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Implementation of the Z-Score Test to Predict Financial Distress as an Early Warning System Effort in Banking Companies Listed on the Indonesia Stock Exchange for the Period 2020-2024

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Abstract

Financial distress in banking institutions remains a critical issue, yet previous studies predominantly focus on manufacturing or non-financial firms, leaving limited empirical evidence on whether the Altman Z-Score is still reliable for banking companies in emerging markets. This research fills that gap by examining the usefulness of the Z-Score as an early warning system and identifying the financial ratios that significantly influence financial distress among banks listed on the Indonesia Stock Exchange during 2020–2024.Using a descriptive-quantitative design and secondary data from 42 banking companies, the study integrates the Z-Score model with multinomial logistic regression to statistically validate distress determinants. The results show that 13 banks experienced financial distress in 2020 and 8 banks in 2024, indicating gradual improvement in financial stability. Multinomial logistic regression confirms that working capital to total assets, retained earnings to total assets, and earnings before interest and taxes significantly affect financial distress status ($p < 0.05$). The Z-Score model is empirically validated as a viable early-warning tool for Indonesian banks with strong classification performance. The study contributes by providing updated empirical evidence on the applicability of the Z-Score in the banking sector—an area with limited prior exploration—and by identifying key predictors of distress during the post-pandemic period. Limitations include the exclusion of macroeconomic variables and the reliance on secondary financial reports. Future research may incorporate macro-financial indicators or machine-learning-based validation to enhance predictive accuracy.

1. Introduction

The Indonesian banking sector plays a central role in maintaining financial system stability, supporting credit distribution, and sustaining economic growth. Despite showing positive performance indicators, such as credit growth of 10.75%, investment of 13.08%, and consumption of 10.83% in 2025, concerns remain regarding the long-term resilience of banks amid increasing global and domestic uncertainties. Indonesian banks continue to face structural challenges, including fluctuating interest rates, exchange-rate volatility, and the risk of non-performing loans, which may escalate into financial distress if not detected early.

Financial distress prediction is particularly relevant for Indonesia because banking failures can trigger systemic risks, reduce credit availability, and undermine public confidence. The Financial Services Authority (OJK) emphasizes the importance of early-warning mechanisms to detect declining financial health, especially due to recurring issues such as capital inadequacy, credit quality deterioration, and tightening liquidity conditions. Therefore, analytical tools capable of identifying distress signals objectively are essential for regulators, investors, and bank management. Among various prediction models, the Altman Z-Score remains widely used due to its simplicity, interpretability, and empirical support across industries. However, competing models such as Springate, Grover, and Zmijewski often produce inconsistent results when applied to financial institutions. Many of these models were originally developed for manufacturing firms and do not fully account for the unique structure of banking balance sheets. Previous studies also show methodological limitations: some rely solely on the Z-Score without statistical validation, others use very limited samples, and several do not compare predictive accuracy across time periods.

This study addresses these gaps by (1) applying the Z-Score specifically to the Indonesian banking sector during 2020–2024, a period marked by post-pandemic recovery and heightened financial volatility, and (2) statistically validating its predictive relevance using multinomial logistic regression. This integrated approach evaluates not only whether banks fall into distress zones but also which financial ratios significantly drive distress outcomes (Abadi & Misidawati, 2023).

Based on these considerations, the objectives of this study are to:

1. analyze the financial distress status of banking companies listed on the Indonesia Stock Exchange using the Altman Z-Score;
2. identify financial ratios that significantly influence distress conditions through multinomial logistic regression; and
3. evaluate the relevance of the Z-Score as an early-warning tool for Indonesian banks.

The hypotheses developed are:

H1: Key financial ratios (working capital, retained earnings, and earnings before interest and taxes) significantly affect the probability of financial distress.

H2: The Z-Score model provides reliable classification of distress status in Indonesian banking firms.

The phenomenon that drives interest in predicting financial distress using the Z-Score model emerges from post-Covid global financial instability, exchange-rate fluctuations, and increases in benchmark interest rates that may suppress lending capacity and weaken banks' financial fundamentals. Rapid credit expansion, reaching 12% annually, also requires banks to strengthen credit quality supervision to prevent potential distress (LPS, 2024).

Despite extensive literature on distress prediction, several theoretical and empirical gaps remain. First, although many studies employ traditional models such as Springate, Grover, Zmijewski, or Ohlson's O-Score, only a few critically examine their applicability to the banking sector. These models were originally developed for non-financial firms and often perform inconsistently when applied to financial institutions with unique balance-sheet structures. More recent studies also introduce machine-learning–based distress prediction; however, these methods frequently lack interpretability, making them less practical for regulators and banking practitioners.

Second, previous research rarely integrates signaling theory as a foundation for interpreting distress indicators. According to signaling theory, deteriorating financial ratios act as warning signals to investors and regulators. Yet, the theoretical connection between financial signals and empirical Z-Score interpretation has not been clearly articulated in many earlier studies. Strengthening this linkage is crucial to justify why financial ratios matter and how they indicate impending distress.

Third, methodological limitations persist. Gupita (2020) compared several models but used a limited dataset. Hikmah (2021) used the Z-Score without statistical validation, and Oktarina (2017) analyzed only a single bank, limiting generalizability. Few studies reassess the Z-Score using robust statistical techniques such as multinomial logistic regression, which allows the probability of distress categories to be empirically tested rather than only classified.

Therefore, this study contributes by:

1) integrating signaling theory to explain how financial ratios serve as distress indicators;
2) applying the Altman Z-Score specifically to the Indonesian banking industry during 2020–2024;
3) conducting statistical validation through multinomial logit regression to identify ratios that significantly influence distress probability;
4) providing a broader comparative perspective by positioning the Z-Score among recent alternative models.

Based on these contributions, this study aims to evaluate the financial distress status of banking companies listed on the Indonesia Stock Exchange, identify key financial signals that affect distress categories, and assess the empirical relevance of the Z-Score as an early-warning mechanism for the Indonesian banking sector.

