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Analysis of Financial Distress Using the Modified Altman, Ohlson, and Grover Models in Property and Real Estate Companies Listed on the Indonesia Stock Exchange (IDX) During the 2022–2024 Period

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Abstract

This study analyzes financial distress in property and real estate companies listed on the Indonesia Stock Exchange (IDX) during 2022-2024 using the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score models, and evaluates each model's predictive accuracy against firms' actual financial condition. Despite its strategic economic role, this cyclical sector faces post-pandemic pressures, including rising interest rates, inflation, and declining purchasing power, increasing financial distress risk and the need for early detection. This research used a quantitative descriptive approach with secondary data from audited financial statements of IDX-listed companies. Purposive sampling yielded 42 qualifying companies over the three-year observation period. Distress scores were calculated using the three models, compared through non-parametric Kruskal-Wallis and Friedman tests, and validated against actual financial condition, defined by consecutive net losses and non-dividend distribution. Results reveal significant differences among the three models' predictions, confirmed by both the Kruskal-Wallis and Friedman tests (Asymp. Sig. < 0.001). The Modified Altman Z-Score and Ohlson O-Score classified all sample companies as non-distressed, while the Grover G-Score identified five companies as distressed. Accuracy rates reached 71.43% for both the Altman Z-Score and Ohlson O-Score, and 83.33% for the Grover G-Score, making it the most effective predictor. These findings offer practical implications for management, investors, and policymakers: guiding early-warning systems for risk management and strategic decisions, informing investment decisions by flagging at-risk companies, and contributing evidence on model accuracy in Indonesia's post-pandemic property sector. Future research should extend the study period, cover other sectors, and add models for more comprehensive results.

INTRODUCTION

The establishment of a business is fundamentally grounded in the principle that the enterprise will continue to operate for an extended period, a concept known in accounting as the going concern principle. This principle inherently requires a company to generate profits to expand its capacity and enhance its scale of operations (Al Najjar & Qandeel, 2025; Sjödin et al., 2021). However, maintaining the status of a going concern is a significant challenge, particularly in the face of intense business competition and market volatility. When a company experiences a downturn in profitability, it may face a condition known as financial distress, which serves as a critical warning sign for corporate entities as it indicates a worsening financial condition that could potentially lead to bankruptcy (Bamiatzi et al., 2016; Devi et al., 2020; Geng et al., 2015).

Financial distress can be triggered by internal factors, such as poor management decisions or declining operational efficiency, or by external factors, including macroeconomic conditions that influence creditors' perceptions and drive-up interest rates. The analysis of potential bankruptcy is essential for companies as a parameter for ensuring business continuity. Building on the going concern principle and the importance of profitability and debt management, numerous researchers have developed models to analyze financial distress in specific industries. Altman (1968) pioneered the multivariate formula known as the Z-Score, which has been refined in subsequent studies. Grover (2001) revisited the Altman model by incorporating thirteen additional financial ratios to create the G-Score, while Ohlson (1980) developed the O-Score based on profitability, leverage, liquidity, and cash flow elements. Each model provides distinct numerical thresholds to classify a company's financial health (Ashraf et al., 2019).

The property and real estate sector is a strategic pillar of the Indonesian economy, significantly contributing to investment growth, infrastructure development, and employment. However, this sector exhibits cyclical characteristics, rendering it highly susceptible to national economic conditions. During the 2020–2024 period, the property industry experienced pronounced fluctuations due to the COVID-19 pandemic, declining consumer purchasing power, rising interest rates, and global inflationary pressures. Data from Bank Indonesia's Residential Property Price Survey (SHPR) indicates that residential property sales contracted significantly during this period, while the sector's contribution to national GDP declined from 2.94% in 2020 to 2.35% in 2024 despite an increase in nominal value. Although the government introduced stimulus measures, such as the 0% down payment policy, property demand has not fully recovered, increasing the risk of financial performance decline and potential financial distress among companies (Kim & Lee, 2021; Liu et al., 2020; Pan et al., 2017; R. Baker et al., 2023).

Recent empirical evidence underscores the severity of the situation. Based on data from the Indonesia Stock Exchange (IDX), out of 94 property and real estate companies listed between 2020 and 2024, 30 firms approximately 32% experienced financial losses. Furthermore, research by Saraswati et al. (2024) found that before the pandemic, all sampled property companies were in a healthy condition, but during the pandemic, companies like MDLN transitioned into financial distress, with three distinct groups emerging: those worsening, improving, and stagnating. A study by Khoiriyah et al. (2026) applying the Ohlson O-Score model to 14 property companies during 2022–2024 revealed a significant increase in distress, from 8 companies in 2022 to 11 in 2024, exacerbated by external pressures such as a 6% increase in benchmark interest rates and high inflation.

