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Effectiveness Analysis for Financial Distress Prediction in the Transportation Sector During the Pandemic: A Comparison of the Altman, Zmijewski, And Grover Models

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ABSTRACT: The COVID-19 pandemic that began in March 2020 had a significant impact on the economic sector, including transportation. The Large-Scale Social Restrictions (PSBB) Policy and the Enforcement of Community Activity Restrictions (PPKM) limited community mobilization, stopped some economic activities, and closed public facilities, thereby reducing business profits. The transportation sector recorded a decrease in operational activities with negative growth of -15.04%. This condition causes the risk of financial distress, which is financial difficulties marked by insufficient company cash to pay debts, which can trigger significant losses up to bankruptcy. This study uses a qualitative method based on the analysis of transportation companies' financial statements for the 2019–2022 period to identify financial distress risks. The three prediction models used are Altman Z-score, Zmijewski, and Grover.

KEYWORDS: Covid-19 Pandemic, Financial Distress, Transportation Sector.

INTRODUCTION

The pandemic was first announced in March 2020 with several cases that claimed hundreds of lives due to the covid-19 virus. With this virus, government regulations that limit community mobilization by implementing the Enforcement of Community Activity Restrictions (PPKM) in the hope that the coronavirus will not spread more widely, resulting in the suspension of several segments of economic activities. As a result, community accessibility is limited and the temporary closure of public facilities causes their profits or income from business profits to decrease (Fitriyani, 2022). This causes business risks that can cause businesses to experience losses or financial crises which can be seen through a decrease in net profit and cash flow from revenue and sales also decrease. The variable costs that follow production changes may not be a big deal, but constant fixed costs become a significant burden for companies. The situation worsened when companies had debts due during the pandemic, all these factors gradually led to financial difficulties (Aprillianto et al., 2021).

The COVID-19 pandemic has had a significant impact on the transportation and warehousing sector, with a drastic decline in operational activities. Based on the COVID-19 Community Mobility Reports, the use of public transportation decreased by -57% during the PSBB and -37% during the relaxation of the PSBB in August 2020 (Nissa, 2020). This decline reflects a severe economic contraction, with the transportation and warehousing sectors recording negative growth of -15.04% (Karina et al., 2021). This situation often triggers financial distress, which is a difficult financial condition when a company is unable to meet its debt obligations (Sudrajat, 2019). Financial distress can damage a company's image, lower investor confidence, and worsen relationships with creditors and employees. Therefore, early prediction and prompt handling are essential to prevent bankruptcy and greater losses. Prediction models such as **the Altman Z-score (1968),** which can be used in various sectors globally, are very useful tools. In addition, the model of Zmijewski (1983), which is empirically proven, provides an additional perspective in analyzing bankruptcy risk. Alternatively, Grover's (2001) model is present as an improvement of Altman with a more concise and accurate approach.

Factors that affect financial distress include low ROA (Return On Assets) will indicate that there is a decline in the performance of the company in converting assets into profits, and this situation can be an indication in the form of conditions that trigger funding difficulties in the company. So, this will be included in a financial distress situation. Next, CR (Current Ratio) looks at how the company can pay off its short-term debt. Next is DAR (Debt to Total Assets Ratio) to measure how much the company's assets are financed by debt. The larger the DAR means the larger the loan that the company uses to generate profits related to the operational activities of the company. Furthermore, it was revealed that sales growth is shown by the acceptance in the sales process in the company's operations (Mappadang et al., 2019). A solution that can be used to overcome losses or financial crises is to attract investors to be able to invest their capital in the company. However, in fact, when a company's situation is not good, this situation cannot be covered because the data is based on financial statements that can be directly accessed on the Indonesia Stock Exchange (IDX). Data as of 15.00 18, October 2023, companies included in the special notation data on the IDX stating applications for bankruptcy declarations, applications for cancellation of peace, or in negative equity conditions as many as 13 companies that are the sample of this study. Among them, PT. AirAsia Indonesia Tbk, PT. Garuda Indonesia (Persero) Tbk, PT. Sidomulyo Selaras Tbk, PT. Berlian Laju Tanker Tbk, PT Blue Bird Tbk, PT Weha Transportasi Indonesia Tbk, PT Adi Sarana Armada Tbk, PT Eka Sari Lorena Transport Tbk, PT Pelayaran Nasional Bina Buana Raya Tbk, PT Samudera Indonesia Tbk, PT Wintermar Offshore Marine Tbk, PT. IMC Pelita Logistik Tbk, PT Humpuss Intermoda Transport Tbk.

