Furthermore, this analysis also offers guidance for banking companies to improve their financial and risk management. Strengthening internal monitoring and control enables banking

institutions to be more proactive in dealing with risks and minimizing the likelihood of bankruptcy. Therefore, the use of the Springate $S\text{-}_{Score}$ model in this analysis plays a crucial role in assisting banking authorities in maintaining stability and the health of the banking industry in Indonesia.

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