2. Literature Review

2.1 Signaling Theory

Spence (1973) has coined signaling theory, which describes a system of information exchange between parties who have information and recipients of information to reduce information asymmetry in the market. Information about the financial health of an entity is not equally distributed across market participants at the same time in this situation. Therefore, entity management serves as a signal sender by voluntarily disclosing a number of financial metrics, such as the timeliness of earnings that investors use to measure organizational performance. In addition, according to signaling theory, financially well-performing companies are more likely to use voluntary disclosure as a tactic to stand out in the market. Since management has access to internal data, they can communicate to investors signals that represent the entity's current condition and future plans. Investors then interpret whether the signal is positive or negative, and examine how the signal will affect market developments. Negative signals may cause the share price to fall, while positive signals may cause the entity's value to increase. Therefore, signal theory highlights how important it is for management to transmit information to investors in a timely and credible manner to reduce uncertainty and improve capital market efficiency (Subroto, 2024).

2.2 Financial Distress

In general, financial distress cannot be accurately anticipated as there are many types of liquidations that occur some time after a company has experienced financial distress. Many internal and external criteria can be used to identify financial distress. While external factors are usually influenced by far-reaching environmental situations that are beyond the company's control, internal factors relate to the company's ability to carry out business operations successfully.

A comprehensive picture of a company's financial health is obtained by integrating a wide range of financial ratio indicators used to examine cash flow statements, total liabilities, accumulated assets, financial situation, and financial performance reports. This process is used to evaluate financial distress. Financial distress is often used as an early warning system that the company is facing an emergency situation towards liquidation. Based on this description, it is concluded that the business is unable to fulfill its obligations to run the company because it is experiencing financial difficulties. Potential financial difficulties can be tested using the Altman equation using the Z-Score strategy (Abadi & Misidawati, 2023) .

2.3 Altman Z-Score

Altman's development of the Z-Score model represents an application of statistical discriminant analysis aimed at predicting corporate financial distress. In the broader context of regression-based analytical approaches, it is essential to distinguish between diagnostic and predictive purposes. Diagnostic regression focuses on explaining the causal relationships among variables. Its primary objective is to determine whether and how independent variables significantly influence a dependent variable, emphasizing statistical inference and theoretical explanation. In contrast, predictive regression prioritizes forecasting accuracy rather than causal interpretation. The concern is not whether variables are statistically significant in a theoretical sense, but whether they improve the model's ability to predict future outcomes.

The Z-Score model clearly falls under the predictive category. Altman integrated multiple financial ratios into a single discriminant function to enhance the model's capacity to classify firms based on their likelihood of bankruptcy. By combining liquidity, profitability, leverage, solvency, and activity ratios, the model provides a more powerful predictive tool than evaluating the ratios individually. Altman's empirical work demonstrated that such an integrated approach significantly improves the ability to identify firms that are financially healthy, vulnerable, or at high risk of failure. Originally developed using 22 financial ratios before being refined to five key variables, the Z-Score model remains one of the most influential predictive tools in bankruptcy research. Its purpose is not to diagnose causal mechanisms behind corporate failure, but to generate a reliable early-warning indicator of financial distress (Abadi & Misdawati, 2023).

The following are several Altman Z-Score models, progressing from the first model that can only be used by the manufacturing sector to a modified model that can be used by all industry sectors:

1) The First Model

In 1968, Edward Altman created a bankruptcy prediction model primarily to evaluate the financial health of industrial companies. This methodology, referred to as the first Z-Score equation, identified the likelihood of corporate bankruptcy by combining multiple financial variables into a single predictive score.

$$Z = 1.2(X1) + 1.42(X2) + 3.3(X3) + 0.6(X4) + 0.999(X5)$$

Description:
(X1) = *Working Capital / Total Aset*
(X2) = *Retained Earning / Total Aset*
(X3) = *Earning Before Interest And Taxes / Total Aset*
(X4) = *Market Capitalization / Book Calue Of Debt*
(X5) = *Sales / Total Asset*

Companies are categorized as not experiencing bankruptcy if the bankruptcy index value is 2.99 or higher. On the other hand, a company is categorized as bankrupt if its bankruptcy index value is 1.81 or less. According to the analysis findings, the accuracy rate of this method to predict bankruptcy is 94%.

2) Second Model
In 1993 Altman reviewed the primary Z-Score model with the point that this prediction model is not only applied in the manufacturing industry but also applied in industries other than manufacturing. The following is the reviewed Altman model (1993):

$$Z = 0.71(X1) + 0.874(X2) + 3.107(X3) + 0.420(X4) + 0.998(X5)$$

Description:
(X1) = *Working Capital / Total Aset*
(X2) = *Retained Earning / Total Aset*
(X3) = *Earning Before Interest And Taxes / Total Aset*
(X4) = *Market Value Of Equity / Book Value Of Debt*
(X5) = *Sales / Total Aset*

Companies with a Z score of 2.90 or more are considered to be in good financial condition according to the modified Altman model, while companies with a Z score of less than 1.20 are considered bankrupt. The gray zone category, which is a zone of uncertainty where the financial health of the company cannot be identified with certainty and requires further examination, is occupied by entities with Z scores between 1.20 and 2.90. Prediction accuracy of up to 95% is demonstrated by this Altman model.

3) Modified Model
Altman modified the bankruptcy prediction model in 1995 to account for the properties of different types of companies. This change was made so that the Z-Score could be implemented universally across all company sectors, both manufacturing and non-manufacturing, including bond-issuing corporate entities in developing countries. Altman reduced the number of components in the model from five to four during the revision process. The following is the new updated Z-Score equation:

$$Z = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$$

Description:
(Z) = *Bankrupcy Index (Z-Score)*
(X1) = *Working Capital / Total Aset*
(X2) = *Retained Earning / Total Aset*
(X3) = *Earning Before Interest And Taxes / Total Aset*
(X4) = *Book Value Of Equity / Book Value Of Total Debt*

Companies with a Z score of 2.60 or more are considered to be in good financial condition according to the modified Altman model, while companies with a Z score of less than 1.10 are considered bankrupt. The gray zone category, which is a zone of uncertainty where the financial health of the company cannot be identified with certainty and requires further examination, is occupied by entities with Z scores between 1.10 and 2.60.