LITERATURE REVIEW

2.1 Literature Review

2.1.1 Impact of the Pandemic on the Transportation Sector

The covid-19 pandemic has resulted in a significant impact that has permeated various aspects of the transportation sector around the world. One of the most visible impacts has been a sharp decline in demand for air, land, and sea transportation. According to data from the Central Statistics Agency, the number of domestic air transport passengers departing in January 2020 was 6.3 million people, down 9.85% compared to December 2019. The number of passengers to foreign (international) destinations decreased by 2.22% to 1.7 million people. The number of domestic sea transportation passengers departing in January 2020 was recorded at 2.2 million people, down 4.10% compared to December 2019. The number of train passengers departing in January 2020 was
34.1 million people, down 8.89% compared to December 2019.

The PSBB (Large-Scale Restrictions) has led to a decline in public confidence in travel involving crowds, and the social isolation measures implemented by many countries have led to a drastic decline in the number of passengers using various modes of transportation. In addition to a significant decline in demand, the transportation sector also experienced an extraordinary level of market uncertainty during the pandemic. This is influenced by factors such as the development of vaccinations, changes in travel patterns, and the government's response to the ongoing pandemic wave. This uncertainty makes long-term planning and investment in the transportation sector difficult, as it is difficult to predict market trends precisely.

This condition also results in great financial pressure for transportation companies. A sharp decline in their revenues, along with operating costs that remain high, has caused some companies to struggle to survive. This increases the risk of financial distress, which can impact the jobs and transportation services provided to the community. In addition, changes in policies and regulations implemented by governments in various countries also play an important role in changing the operational landscape of the transportation sector. Travel restrictions, strict hygiene protocols, and international travel-related rules have changed the way transportation companies operate and serve their customers. Overall, the COVID-19 pandemic has presented serious challenges to the transportation sector, and its impact will continue to be felt in a time that cannot be precisely predicted as we seek to address future changes in demand, regulatory and policy dynamics.

2.1.2 Risk of Financial Distress

The risk of financial distress is the possibility that a company faces serious financial difficulties and may face bankruptcy. This concept was first introduced by Edward I. Altman (Kumajas, 2022). The risk of financial distress can arise due to several factors, especially in the transportation sector, the main cause of this financial distress risk is a drastic decrease in demand for transportation services. The pandemic forced the imposition of travel restrictions and reduced social mobility, resulting in a significant decrease in demand for air, land, and sea transportation. As a result, many transportation companies have experienced a sharp decline in revenue, and this has led to serious financial pressures.

In addition, high levels of market uncertainty are also factors that contribute to the risk of financial distress in the transportation sector. When demand will fully recover and the extent to which the impact of the pandemic will continue is still a big question. This high level of uncertainty makes strategic planning and risk management more complicated for transportation companies trying to stay afloat. Ever-increasing financial pressures are also a serious problem. Many transportation companies have been forced to take drastic measures, such as increasing their debts, facing difficulties in paying employee salaries, or even facing the risk of bankruptcy. This situation further complicates companies' efforts to maintain their financial stability in the face of the prolonged impact of this pandemic.

2.1.3 Model Altman Z-Score

Several studies have been conducted to evaluate the effectiveness of financial ratio analysis in predicting business failure or bankruptcy. One of the studies related to this prediction is the double discriminant analysis conducted by Edward I Altman in 1968. Altman conducted research to identify financial ratios that are commonly used to predict bankruptcy in the various countries that are the focus of his study. The altman z-score bankruptcy model is a tool used to assess the level of risk of a company's bankruptcy by calculating various ratios and combining them in one discriminatory equation. Z-Score is a score generated from standard calculations that indicates the level of likelihood of a company's bankruptcy. The altman z-score formula is a multivariable formula used to assess the financial health of a company (Kusumayuda, 2022).