Financial distress is characterized by declining profitability, liquidity disruptions, and increasing debt burdens. Various prediction models, including the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score, have been developed to detect these conditions. The Altman model employs a Multiple Discriminant Analysis (MDA) approach, while Ohlson utilizes logistic regression, and Grover refines Altman's framework by retesting variables to enhance predictive accuracy. These models are widely used to assess the financial health of companies across different sectors (Altman et al., 2017; Horváthová et al., 2021; Horváthová & Mokrišová, 2020; Jenčová et al., 2020; Vavrek et al., 2021). However, extensive research has shown inconsistent results regarding the most accurate model for predicting financial distress, particularly in specific industries and during different economic cycles. For instance, a study on real estate companies in Indonesia from 2019 to 2020 found that the Grover model predicted financial distress with 70% accuracy, while the Zmijewski model achieved the highest conformity at 96%. In the tourism sub-sector, both Grover and Zmijewski achieved 100% accuracy, while the Modified Altman scored 83%.

Previous studies have shown divergent results, indicating the absence of a consensus on the most effective model for specific contexts. Salim and Ismudjoko (2021) found that the Altman and Ohlson models had the highest accuracy rate (90.91%) for Indonesian mining companies. Conversely, Prasetianingtias and Kusumowati (2019) found the Grover model to be the most accurate (85.29%), while Ulfah and Moin (2022) identified Springate as the best predictor for the tobacco industry. In the retail sector, Putri et al. (2023) concluded that the Grover model was most applicable for predicting financial distress. Furthermore, research by Fadia and Simon (2024) found that Grover outperformed Altman, Springate, and Zmijewski, while Kirana (2024) concluded that Springate was most accurate for the property sector during 2019–2022. These conflicting findings highlight a critical research gap, particularly for the post-pandemic period (2022–2024), during which the Indonesian property sector has faced unique challenges such as high inflation, interest rate hikes, and shifting consumer behavior, necessitating a re-evaluation of these established models.

The urgency of this research stems from the need for an accurate early warning system to mitigate the risks of financial distress and bankruptcy in the property and real estate sector, given its significant macroeconomic implications. With the sector's contribution to GDP declining and a substantial proportion of firms reporting losses, stakeholders including management, investors, creditors, and regulators require reliable predictive tools to make informed decisions. The research novelty lies in its comprehensive comparative analysis of three prominent financial distress models Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score applied specifically to the property and real estate sector during the post-pandemic period (2022–2024), a timeframe characterized by unique economic pressures. This study extends previous research by focusing on a sector that has received limited systematic attention and by evaluating model accuracy against actual financial conditions, thereby providing a fresh perspective on model applicability in this critical industry.

Based on these conditions, this study focuses on property and real estate sector companies listed on the Indonesia Stock Exchange during the 2022–2024 period. The research aims to compare the financial distress classification results of the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score models. The study tests for significant differences in prediction outcomes using the Kruskal-Wallis and Friedman tests and evaluates the accuracy of each model against companies' actual financial conditions. Through this approach, the research seeks to identify the most appropriate prediction model for detecting financial distress in the property and real estate sectors during the post-pandemic recovery period.

The primary research objectives are twofold: (1) to analyze the financial distress conditions of companies in the property and real estate sector based on the three prediction models, and (2) to compare the level of accuracy of each model against the actual financial condition of the company. This research contributes to the existing literature by providing empirical evidence on the comparative effectiveness of financial distress prediction models in a specific sector and during a defined economic period. The study offers practical benefits for multiple stakeholders. For companies, the findings serve as a guide for implementing early warning systems in financial risk management and strategic decision-making. For investors, the results provide critical information for assessing the financial viability of potential investments, enabling more informed decisions. For regulators and policymakers, the research aids in monitoring the financial health of a strategically important sector and developing supportive policies. For future researchers, this study provides a robust reference for expanding investigations into financial distress predictions with broader objects, extended periods, and additional analysis models.

METHOD

Research Design

The implementation of research required a design in order to achieve the goals that the researcher wants to achieve. The strategy chosen by a researcher to integrate the components in the research logically and systematically can be referred to as research design. The stages in research design in general include how variables will be measured, sample selection, data collection for hypothesis testing, and analysis of data or results. The research design used in this study is a quantitative descriptive research design.