2.4 Framework

Referring to the formulation of the problems and theories that have been described, the authors present a conceptual framework with the aim of facilitating understanding of the flow in this study, the framework used is shown in Figure 1.

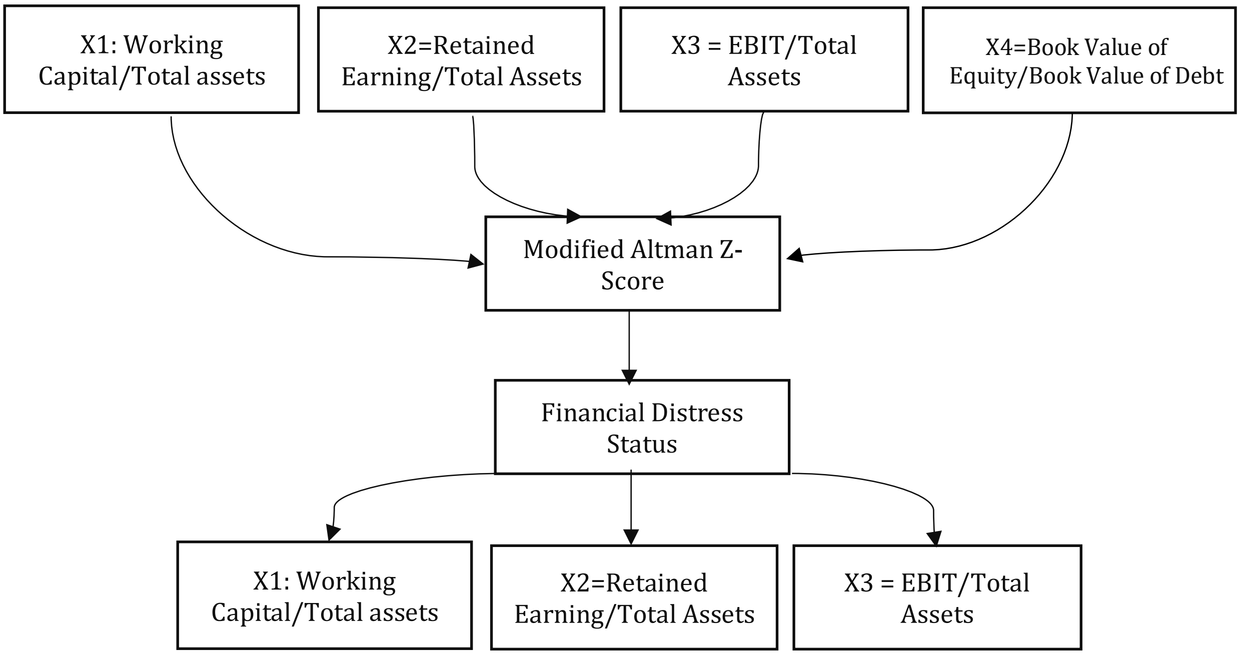

Fig. 1 *Conceptual framework illustrating the theoretical relationship between financial ratios, the Modified Altman Z-Score, and financial distress status*

The conceptual framework of this study, depicted in figure 1, outlines the theoretical relationships underpinning the investigation. Grounded in Signaling Theory (Spence, 1973), the model posits that a firm's management signals its financial health to the market through its published financial statements. These signals are captured by four key financial ratios, which serve as the independent variables in this study:

- X1: Working Capital to Total Assets (a signal of liquidity and short-term viability).
- X2: Retained Earnings to Total Assets (a signal of cumulative profitability and leverage).
- X3: EBIT to Total Assets (a signal of operating efficiency and profitability).
- X4: Book Value of Equity to Book Value of Debt (a signal of solvency and long-term stability).

These individual signals are integrated into a composite measure of corporate health, the Modified Altman Z-Score (Altman, 1968). The Z-Score acts as a robust, synthesized indicator that quantifies the overall financial strength of a company. A higher Z-Score signifies a stronger financial position. The model further proposes that this composite score directly predicts the firm's Financial Distress Status, the dependent variable. A lower Z-Score indicates a higher probability of being classified into a state of financial distress, while a higher Z-Score indicates a higher probability of being classified as non-distressed, with a grey zone representing an area of uncertainty.

Consistent with the logic of the Altman Z-Score model and Signaling Theory, a negative relationship is hypothesized between each financial ratio (X1-X4) and the likelihood of financial distress. That is, an improvement in any of these ratios is expected to increase the Z-Score, thereby decreasing the probability of the firm being categorized as financially distressed. Based on this framework, the following hypotheses are proposed:

- H1: X1 (Working Capital/Total Assets) has a significant negative effect on the likelihood of financial distress.
- H2: X2 (Retained Earnings/Total Assets) has a significant negative effect on the likelihood of financial distress.
- H3: X3 (EBIT/Total Assets) has a significant negative effect on the likelihood of financial distress.

- H4: X4 (Book Value of Equity/Book Value of Debt) has a significant negative effect on the likelihood of financial distress.
- H5: The Modified Altman Z-Score has a significant negative effect on the likelihood of financial distress."

3. Methodology

3.1 Object of Research

The research was conducted in the banking sector listed on the Indonesia Stock Exchange (IDX) during the 2020-2024 period. There are 42 banking companies on the Indonesia Stock Exchange, but they will be regrouped according to the criteria contained in the sample and population. The main focus of this research is to develop an early warning system for the banking industry by recognizing and evaluating the financial health indicators of banks listed on the IDX. It is expected that this system will provide strategic support for the finance division in predicting and handling future financial problems.