2.1.4 Model zmijewski

This bankruptcy prediction model was developed by Zmijewski in 1983. Zmijewski (1984) uses the analysis of liquidity ratios, laverage, and measures the performance of a company. In this model, the description used is that if the calculation through the formula produces a number of less than 0, it can be said that the company is still healthy or not experiencing financial difficulties. However, if it is more than 0, the company is predicted to go bankrupt (Sari, 2019).

2.1.5 Grover Model

The grover model is a model that was produced by redesigning and re- evaluating the altman z-score model conducted in 2001. In 1968, Jeffrey S. Grover conducted a study using samples that matched the altman z-score model. In his research, the cut-off value of this model is, if the G-Score value is less than or equal to 0.01, then the company is considered not to have experienced bankruptcy. However, if the g-score value exceeds 0.02, then the company is considered bankrupt (Sudrajat, 2019).

2.2 Previous Research

This study refers to previous relevant research related to the influence of validity analysis for financial distress prediction in the post-pandemic transportation sector: a comparison of the Altman Z-Score, Zmijewski, and Grover models. Research conducted by M. Agus Sudrajat (2019) compared three bankruptcy prediction models, namely Altman Z-score, Zmijewski, and Grover. Of the three models, the Grover model (G-Score) proved to be the most accurate in predicting bankruptcy with an accuracy rate of 85.14%. This study shows that the Grover model is able to provide more accurate predictions in identifying companies that are in financial distress.

Furthermore, Elisa Friska Anggraini (2024) conducted a comparative analysis of the Altman Z-score, Grover, and Fulmer models to predict financial distress in cosmetics sub-sector manufacturing companies listed on the IDX. The results of this study show that the Grover and Fulmer models have the same level of accuracy, which is 83.3%, in predicting financial distress. On the other hand, Septiana (2023) analyzed bankruptcy predictions using the Altman Z-score and Springate methods at PT. Indonesia Transport and Infrastructure Tbk. Both models provide the same prediction results, with a ratio value below the cut-off, which states that the company is bankrupt. This research underscores the importance of selecting the right model for bankruptcy analysis in various industry sectors.

Previous research has explored a variety of indicators to detect a company's financial risk, especially in contexts where financial failure is not defined as bankruptcy. (Ninh et al, 2022) uses the EBITDA (earnings before interest, taxes, and depreciation) ratio to interest payments, indicating that a company is considered to be in a financial distress zone if the ratio is less than 1. This approach highlights the importance of financial ratios in identifying a company's financial condition before it reaches a total failure rate. Meanwhile, (Campbell et al, 2022) emphasized the use of cash flow as a key indicator, focusing on negative net cash flows from post-interest operations as an early sign of financial problems. This cash flow-based approach provides a relevant alternative perspective, especially for companies experiencing liquidity difficulties despite not showing signs of formal insolvency. This research emphasizes the need for a multidimensional understanding of financial indicators in detecting financial risks.

This study has a difference in comparing the results of the analysis of the method used with the accuracy level test and uses two types of errors, namely type error 1 and type error 2 to show the number of errors when the sample of companies is predicted to go bankrupt but is actually not bankrupt, which will also be associated with the reality conditions in the special notation of the Indonesia Stock Exchange (IDX). Meanwhile, in previous research, many used type error 1. The sample used was transportation companies listed on the Indonesia Stock Exchange (IDX) during the covid-19 pandemic period, from 2020 at the beginning of the emergence of the covid-19 issue to 2022 when Indonesia was experiencing a pandemic period in which companies experienced negative equity or decline and were under supervision. The impact of the decline includes financial distress which is measured using three methods, namely Altman Z- Score, Zmijewski, and Grover. The determinant of the Company's reality conditions is seen from the results of the accuracy level that has been calculated using the accuracy calculation formula and looking at the facts of special notation on the Indonesia Stock Exchange (IDX).

RESEARCH METHODS

3.1 Research methods and data sources

In-depth analysis was carried out by adopting a quantitative approach using financial report data with an explanatory research design. This approach allows us to explore the relationship between the influence of the use of the Altman Z-Score Model, the Zmijewski Model, and the Grover Model on post-pandemic financial distress risk. To collect secondary data from the financial statements of transportation sector companies listed on the IDX. Through a careful data collection process, valuable insights can be gained about the trends and patterns of these companies, which will then be analyzed using trend analysis with financial data for the 2019 period
– 2022. Secondary information collection is also obtained from publication information sources, official information sources of functional agencies, and from the book system.