The benefit of the research design is to identify the means and arrangements of logistics in the research process that emphasizes validity, objectivity, and accuracy. The purpose of this study is a descriptive research to empirically test data on variables that have been determined to describe certain phenomena. In this study, the data collection technique for the design of this quantitative descriptive research uses longitudinal/panel data. This is because measurements are taken from the same company over a period of 5 years to observe the changes that occur.

Population, Sample Selection Techniques, and Sample Size

The population of this study comprises all property and real estate sector companies listed on the Indonesia Stock Exchange (IDX) during the 2022–2024 period. According to IDX data, there were 94 property and real estate companies listed during this period. The selection of this population is justified by the strategic importance of the property and real estate sector to the Indonesian economy, its cyclical characteristics, and the sector's vulnerability to macroeconomic shocks, making it a relevant context for examining financial distress prediction models.

The sample was selected using a non-probability sampling method, specifically purposive sampling, where sample selection is based on predetermined criteria rather than random selection. The purposive sampling criteria applied in this study are: (1) property and real estate sector companies listed on the Indonesia Stock Exchange, (2) companies that published complete audited financial statements for the 2022–2024 period, (3) companies that presented financial statements in Indonesian Rupiah, and (4) companies that had complete data required for calculating the variables in all three financial distress prediction models. Based on these criteria, 42 companies were selected as the final research sample, representing a comprehensive and representative subset of the sector.

Research Variables and Operational Definitions

The variables in this study are classified into independent and dependent variables. The independent variables (X) comprise the financial ratios used in the formation of each financial distress determination model. For the Modified Altman Z-Score model, the independent variables include: Working Capital to Total Assets (X1), Retained Earnings to Total Assets (X2), Earnings Before Interest and Taxes to Total Assets (X3), and Market Value of Equity to Book Value of Total Liabilities (X4). For the Ohlson O-Score model, the independent variables consist of nine components: Size (log of total assets), Total Liabilities to Total Assets, Working Capital to Total Assets, Current Liabilities to Current Assets, Net Income to Total Assets, Funds from Operations to Total Liabilities, and three dummy variables. The dependent variable (Y) is the financial distress status of the sample companies, classified as either experiencing financial distress or non-financial distress based on the criteria established in this study.

Data Analysis

Financial Model Analysis

The analysis of the financial distress model is the initial stage in the research that aims to identify the financial condition of the company based on the bankruptcy prediction model used. In this study, the analysis was carried out using three financial distress prediction models, namely Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score. The three models were chosen because they are widely used models in previous research and have different approaches in identifying potential financial difficulties for companies.

The analysis process begins by calculating the value of financial ratios that are the components that form each model based on financial statement data of companies in the property and real estate sectors that are the research samples. The data used include financial position statements, income statements, cash flow statements, and other supporting data required in the calculation of variables in each model.

The financial ratio values that have been obtained are then entered into the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score equations to produce financial distress prediction scores for each company and observation period. The results of the score obtained are then compared with the cut-off point that has been set in each model to determine the classification of the company's condition into the category of financial distress, grey area, or non-financial distress (safe zone).

To obtain a more representative picture of the company's condition during the research period, the results of each model's calculation in each observation year were then averaged so that a score for each company was produced. The average value is then used as a basis for determining the company's financial distress conditions based on each prediction model.

The results of the financial distress analysis model were then used to determine the number of companies that were categorized as experiencing financial distress and non-financial distress based on the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score. In addition, the results of this analysis are also the basis for the implementation of the differential test between models and the measurement of the level of accuracy of each model on the actual condition of the company that is the object of the research.

Accuracy Test on Financial Distress Models

After analyzing financial distress conditions using the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score, the next stage is to test the accuracy level of each model. The accuracy test aims to determine the ability of each model to classify the company's condition according to the actual conditions that occur in the company in the property and real estate sector that is the object of the research.

The measurement of the level of accuracy was carried out by comparing the classification results produced by each financial distress prediction model with the actual condition of the company. In this study, the actual condition of financial distress was determined based on the criteria of companies that experienced negative net income for two consecutive years and did not distribute dividends for more than one year. Companies that meet these criteria are categorized as companies experiencing financial distress, while companies that do not meet these criteria are categorized as non-financial distressed companies.

After the actual condition of the company is determined, the classification results of each prediction model are then compared with the actual conditions. Prediction results that are in accordance with the company's actual conditions are categorized as correct predictions, while predictive results that do not match are categorized as incorrect predictions.