3.2 Research Type

This research utilizes descriptive quantitative techniques as a logical and effective research methodology in examining a phenomenon. Descriptive quantitative research focuses on collecting numerical data and analyzing factual information to answer problem definitions and test hypotheses. This research belongs to group 3 where researchers test hypotheses regarding the relationship between the proportion of financial ratios calculated using the Z-Score strategy to anticipate financial distress situations in banks.

3.3 Reseacrh Population and Sample

Population refers to a set of explicitly defined entities that have a certain number and characteristics and have been established in an empirical study to be analyzed and used as the basis for scientific conclusions (Salma, 2023). Banking business entities listed on the Indonesia Stock Exchange from 2020 to 2024 are the population of this study. During this period, the Indonesia Stock Exchange listed 47 banking sector corporations.

The sample is defined as a fraction of the whole and the characteristics inherent in the population. Purposive sampling is the method applied in this research to obtain data in a non-probability sample strategy. A non-probability approach is a sample collection method that does not provide each component of the population with an equal chance of being selected as a sample. On the other hand, purposive sampling is the process of selecting a sample based on specific factors that suit the research objectives (Abunawas, 2023) .

The sample parameters that will be used in this research are as follows:

1) Banking sector business entities listed on the Indonesia Stock Exchange;
2) Banks that have published financial reports from 2020-2024;
3) Banks that have complete financial information according to the criteria for calculating the modified Z-Score formula;
4) Company entities that record financial reporting in rupiah currency.

3.4 Data Analysis Techniques

There are several data analysis techniques applied in this research to process data and extract relevant information. Secondary data from the Indonesia Stock Exchange was collected and then selected using the predetermined population and sample criteria. To answer the research problems and hypotheses proposed, statistical calculations and analysis were carried out. SPSS version 27 software is used as a data processing medium intended to analyze quantitative data in this study.

1) Descriptive Statistics

   Descriptive statistical techniques will be used to analyze data that has been collected, compiled, and processed. This research uses SPSS software version 27 to process data. SPSS software functions as a tool for data management and providing information about the variables studied. Average value, standard deviation, variance, maximum, minimum, sum, range, kurtosis, and skewness are some of the numerical descriptions or diagrams produced by descriptive statistical analysis (Ghozali, 2021).

2) Modified Altman Z-Score Model

   The Altman Z-Score is a strategy for forecasting the likelihood of an entity's bankruptcy by combining a number of financial ratios into a statistically measurable prediction model. In order to identify the differences between businesses that will go bankrupt and those that will not, the model was first created by integrating five related financial ratios. Adapting the Z-Score model to other types of businesses, Altman made changes over time. To optimize the weighting of factors and classifications used in the bankruptcy prediction model, as well as to account for variations in the size of a company's resources, one of the variables was eliminated in the modified version. This was done because the ratio showed marked variations based on business size (Abadi & Misidawati, 2023) . The modified Alltman Z-Score model equation is as follows:

$$Z = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$$

Deskription:
(Z) = *Bankrupcy Index (Z-Score)*
(X1) = *Working Capital / Total Aset*
(X2) = *Retained Earning / Total Aset*
(X3) = *Earning Before Interest And Taxes / Total Aset*
(X4) = *Book Value Of Equity / Book Value Of Total Debt*

Companies with a Z score of 2.60 or more are considered to be in good financial condition according to the modified Altman model, while companies with a Z score of less than 1.10 are considered bankrupt. The gray zone category, which is a zone of uncertainty where the financial health of the company cannot be identified with certainty and requires further examination, is occupied by entities with Z scores between 1.10 and 2.60.

3) Autocorrelation Analysis
An autocorrelation check is performed to identify whether the regression model shows a relationship between period t (current) and period t-1 (past). If there is a relationship, it is called an autocorrelation problem. Temporal dependence between successive observations causes autocorrelation, which makes the residuals not independent across time periods. For the estimation results to be effective and objective, a good regression model must be free from autocorrelation. The Lagrange Multiplier test (LM test) is used in this study to test for autocorrelation because there are more than 100 observations, so it is a better tool for identifying autocorrelation in large samples (Ghozali, 2021).

4) Multinomial Logit Regression Analysis
Regression calculation is actually the same as discriminant testing, specifically testing whether the possibility of the dependent variable occurring can be anticipated by the independent variable. As explained, this study uses independent variables, namely working capital / total assets (X1), retained earnings / total assets (X2), earnings before interest and taxes / total assets (X3), book value of equity / book value of total debt (X4) and the dependent variable is Z-Score. However, discriminant testing is less effective for looking at the factors in this test because discriminant testing and Z-Score testing have different objectives and strategies, such as descriptive analysis must use the assumption of data normality in the independent variables while Z-Score testing does not have to use the assumption of data normality in the variables. Appropriate regression analysis is used to test whether the possibility of the dependent variable occurring can be anticipated using the independent variables. Logistic regression testing is divided into 3 strategies, namely binary logistic for 2 categories, multinomial logistic for more than 2 categories without requiring a rank order, and ordinal logistic, which is a strategy that requires the use of position settings in each category. In this test, 3 categories are used, namely financial distress (code 0), gray zone (code 1), and non-financial distress (code 2). In accordance with the purpose of the test, this test does not aim to determine the ranking between companies so there is no need for position settings. Thus, this test is suitable for using logistic regression with a multinomial logit strategy (Ghozali, 2021) .

4. Results

4.1 Company Profile

Generally, the main role of banking organizations is as financial intermediaries, offering services to their customers to collect public funds and redirect them to the public sector. Various deposit products, including time deposits, current accounts, and savings accounts, are used in the process of collecting funds. Money is collected from people or organizations who have extra money and are looking for a safe place to store it. The money is then channeled to those who need financing after being controlled by the bank. The purpose of this distribution of funds is to help the general financial needs of the community. In Indonesia, there are 47 banking sectors that have been listed on the Indonesia Stock Exchange, but in this research only tested 42 banking sectors that met the sample criteria.