3.2 Objects of Research

The object of the study consisted of 13 transportation sector companies listed on the IDX for the sample time period used, namely 2019 - 2022 during the pandemic. By focusing on a specific sector, it can gain valuable insights into the sustainability of the industry as a whole measured by the financial state of the company. Companies that consistently publish complete financial statements and focus on the transportation sector have been significantly impacted by the pandemic. The selection of the sample was based on companies included in the special notation data on the IDX that declared applications for declaration of bankruptcy, applications for cancellation of peace, or in bankruptcy conditions and companies that actively published financial statements until 2022 were chosen as samples because this period included major crises, namely the COVID-19 pandemic in 2020, each of which had a significant impact on the global economy.

Table 3.1 Objects of Research Enterprises

Company Code	Company Name
CMPP	PT. AirAsia Indonesia Tbk
GIAA	PT. Garuda Indonesia (Persero) Tbk
SDMU	PT. Sidomulyo Selaras Tbk
BLTA	PT. Berlian Laju Tanker Tbk
BIRD	PT Blue Bird Tbk
WEAVE	PT Weha Transport Indonesia Tbk
ASSA	PT Adi Sarana Armada Tbk
LRNA	PT Eka Sari Lorena Transport Tbk
BBRM	PT Pelayaran Nasional Bina Buana Raya Tbk
SMDR	PT Samudera Indonesia Tbk
WINS	PT Wintermar Offshore Marine Tbk
PSSI	PT. IMC Pelita Logistik Tbk
HITS	PT Humpuss Intermoda Transport Tbk

3.3 Data Analysis Techniques

The data analysis technique used is a descriptive analysis based on financial data on company performance which is measured with three approach models for financial distress, namely the Altman Z-Score model, the Zmijewski model, and the Grover model to see changes from the period used, namely 2019-2022, which is the year when covid-19 occurred. Next, evaluating which model better reflects the actual state of financial distress risk prediction. In this analysis technique, the formula of each model is used, namely the Altman Z-Score Model, the Zmijewski Model, and the Risk Grover Model using Microsoft Excel media. Next, the data was tested using an accuracy level calculation to find out the results of the accuracy of the three models using the formula, Accuracy Rate = (Number of correct predictions / Number of samples) x 100%.

3.3.1 Research Proxies

This study uses secondary data, sourced from the financial statements of thirteen public companies listed on the main board of the Indonesia Stock Exchange, in the sub- sector category of 46 transportation. The financial statement data was obtained through an official report from the Indonesia Stock Exchange. The data used in this study are financial statements from the selected sample companies, with the period 2019-2022.

- **Altman Z-Score model:**

Z-Score = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4.

Information:

X1 = Working Capital/Total Asset X2 = Retained Earning/Total Assets

X3 = Earning Before Interest and Taxes/Total Asset X4 = Market Value of Equity/Book Value of Debt

The "cut off" values for this index are: $Z < 1.1$: Bankrupt, $1.1 < Z < 2.6$: Gray area or gray area, $Z > 2.6$: Healthy/not bankrupt (Sudrajat, 2019).

- **Model Zmijewski :**

Z = -4.3 –4.5X1+ 5.7X2+ 0.004X3.

Information:

X1= ROA (Return On Asset) X2= Leverage (Debt Ratio) X3= Liquidity (Current Ratio). In this model, the description used is that if the calculation through the formula produces a number of less than 0, it can be said that the company is still healthy or not experiencing financial difficulties. However, if it is more than 0, the company is predicted to go bankrupt.

- **Model Grover :**

G-Score = 1.650X1 + 3.404X3 –0.016ROA + 0.057.

information:

X1 = Working Capital/Total assets

X3 = Earnings Before Interest and Taxes/Total Assets ROA = Net Income/Total Assets.

If the G-Score value is less than or equal to 0.01, then the company is considered not to have experienced bankruptcy. However, if the g-score value exceeds 0.02, then the company is considered bankrupt.