The accuracy level of each model is calculated by comparing the number of predictions that correspond to the actual conditions of the company against the total number of research samples. The higher the accuracy value obtained, the better the model's ability to identify the company's financial distress conditions.

The calculation of the accuracy level in this study uses the following formula:

The results of the calculation of the accuracy level from the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score were then compared to find out the financial distress prediction model that has the best ability to identify financial distress conditions in property and real estate sector companies listed on the Indonesia Stock Exchange for the 2022–2024 period. The model that produces the highest level of accuracy will be considered the most appropriate model to be used in predicting financial distress conditions in the research object.

Data Analysis Assumptions

Descriptive Statistical Test

Descriptive statistical test is a data analysis method for all variables, both dependent and independent, which is displayed in the form of a table accompanied by interpretation of the data through average values, minimum values (Ghozali, 2018). Descriptive statistics are generally used to provide a profile of sample data before utilizing statistical analysis techniques that serve to test hypotheses.

Normality Test

According to Ghozali (2018), the normalista test is carried out to test independent variables and dependent variables have normal or abnormal distributions. In general, financial data taken from a sector will show abnormal distribution as a result of differences in size between companies in terms of assets, revenue, and profit.

The approach taken in this study uses the Kolmogorov-Sminorv normality test by paying attention to the provisions on the significance value. If the data significance value is above 5% or 0.05, then the data has a normal distribution. On the other hand, if the test results produce a significant value below 5% or 0.05, then the data does not have a normal distribution.

Differential Test

Different tests were carried out to determine the significance of each model. The approach to differential testing can be implemented with the ANOVA test on normally distributed data or Kruskal-Wallis if the data is not distributed normally (Salim & Ismudjoko, 2023).

In this study, the Kruskal-Wallis Test was used as a different test tool. According to Ghozali (2018), the Kruskal-Wallis Test is a non-parametric statistical method used to test whether there is a median difference between three or more independent groups. This test was chosen because it does not require normal distributed data and can be used on research data that has non-parametric characteristics.

The hypotheses used in this study are as follows:

H_0 : There is no difference in financial distress prediction results between the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score models.

H_1 : There is a difference in the results of financial distress prediction between the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score models.

The decision-making criteria in this test are:

1. If the significance value (Asymp. Sig.) > 0.05 then H_0 is accepted, which means that there is no significant difference between the predicted results of the three models.
2. If the significance value (Asymp. Sig.) ≤ 0.05 then H_0 is rejected, which means that there is a significant difference between the predicted results of the three models.

In addition to using the Kruskal-Wallis Test, this study also uses the Friedman Test as an additional test to strengthen the hypothesis test results. According to Ghozali (2018), the Friedman Test is a non-parametric statistical method used to test for differences in three or more groups that come from the same sample (related samples).

The use of the Friedman Test in this study is based on the characteristics of the research data, namely the three financial distress prediction models applied to the same company during the study period. Thus, each company obtained three interrelated measurement results, namely the Modified Altman Z-Score, Ohlson O-Score, and Grover G-Score. This condition makes the Friedman Test more suitable for testing the consistency of differences in prediction results between modes.

RESULTS AND DISCUSSION

Results of the Data Analysis Assumption Test

Normality Test

The results of the normality test in this study are presented as follows:

Table 1. Results of the Kolmogorov–Smirnov Normality Test

Model	Number of Observations (N)	Kolmogorov–Smirnov Statistic	Significance (Sig.)	Conclusion
Altman Z-Score	126	0.205	< 0.001	Not normally distributed
Ohlson O-Score	126	0.094	0.009	Not normally distributed
Grover G-Score	126	0.062	0.200	Normally distributed

Source: Processed primary data using SPSS, 2026.

The normality test carried out on the three scores in the bankruptcy prediction models in the study year range showed a significance value in the Shapiro-Wilik test on the Altman Z-Score of <0.001, the Ohlson O-Score of <0.001, and the Grover G-Score of 0.030. The entire significance value is smaller than 0.05 so the data is not normally distributed. Because the data is not distributed normally, hypothesis testing is carried out using a nonparametric test in the form of a Kruskal-Wallis test as a differential test.