4.2 Statistical Descriptive Analysis

Researchers utilize a descriptive statistical model to handle and analyze the information that has been collected and the information that has been calculated according to the equation. The handling of this information used an adaptation of the SPSS 27 computer program to facilitate the analyst in obtaining important information by clarifying the factors used. Through statistical indicators such as mean, standard deviation, variance, maximum value, minimum value, total number, range, kurtosis, and slope that reflect the degree of asymmetry of the data distribution, graphical measurements in descriptive statistics help to visually represent or explain the characteristics of the data. Data users can more easily and effectively understand complex information thanks to this graphical presentation, which makes it easier to interpret measurements of central tendency, dispersion, and distribution shape (Ghozali, 2021) . The results of this research descriptive statistical test are shown in Table 1.

Table 1 *Descriptive statistical test results working capital to total assets (X1)*

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
X1	210	-0.28	1.41	0.2539	0.23779
Valid N (listwise)	210				

The number of data samples subjected to this research is indicated by the value of N, which is based on the findings in Table 1. A total of 210 financial records from banking organizations were used in this study, which was conducted over five periods spanning between 2020 and 2024. With a minimum value of -0.28 and a maximum value of 1.41, the variable working capital to total assets (X1) shows significant data variance with both positive and negative values. The average value of this variable is 0.2539, which indicates that although there is a distribution of negative values, the values tend to be positive, and the standard deviation value of 0.23779 indicates that the data is not too far from the average.

Table 2 *Descriptive statistical test results retained earning to total assets (X2)*

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
X2	210	-0.74	0.34	0.0126	0.14289
Valid N (Listwise)	210				

Based on the results of Table 2, the value of N is the amount of data that is the object of research. This research was conducted for 5 periods starting from 2020-2024 and obtained data as many as (N) 210 samples of financial statements of financing companies. The Profitability variable (X2) has a minimum value of -0.74 and a maximum value of 0.34 which indicates that there is a fairly wide range and has negative and positive values. On average, it has a value of 0.0126, this value is close to 0, which indicates that the X2 data is evenly distributed between negative and positive values or tends to be symmetrical. X2 has a standard deviation value of 0.14289 which is smaller than the average, meaning that the data is not too far from the average.

Table 3 *Descriptive statistical test results earning before interest and taxes to total assets (X3)*

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
X3	210	-0.20	0.29	0.0107	0.03639
Valid N (Listwise)	210				

The number of data samples used in this study is indicated by the N value in Table 3. This study includes a sample of 210 financial statements from banking sector organizations and is conducted over five time periods from 2020 to 2024. Although the range of variation is quite small, the variable earnings before interest and taxes to total assets (X3) shows a minimum value of -0.20 and a maximum value of 0.29, which indicates considerable volatility in the data. The mean value of X3 is 0.0107 which is close to 0, meaning that the data is evenly distributed between positive and negative values. The standard deviation value of 0.03639 indicates that the X3 data tends to be highly concentrated around the mean.

Table 4 *Descriptive statistical test results book value of equity to book value of total debt (X4)*

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
X4	210	0.05	5.19	0.4343	0.66810
Valid N (Listwise)	210				

The number N, which represents the number of samples used in this study, is 210 financial statements of banking companies collected over five years from 2020 to 2024. Based on the data shown in Table 4, it shows a fairly wide range of values, with the variable book value of equity to book value of total debt (X4) showing a minimum value of 0.05 and a maximum value of 5.19. The average of this variable is 0.4343, which is quite close to the value of 1, indicating that the distribution of X4 variable values is very diverse. The average value is 0.4343, this value is close to 1, which means that the distribution of values on X4 is very wide and the standard deviation value is quite wide, amounting to 0.66810.

4.3 Modified Altman Z-Score Model

The analysis in this study utilizes the modified Altman Z-Score statistical method to identify potential financial difficulties in business institutions. The research begins with the collection of financial statement data from various banks over a five-year period (2020-2024). The data is then processed and each variable is analyzed using the Z-Score formula to obtain financial risk indicators for each company.

The classification of the analysis results is divided into three categories, namely: financial distress (Z- Score below 1.10), gray zone (Z-Score between 1.10 and 2.60), and non-financial distress (Z-Score above 2.60). The results show that there are differences in the number of companies in each category each year. In 2020, there were 13 banks in financial distress, 6 in the healthy category, and 23 classified in the gray zone. Whereas in 2024, the number of banks in financial distress decreased to 8, while the number of healthy banks increased to 14, and the other 20 banks were still in the gray zone.

This change in category distribution reflects the dynamics and fluctuations in financial risk in the banking sector, as well as showing that some companies have managed to improve their position. These findings provide a comprehensive picture of the collective financial condition of banks during the study period, and can be used as an important basis for management and decision-making efforts related to financial risk management.

4.4 Autocorrelation Analysis

Autocorrelation analysis aims to detect whether the regression identifies a relationship between period t (current) and period t-1 (past). If there is a relationship, it is called an autocorrelation problem. Autocorrelation occurs because consecutive perceptions from period to period are interrelated. This problem is caused because the residuals are not free from one perception to another. This condition is often found in information that uses *time series*. A good regression is a regression that is free from autocorrelation.

The following are the results and autocorrelation analysis:

1) Variables Entered/Removed
   Before performing the autocorrelation test on the model residuals, the variables entered and removed from the model are checked in the first step of the regression analysis to ensure that the variables are appropriate. The output of the autocorrelation test for entered/removed variables is in Table 5.

Table 5 *Autocorrelation test results entered variables*

Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	X4, X2, X3, X1[b]		Enter

a. Dependent Variable: Z
b. All requested variables entered.

This study uses the Enter strategy, which means that all independent factors X1, X2, X3, and X4 are entered simultaneously into the regression model to see their impact on the dependent variable, *Z-Score*. No variables were excluded from the model, so this study tests the contribution of all these variables simultaneously to Z.