3.5 Calculation of Accuracy Levels

The measurement of the accuracy level in this study consisted of three models, namely the Altman (Z-Score), Zmijewski (X-Score), and Grover (G-Score) models, calculated to determine the number of correct and false predictions from each model. Then, the prediction results of the three models are compared to determine the most accurate prediction model in predicting bankruptcy, taking into account the facts recorded in a special memorandum listed on the Indonesia Stock Exchange.

The accuracy rate is calculated to find out the correct number of predictions using the following formula: Accuracy Rate = (Number of correct predictions / Number of Samples) x 100%. In addition to the level of accuracy of each model used to predict bankruptcy, another consideration is the error rate. Errors are divided into two types, namely Type I and Type II. Type I error is a mistake in which a sample of companies is predicted not to go bankrupt but turns out to be bankrupt in reality. Meanwhile, Type II errors occur when a sample of companies is predicted to go bankrupt but is not actually bankrupt.

The error rate is calculated by the following formula:

Type I Error = (Number of Type I errors / Number of samples) x 100% Type I Error = (Number of Type II errors / Number of samples) x 100%

RESULTS AND DISCUSSION

4.1 Altman Z-Score Model Results

The following are the results of the calculation of the Altman Z-Score model which has been processed based on financial statements for the 2019-2022 period.

Table 4. 1 Altman Z-Score Model Calculation Results

Codes	2019	Reality Condition	2020	Reality Condition	2021	Reality Condition	2022	Reality Condition
BIRD	4.4018	asset > liability (ND)	-1.0867	asset > liability (ND)	5.6971	asset > liability (ND)	5.6204	asset > liability (ND)
GIAA	-3.166	asset > liability (ND)	-4.0645	enter special notation in BEI (FD)	-9.699	asset < liability (FD)	3.1113	enter special notation in BEI (FD)
SDMU	-2.211	asset > liability (ND)	-5.2312	asset > liability (ND)	-4.703	asset > liability (ND)	0.4854	enter special notation in BEI (FD)
WEHA	1.1279	asset > liability (ND)	-0.5629	asset > liability (ND)	0.1807	asset > liability (ND)	3.1293	asset > liability (ND)
ASSA	-0.228	asset > liability (ND)	-0.5282	asset > liability (ND)	0.5559	asset > liability (ND)	0.3285	asset > liability (ND)
LRNA	6.96	asset > liability (ND)	3.3247	enter special notation in BEI (FD)	3.6468	asset > liability (ND)	2.6407	asset > liability (ND)
SMDR	2.2074	asset < liability (FD)	2.1284	asset < liability (FD)	3.9522	asset > liability (ND)	6.3214	asset > liability (ND)
WINS	1.2372	asset > liability (ND)	2.3284	asset > liability (ND)	5.3882	asset > liability (ND)	6.4917	asset > liability (ND)
BLTA	8.3719	asset > liability (ND)	8.5798	asset > liability (ND)	9.7717	asset < liability (FD)	9.4058	enter special notation in BEI (FD)
CMPP	0.6492	asset < liability (FD)	-7.4619	enter special notation in BEI (FD)	-9.588	asset < liability (FD)	-9.8	asset < liability (FD)
BBRM	2.1828	asset > liability (ND)	0.4511	asset > liability (ND)	3.8773	asset > liability (ND)	9.4221	asset > liability (ND)
HITS	2.0905	asset > liability (ND)	1.2968	asset > liability (ND)	1.219	asset > liability (ND)	2.4211	asset > liability (ND)
PSSI	2.8122	asset > liability (ND)	3.4355	asset > liability (ND)	5.4924	asset > liability (ND)	8.4133	asset > liability (ND)

Information: Yellow; not healthy, Grey Area, Green; healthy, ND; Non-Distress, FD; Financial Distress.

Based on the results of the calculation above using the Altman Z-Score model, there are 7 companies that are experiencing financial difficulties, 5 companies that are in the gray zone or Grey Area, and 3 companies that are included in the healthy category or do not experience financial problems. However, in certain periods, there are companies that experience fluctuations, such as BIRD, which in 2019 was indicated to be healthy, then in 2020 was included in the category of experiencing financial difficulties, and returned to health or did not experience financial difficulties in the 2021– 2022 period. These results will be associated with the calculation of accuracy level, error type 1, and error type 2 to determine whether the calculation of the Altman Z- Score model reflects the actual reality conditions. This analysis will also be associated with the financial statements for the 2019–2022 period as well as the list of special notations listed on the Indonesia Stock Exchange.