2) Model Summary
The Durbin-Watson values, which are used to determine whether there is autocorrelation in the residuals of a regression model and whether the residual errors in period t and the previous period are correlated, are revealed in the summary of Table 6.

Table 6 *Autocorrelation test results model summary*

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.799[a]	0.638	0.631	0.437	0.970

a. Predictors: (Constant), X4, X2, X3, X1
b. Dependent Variable: Z

The R (Correlation Coefficient) value shows 0.799, which means that the relationship between the independent variables X1, X2, X3, and X4 with the dependent variable Z is strong. The R Square value of 0.638 means that 63.8% of the variation is explained by the independent variables, while the remaining 36.2% is explained by other factors outside the model. Meanwhile, the Adjusted R Square value shows 6.31%, meaning that adjustments to the number of predictors do not greatly reduce the strength of the model, so the model is quite good. Std. Error of the Estimate with a value of 0.437 shows a small value, the smaller the value the better the model in predicting Z and the durbin-watson value of 0.970 is less than 2, indicating a positive autocorrelation.

3) Anova
The autocorrelation test is conducted to ensure that the residuals of the model do not show sequential correlation patterns after the significance of the regression model as a whole is assessed using anova analysis of variance which is found in Table 7:

Table 7 *Anova autocorrelation test results*

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	68.909	4	17.227	90.385	.000[b]
	Residual	39.072	205	0.191		
	Total	107.981	209			

a. Dependent Variable: Z
b. Predictors: (Constant), X4, X2, X3, X1

Overall, the regression model performed very well in explaining the variation in the dependent variable Z, as indicated by the F statistic value of 90.385. In addition, the regression model has a substantial simultaneous effect on variable Z, as represented by a significance value (Sig) of less than 0.05. In other words, changes in the dependent variable Z are significantly influenced by the independent variables X1, X2, X3, and X4.

4) Coefficients
To ensure that the prediction errors are not serially related between data, the residuals of the regression coefficients derived from the model will be checked for autocorrelation which is presented in Table 8.

Table 8 *Autocorrelation test results coefficients*

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	0.432	0.045		9.595	0.000		
	X1	2.160	0.189	0.714	11.410	0.000	0.450	2.221
	X2	1.097	0.242	0.218	4.526	0.000	0.761	1.315
	X3	3.428	0.951	0.174	3.605	0.000	0.761	1.313
	X4	-0.092	0.067	-0.086	-1.387	0.167	0.461	2.170

a. Dependent Variable: Z

a. X1 coefficient B 2.160, Beta 0.714, Sig. 0 means that X1 has a significant effect on Z. The value of X1 has the largest Beta value among other independent variables, which means that the value of X1 is the most dominant on Z;
b. X2 coefficient value B 1.097, Beta 0.218, Sig. 0 means that X2 significantly affects Z, but the value of X2 is smaller than X1;
c. X3 coefficient value B 3428, Beta 0.174, Sig 0 means that X3 also significantly affects Z, but relatively small;
d. X4 coefficient value B -0.092, Beta -0.086, Sig 0.167 means that X4 is not significant because the sig value> 0.05, so it has no effect on Z. X4 can be omitted if you want to do further regression tests;
e. Collinearity Statistics on Tolerance and VIF all VIF values are <10 and Tolerance>0.1, indicating no serious multicollinearity problems between variables.

5) Coefficient Correlations
While the autocorrelation test looks at the correlation of residuals between periods of the regression model, correlation analysis between coefficients is used to assess multicollinearity, which is listed in Table 9.

Table 9 *Autocorrelation test results coefficient correlations*

Coefficient Correlations[a]

Model			X4	X2	X3	X1
1	Correlations	X4	1.000	0.037	-0.032	-0.726
		X2	0.037	1.000	-0.459	-0.106
		X3	-0.032	-0.459	1.000	-0.054
		X1	-0.726	-0.106	-0.054	1.000
	Covariances	X4	0.004	0.001	-0.002	-0.009
		X2	0.001	0.059	-0.106	-0.005
		X3	-0.002	-0.106	0.905	-0.010
		X1	-0.009	-0.005	-0.010	0.036

a. Dependent Variable: Z

a. X1 and X4 have a negative and quite strong correlation at a value of -0.726, meaning that if X1 increases, X4 tends to decrease and vice versa. This correlation needs to be considered because it can cause multicollinearity if the value is very high close to -1 or close to 1. If the values of XI and X4 are used for further regression analysis and one of them is not removed, it can affect the results of the regression coefficient to be unstable;
b. X2 and X3 have a moderate negative correlation with a value of -0.459, this correlation moves in the opposite direction, namely if X2 increases, X3 tends to decrease and vice versa;
c. Other correlations have small values close to 0 so there is no significant correlation problem.

6) Collinearity Diagnostics
Collinearity diagnostics are used to find multicollinearity problems in the model presented in Table 10.

Table 10 *Autocorrelation test results collinearity diagnostics*

Collinearity Diagnostics[a]								
				Variance Proportions				
Model		Eigenvalue	Condition Index	(Constant)	X1	X2	X3	X4
1	1	2.667	1.000	0.04	0.03	0.02	0.03	0.03
	2	1.241	1.466	0.02	0.01	0.31	0.18	0.01
	3	0.524	2.257	0.12	0.01	0.42	0.55	0.09
	4	0.434	2.478	0.47	0.00	0.24	0.24	0.19
	5	0.134	4.457	0.35	0.96	0.02	0.00	0.67

a. Dependent Variable: Z

An eigenvalue close to 0 indicates the possibility of high multicollinearity. In Table 10, the eigenvalue that is close to 0 occurs in model dimension 5, which is 0.134. A high index condition > 15 usually indicates high multicollinearity. In Table 10, the highest value is 4.457 which is found in dimension 5. Dimension 5 also shows a high variance for X1 and X4, indicating a correlation relationship.