Table 4. 2 Calculation of the accuracy level of the Altman Z-Score model

Calculation of the accuracy level of the Altman Z-Score model				
Year	Appropriate Predictions	Prediction Results		Sum
		Type Error 1	Type Error 2	
2019	37	0	2	39
2020	34	1	4	39
2021	36	0	3	39
2022	35	2	2	39
Sum	142	3	11	186
Accuracy Rate =				**76%**
Error Type 1 =		**2%**		
Error Type 2 =		**6%**		

Based on Table 3, the Altman Z-Score model shows an accuracy of 76%, with a prediction error of type I of 2% and type II of 6%. Here are the details of the calculation:

1. In 2019, out of 39 research objects, as many as 37 objects were predicted to be bankrupt by looking at the reality conditions of financial statements and IDX special notation, while 2 other objects experienced prediction errors (bankrupt, in the reality condition they are not bankrupt) which are included in type II error, and there is no type I error.
2. In 2020, out of 39 research objects, there were 34 objects with correct predictions and reflecting reality conditions. The other 5 objects experienced prediction errors with the number of Type errors I as many as 1 and Type error II as many as 4.
3. In 2021, out of 39 research objects, there were 36 objects with correct predictions and reflecting reality conditions. The other 3 objects experienced prediction errors with a total of 3 Type II errors and no Type I errors.
4. In 2022, of the 39 research objects analyzed, 35 objects were predicted to go bankrupt accurately, with 2 companies experiencing type I errors (not bankrupt in real conditions, predicted bankrupt in the calculations) and 2 companies experiencing type II errors (bankrupt in reality conditions but predicted not bankrupt in the calculations).

4.2 Results of the Zmijewski Model

The following are the results of the calculation of the Zimjewski model which has been processed based on financial statements for the 2019-2022 period.

Table 4. 3 Zmijewski Model Calculation Results

Codes	2019	Reality Condition	2020	Reality Condition	2021	Reality Condition	2022	Reality Condition
BIRD	-2.94	asset > liability (ND)	-2.605	asset > liability (ND)	-3.043	asset > liability (ND)	-3.256	asset > liability (ND)
GIAA	15.35	asset > liability (ND)	151.7	enter special notation in BEI (FD)	8.854	asset < liability (FD)	0.108	enter special notation in BEI (FD)
SDMU	0.811	asset > liability (ND)	2.252	asset > liability (ND)	1.724	asset > liability (ND)	1.187	enter special notation in BEI (FD)
WEHA	-1.88	asset > liability (ND)	-0.959	asset > liability (ND)	-1.184	asset > liability (ND)	-2.747	asset > liability (ND)

ASSA	-0.26	**asset > liability (ND)**	-0.24	**asset > liability (ND)**	-0.384	**asset > liability (ND)**	-0.537	**asset > liability (ND)**
LRNA	-3.41	**asset > liability (ND)**	-2.478	**enter special notation in BEI (FD)**	-2.672	**asset > liability (ND)**	-2.501	**asset > liability (ND)**
SMDR	-0.79	**asset < liability (FD)**	-0.977	**asset < liability (FD)**	-1.974	**asset > liability (ND)**	-3.062	**asset > liability (ND)**
WINS	-1.86	**asset > liability (ND)**	-1.923	**asset > liability (ND)**	-6.053	**asset > liability (ND)**	-23.73	**asset > liability (ND)**
BLTA	57.05	**asset > liability (ND)**	54.65	**asset > liability (ND)**	-1.571	**asset < liability (FD)**	-2.069	**enter special notation in BEI (FD)**
CMPP	1.232	**asset < liability (FD)**	6.167	**enter special notation in BEI (FD)**	9.218	**asset < liability (FD)**	10.04	**asset < liability (FD)**
BBRM	0.323	**asset > liability (ND)**	1.651	**asset > liability (ND)**	-0.061	**asset > liability (ND)**	-2.994	**asset > liability (ND)**
HITS	-0.65	**asset > liability (ND)**	-0.484	**asset > liability (ND)**	0.044	**asset > liability (ND)**	-0.795	**asset > liability (ND)**
PSSI	-2.54	**asset > liability (ND)**	-2.524	**asset > liability (ND)**	-3.346	**asset > liability (ND)**	-4.289	**asset > liability (ND)**

Information: Green; Healthy, Yellow; Not Healthy, ND; Non-Distress, FD; Financial Distress.