Based on this autocorrelation analysis, the results show that there is a fairly high correlation between X1 and X4. The value of X4 also obtained insignificant results. To produce a better regression analysis, the authors exclude X4 as an independent variable in further regression analysis. So that there are only 3 variables that will be tested in the multinomial logit regression, namely, the variable *working capital to total assets* (X1), *retained earnings to total assets* (X2) and the variable *earning before interest and taxes to total assets (X3)*.

4.5 Multinomial Logit Regression Analysis

When there are more than two categories in the dependent variable, a statistical technique known as logistic regression analysis is used. Z is the dependent variable analyzed in this study and is divided into three categories, namely "*Financial Distress*" with code 0, "*Grey Zone*" with code 1, and "*Non-Financial Distress*" with code 2. With a sample size of 210 data collected from financial documents of banking entities for five periods from 2020 to 2024 which were then analyzed using SPSS software version 27. The completeness of the data and the absence of missing 0 data can be seen in the results in the following table:

1) Case Processing Summary
To ensure the accuracy and completeness of the data examined, Table 11 presents the data processing used in the multinomial logit regression analysis, including quantification of valid cases and missing cases.

Table 11 *Multinomial logit regression test results case processing summary*

Case Processing Summary			
		N	Marginal Percentage
Z	*FINANCIAL DISTRES*	55	26.2%
	GREY ZONE	102	48.6%
	NON-FINANCIAL DISTRESS	53	25.2%
Valid		210	100.0%
Missing		0	
Total		210	
Subpopulation		210[a]	

a. The dependent variable has only one value observed in 210 (100,0%) subpopulations.

Based on the results of data processing in Table 11, it can be observed that there is no missing data (missing=0) with a total of 210 data. The majority of cases (48.6%) are in the "*Gray Zone" category,* (26.2%) in the *"Financial Distress"* category, and (25.2%) in the "*Non-Financial Distress*" category. This data shows a fairly balanced distribution between *distress* and *non-distress* cases, although the largest proportion is in the *gray zone*;

2) Model Fit
Table 12 contains an evaluation of how well the multinomial logit regression model fits the empirical data to evaluate the effectiveness of the model in exposing variability in the dependent variable.

Table 12 *Multinomial logit regression test results model fit*

Model Fitting Information				
	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	440.633			
Final	14.299	426.334	6	0.000

Table 12 indicates that the addition of independent variables to the model improves the model's performance in exposing data variability compared to a model that only has an intercept. This is evidenced by the decrease in the -2 Log Likelihood value from 440.633 *(Intercept Only*) to 14.299 (Final). Chi-Square value 426.334 with df 6 and Significance 0, this result shows very significant. This means that the addition of predictors to the model statistically provides a very meaningful improvement in the fit of the data. The likelihood of the results occurring by chance is very small, so this model fit is very feasible to use for further analysis.

3) Goodness Of Fit
Table 13 the degree of alignment of the multinomial logit regression model with the observed data was evaluated using the Goodness of Fit metric, which tests the overall fit of the model using certain inferential statistics.

Table 13 *Goodness of fit multinomial logit regression test results*

Goodness-of-Fit			
	Chi-Square	df	Sig.
Pearson	23.422	412	1.000
Deviance	14.299	412	1.000

The results of Table 13 provide information that the chi-square is 23.422 for the pearson coefficient and the chi-squuare is 14.299 for the deviance coefficient with both the same significance value of 1.000 or (α>0.05). This high sig value indicates that the data does not experience a lack of fit or the multinomial logit regression model is in accordance with the data.

4) Pseudo R-Square
In multinomial logit regression, Pseudo R-squared is used as a quantitative indicator to show how well the model explains data variation. Although it is not comparable to the coefficient of determination in linear regression, it gives an idea of the proportionality of the variation explained by the model as shown in Table 14.

Table 14 *Multinomial logit regression test results pseudo R-square*

Goodness-of-Fit			
	Chi-Square	df	Sig.
Pearson	23.422	412	1.000
Deviance	14.299	412	1.000

Based on the information in Table 14 above, it is explained that the results of the cox and snell coefficient value of 0.869 indicate that the model is able to explain 86.9% of the variation in the data. The negelkerke coefficient value is 0.990 which means that this model is able to explain 99% of the variation in the data which is very high. Furthermore, the McFadden coefficient has a value of 0.968, indicating that this model has a very strong predictive ability of 96.8%. all Pseudo R-Square values are very high close to 1, indicating that the model used today is very good at explaining data variations.

5) Likelihood Ratio Test
By comparing the likelihood value between the whole model and the model without predictors, the Likelihood Ratio test is used to thoroughly assess the relevance of the model and confirm that the independent variables simultaneously influence the dependent variable. The following Likelihood Ratio output is in Table 15.

Table 15 *Multinomial logit regression test results likelihood ratio test*

Likelihood Ratio Tests				
	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	339.657	325.359	2	0.000
X1	371.929	357.630	2	0.000
X2	94.430	80.131	2	0.000
X3	79.269	64.970	2	0.000

The.chi-square.statistic is the difference in -2 log-likelihoods between the final.model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Table 15 displays the results of the Likelihood Ratio Test for the regression model which serves to test the significance of the contribution of each variable in the model. All variables X1, X2, X3 and intercept are statistically highly significant because sig <0.05. the largest contribution is in X1, if X1 is removed then the model becomes much worse in explaining the data, because in X1 the Chi-Square value is very large compared to other variables, which is 325,359. then the variable that has the second scattered contribution is the X2 variable. Then the last order variable is X3;

6) Parameter Estimation
Table 16 displays the estimated parameters of the multinomial logit regression model, or coefficients, which show how each independent variable affects the probability of falling into a particular category of the dependent variable.