Based on the results of calculations using the Zmijewski model, there are 8 companies that do not experience financial problems and 5 companies that are predicted to be bankrupt or facing financial difficulties. However, in certain periods, some companies showed fluctuations, such as BLTA and BBRM, which in 2019 and 2020 were indicated to be unhealthy or experiencing financial difficulties, but in 2021– 2022 they were again included in the healthy category or did not face financial problems. These results will be further analyzed by linking them to the calculations of accuracy level, error type 1, and error type 2 to determine whether the Zmijewski model's predictions really reflect true financial conditions. In addition, this analysis will also be associated with the financial statements for the 2019–2022 period as well as special notations listed on the Indonesia Stock Exchange.

Table 4. 4 Calculation of the accuracy level of the Zmijewski model

Calculation of the accuracy level of the Zmijewski model				
Year	**As Predicted**	**Prediction Results**		**Sum**
		Error Type 1	**Error Type 2**	
2019	34	1	4	39
2020	34	2	3	39
2021	38	0	1	39
2022	38	1	0	39

Sum	144	4	8	186
Accuracy Rate =				**77%**
Error Type 1 =				**2%**
Error Type 2 =				**4%**

Based on Table 5, the Zmijewski model shows an accuracy of 77%, with a type I prediction error of 2% and type II of 4%. Here are the details of the calculation:

1. In 2019, out of 39 research objects, as many as 34 objects were predicted to be bankrupt by looking at the reality conditions of financial statements and IDX special notation, while 1 research object experienced a prediction error type I, namely in the calculation it was declared not bankrupt, but in the reality condition it was experiencing financial difficulties or financial unhealth. The other 4 research objects experienced (bankrupt, in the condition of reality not bankrupt) which were included in type II error.
2. In 2020, out of 39 research objects, there were 34 objects with correct predictions and reflecting reality conditions. The other 2 objects experienced prediction errors with the number of Type error I and Type error II as many as 3 research objects.
3. In 2021, out of 39 research objects, there were 38 research objects with correct predictions and reflecting reality conditions. 1 other research object experienced prediction errors with a number of Type errors II and no Type errors I.
4. In 2022, of the 39 research objects analyzed, 38 companies are predicted to go bankrupt appropriately, with 1 company experiencing type I error (not going bankrupt under real conditions.

4.3 Results of the Grover Model

The following are the results of the calculation of the Grover model which has been processed based on the financial statements for the 2019-2022 period.

Table 4. 5 Calculation Results of the Grover Model

Codes	2019	Reality Condition	2020	Reality Condition	2021	Reality Condition	2022	Reality Condition
BIRD	0.287	**asset > liability (ND)**	-1.252	**asset > liability (ND)**	0.27	**asset > liability (ND)**	0.408	**asset > liability (ND)**
GIAA	-0.78	**asset > liability (ND)**	-1.265	**enter special notation in BEI (FD)**	-3.33	**asset < liability (FD)**	1.963	**enter special notation in BEI (FD)**
SDMU	-0.88	**asset > liability (ND)**	-1.705	**asset > liability (ND)**	-1.24	**asset > liability (ND)**	0.199	**enter special notation in BEI (FD)**
WEHA	0.02	**asset > liability (ND)**	-0.764	**asset > liability (ND)**	-0.23	**asset > liability (ND)**	0.446	**asset > liability (ND)**
ASSA	-0.06	**asset > liability (ND)**	-0.156	**asset > liability (ND)**	0.15	**asset > liability (ND)**	0.004	**asset > liability (ND)**
LRNA	0.101	**asset > liability (ND)**	-0.458	**enter special notation in BEI (FD)**	-0.27	**asset > liability (ND)**	-0.26	**asset > liability (ND)**
SMDR	-0.15	**asset < liability (FD)**	0.222	**asset < liability (FD)**	0.9	**asset > liability (ND)**	1.51	**asset > liability (ND)**
WINS	-0.34	**asset > liability (ND)**	-0.101	**asset > liability (ND)**	0.26	**asset > liability (ND)**	0.215	**asset > liability (ND)**
BLTA	3.27	**asset > liability (ND)**	-32.19	**asset > liability (ND)**	0.43	**asset < liability (FD)**	0.504	**enter special notation in BEI (FD)**
CMPP	-0.68	**asset < liability (FD)**	-2.952	**enter special notation in BEI (FD)**	-3.29	**asset < liability (FD)**	-3.19	**asset < liability (FD)**
BBRM	-0.14	**asset > liability**	-	**asset > liability (ND)**	-	**asset > liability**	0.34	**asset > liability (ND)**

		(ND)	1.592		0.34	(ND)		
HITS	0.203	asset > liability (ND)	-0.018	asset > liability (ND)	-0.18	asset > liability (ND)	0.281	asset > liability (ND)
PSSI	0.217	asset > liability (ND)	0.249	asset > liability (ND)	0.83	asset > liability (ND)	1.24	asset > liability (ND)

Information: Green; Healthy, Yellow; Not Healthy, ND; Non-Distress, FD; Financial Distress.

Based on the calculation results using the Grover model, there is one company, namely CMPP, that did not experience financial problems during the 2019–2022 period. Meanwhile, other companies show significant fluctuations with changes in financial conditions that vary from period to period. These results will be further analyzed by associating them with accuracy level calculations, error type 1, and error type 2 to assess whether the Grover model's predictions actually reflect actual financial conditions. In addition, the analysis will also be associated with the financial statements for the 2019–2022 period as well as special notations listed on the Indonesia Stock Exchange.

Table 4. 6 Calculation of the Accuracy Level of the Grover Model

Calculation of the Accuracy Level of the Grover Model				
Year	As Predicted	Prediction Results		Sum
		Error Type 1	Error Type 2	
2019	31	2	6	39
2020	34	3	2	39
2021	31	2	6	39
2022	32	1	6	39
Sum	128	8	20	186
Accuracy Rate =				**69%**
Error Type 1 =				**4%**
Error Type 2 =				**11%**

Based on Table 5, the Zmijewski model shows an accuracy of 69%, with a type I prediction error of 4% and type II of 11%. Here are the details of the calculation:

1. In 2019, out of the 39 total research objects, as many as 31 objects were predicted to be bankrupt by looking at the reality conditions of financial statements and IDX special notation, while 2 objects experienced prediction errors of type I errors, namely in the calculation they were declared not bankrupt, but in reality conditions they were experiencing financial difficulties or were not financially healthy. The other 6 research objects experienced (bankrupt, in the condition of reality not bankrupt) which were included in type II error.
2. In 2020, out of 39 research objects, there were 34 objects with correct predictions and reflecting reality conditions. The other 3 research objects experienced prediction errors with a total of 2 Type errors I and Type errors II.
3. In 2021, out of the 39 total research objects, there were 31 objects with correct predictions and reflecting reality conditions. The other 2 objects experienced prediction errors with the number of error type I and 6 experienced errors in error type II.
4. In 2022, of the 39 research objects analyzed, 32 objects were predicted to go bankrupt accurately, with 1 object experiencing type I error (not bankrupt under reality conditions and 6 other objects experiencing type II error errors (bankrupt under reality conditions, but not bankrupt in the grover model calculation).

CONCLUSION

Based on the results of analysis and hypothesis testing, it was found that there was a difference in bankruptcy predictions between the Altman, Zmijewski, and Grover models in transportation industry subsector companies listed on the Indonesia Stock Exchange for the 2019-2022 period. The Zmijewski model proved to be the most accurate in predicting bankruptcy, with an accuracy rate of 77%, the Altman Z-Score model with an accuracy rate of 76% and the lowest was the Grover model with an accuracy rate of 69%. Bankruptcy prediction through the Zmijewski model identifies several companies that have the potential to experience financial distress, such as CMPP (2019-2022), SDMU (2022), GIAA (2020-2022), LRNA (2020), and SMDR (2019- 2020). These findings confirm the relevance of the Zmijewski model in measuring bankruptcy risk in the transportation sector. With its high accuracy, this model can be used as an important guide for investors and company management in making more effective financial decisions.

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