Table 16 *Multinomial logit regression test results parameter estimates*

Parameter Estimates

Z[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
FINANCIAL DISTRESS	Intercept	40.158	10.945	13.463	1	0.000			
	X1	-89.979	17.913	25.231	1	0.000	8.369E-40	4.732E-55	1.480E-24
	X2	-131.579	38.018	11.978	1	0.001	7.178E-58	3.127E-90	1.648E-25
	X3	-27.443	11.661	5.539	1	0.019	1.207E-12	1.433E-22	0.010
GREY ZONE	Intercept	31.531	10.681	8.715	1	0.003			
	X1	-47.111	13.925	11.446	1	0.001	3.466E-21	4.862E-33	2.471E-09
	X2	-72.427	35.210	4.231	1	0.040	3.511E-32	3.756E-62	0.033
	X3	-22.302	10.817	4.251	1	0.039	2.062E-10	1.278E-19	0.333

a. The reference category is: *NON FINANCIAL DISTRESS.*

The test results using parameter estimates show that:

a. In the *financial distress* category, all independent variables X1, X2 and X3 have a significant negative effect on *financial distress*. This condition occurs because the sig value <0.05. The significant value has a negative effect, meaning that an increase in the independent variable will reduce the chance of the company being in the *distress* category compared to *non-distress*;
b. In the *gray zone* category, the variables X1, X2 and X3 have a significant effect on *financial distress*. This is because the sig value on X1, X2 and X3 <0.05. The significant value has a negative effect, meaning that an increase in the independent variable will reduce the chances of the company being in the *distress* category compared to *non-distress*;
c. The coefficient value of Exp(B) on both independent variables shows a small value < 1, this means that any increase in the value of X1, X2, and X3 will reduce the chances of the company entering the *financial distress* and *gray zone* categories.

7) Classification
Based on the prediction probability of the model, the classification analysis in Table 17 is used to assess the ability of the multinomial logit regression model to group cases into relevant dependent variable categories.

Table 17 *Multinomial logit regression test results classification*

Classification

Observed	*Predicted* *FINANCIAL DISTRES*	*GREY ZONE*	*NON-FINANCIAL DISTRESS*	*Percent Correct*
FINANCIAL DISTRES	55	0	0	100.0%
GREY ZONE	0	101	1	99.0%
NON-FINANCIAL DISTRESS	0	2	51	96.2%
Overall Percentage	26.2%	49.0%	24.8%	98.6%

Based on the data presented in Table 17 of the classification, it can be analyzed that the multinomial logit regression model has the ability to predict the overall model correctly by 98.6% and the remaining 1.9% is a wrong guess. The predictive ability includes the "*Financial Distress*" category of 100%, the "*Gray Zone*" category of 99% and the "*Non-Financial Distress*" of 96.2%. The model is very robust, almost all cases are predicted correctly and the error rate is very small. There are only 3 cases that are misclassified, namely in the *gray zone* 1 case and in non-financial *distress* 2 cases, this is synchronized with the pseudo R-Square analysis and very good goodness-of-fit.

5. Discussion

Analysis using a modified Altman Z-Score shows an improvement in the financial health of banking companies in Indonesia during 2020-2024, which is reflected in a decrease in the number of companies experiencing financial distress and an increase in companies in the healthy category, although the gray zone category is still quite large, indicating the risk of financial uncertainty. This improvement is influenced by government policies, restructuring, and increased efficiency and risk management after the Covid-19 pandemic.

Meanwhile, the multinomial logit regression results strengthen the accuracy of the prediction, with the model's ability to explain data variation between 86.9% to 99% and very high classification results and show that an increase in certain independent variables significantly reduces the risk of financial distress. Compared to the Altman model, the logit approach shows similar classification results, with slight differences due to the elimination of insignificant variables, so the two methods complement each other in analyzing and predicting the financial condition of companies, and provide an important basis for strategic decision-making and risk management.

6. Conclusion

a. The results of identifying the application of the *Z-Score* test to *financial distress* as an *early warning system effort* in the banking sector listed on the Indonesia Stock Exchange, it can be concluded that the results of this *Z-Score* analysis not only provide a quantitative picture of the company's financial condition, but also indicate the dynamics of post-pandemic economic recovery and the challenges that the company still faces during the period 2020 to 2024. Therefore, the use of the Altman *Z-Score* methodology has proven effective in forecasting the *financial distress* condition of an entity so that it can be used as a basic signal for strategic decision making by management and other stakeholders;

b. The results of the *Z-Score* test using multinomial logit regression show a significant negative effect of variables X1, X2 and X3. That means if the three variables increase, the *financial distress* will decrease and vice versa. In this study also found variables that did not significantly affect *financial distress*, namely variable X4. The *financial distress* test using multinomial logit regression has excellent data compatibility and a very low expectation error rate, so it can be relied upon to forecast the condition of financial distress in the company.

6.1 Research limitations

This study has several limitations, namely not assessing in depth the development of HR competencies in the field of risk management, the results are still limited as a reference for financial managers and investors so that caution is needed in generalization and has not included external factors or non-financial indices in the analysis. Future research is recommended to combine external aspects so that the results are more comprehensive.

6.2 Research implications

In order to increase the effectiveness and develop the findings in this study, the researchers provide the following suggestions:

a. Management should foster and develop the competence of human resources related to financial risk analysis and risk management so that the utilization of the framework can run effectively;

b. Financial managers and capital market investors can make this research a reference in managing the company's financial health;

c. Further research can make an estimate of *financial distress* conditions by combining the *Z-Score* strategy with *non-financial* indices such as external company components to obtain more comprehensive results.

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Conflict of Interest

The authors declare that there is no conflict of interest related to the publication of this journal.

Author Contribution

The authors confirm the contribution of the researchers to this journal as follows: ***Research concept and design****: Hesti Ima Yohana; Yohan Bahktiar;* ***data collection****: Hesti Ima Yohana;* ***Analysis and interpretation of results****: Hesti Ima Yohana; Yohan Bakhtiar; Ahmad Saifi Athoillah****; journal drafting****: Hesti Ima Yohana; Ahmad Saifi Athoillah.*

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