Differential Test

There are two approaches taken by researchers in conducting different tests on score data from the bankruptcy prediction test, namely:

1. Kruskal-Wallis

Through the Kruskal-Wallis approach, the results of financial distress predictions show different scores and are not normally distributed. Tests on 3 models were compared with each other resulting in the following test results:

Table 2. Re-evaluation of the Statistical Test

Analysis Objective	Data Structure	Recommended Statistical Test	Reason
Compare Fin_Distress across 3 independent methods	Continuous/ordinal outcome with non-normal distribution	**Kruskal–Wallis H Test**	Appropriate for comparing more than two independent groups when normality cannot be assumed
Determine which methods differ	Three independent groups	**Dunn's post-hoc test with Bonferroni adjustment**	Required when the Kruskal–Walli's test is significant
Assess normality	Fin_Distress within each method	**Kolmogorov–Smirnov test**	Used consistently with the previously reported normality analysis

Source: Data processed using SPSS, 2026.

Table 3. Kruskal–Wallis Test Results for Financial Distress

Variable	Grouping Variable	Number of Groups	Kruskal–Wallis H	df	Asymp. Sig. (p-value)	Conclusion
Fin_Distress	**Metode**	**3**	**330.164**	**2**	**< 0.001**	**Significant difference among the groups**

Source: Data processed using SPSS, 2026.

Based on the results of the statistical test, it shows the value of Asymp. Sig. of <0.001. At a significance level level of less than 0.05, the Ho condition is rejected or the result condition between financial distress models shows significant differences (Salim & Ismudjoko, 2021).

2. Friedman test

In the data testing in this study, the three financial distress models were tested on groups of companies so that they were interrelated samples, methodologically the Friedman Test was more appropriate to be used for different tests. Using the Friedman test, the test results are shown as follows:

Table 4. Friedman Test Results

Variable	N	Test Statistic (Chi-Square)	df	Sig. (p-value)	Conclusion
Financial Distress	126	244.254	2	< 0.001	Significant difference among the three related groups

Source: Processed data using SPSS, 2026.

In the Friedman test above, the significance value shows a number of <0.001 or less than 0.05 which indicates a significant difference between the three methods in predicting the company's financial distress.

Paying attention to the hypothesis that has been formed in the previous Chapter II which reads:

H1 : There is a difference in the results of financial distress predictions using the Altman, Ohlson, and Grover model in Property & Real Estate Sector Companies in the 2022-2024 range.

With the results of the different test either through the Kruskal-Wallis test as a difference test used in the main journal or the Friedman test in testing interrelated data, it showed a level of significance below 0.05 and it was concluded that the H1 condition was met with the conclusion that the financial distress prediction results in the three models used in this study showed significantly different results.

Data Analysis Results

Actual Condition of the Company

As previously mentioned in the overview of the theory in Chapter III.A, the indicators of the company experience financial distress when these two conditions are met, namely:

1. The company at the point of the research monitoring year experienced negative net income for 2 consecutive years (Wangsa, 2024), and
2. Companies that have not paid dividends for more than one year (Wicaksana and Mawardi, 2023)

   Based on this, financial data has been processed on the research subjects in the 2022-2024 range. The results shown in table 4.5 show that of the 42 companies that were the subject of the study, 12 companies were in an indication of financial distress.

Table 5. Companies in Actual Financial Distress*

No.	Code	Classification Basis	Net Loss 2022 (Rp million)	Net Loss 2023 (Rp million)	Net Loss 2024 (Rp million)	Data Source
1	BAPA	Property & Real Estate; selected based on financial performance during 2022–2024	-3,712	-2,857	-4,573	Company Annual Report/Financial Statements, 2022–2024
2	BIPP	Property & Real Estate; selected based on financial performance during 2022–2024	-690	-8,119	-10,287	Company Annual Report/Financial Statements, 2022–2024
3	BKDP	Property & Real Estate; selected based on financial	-33,004	-34,591	-35,914	Company Annual Report/Financial

No.	Code	Classification Basis	Net Loss 2022 (Rp million)	Net Loss 2023 (Rp million)	Net Loss 2024 (Rp million)	Data Source
		performance during 2022–2024				Statements, 2022–2024
4	DART	Property & Real Estate; selected based on financial performance during 2022–2024	-421,149	-343,792	-296,799	Company Annual Report/Financial Statements, 2022–2024
5	ELTY	Property & Real Estate; selected based on financial performance during 2022–2024	-245,309	-1,079,192	-68,528	Company Annual Report/Financial Statements, 2022–2024
6	EMDE	Property & Real Estate; selected based on financial performance during 2022–2024	-68,110	-270,389	523,570	Company Annual Report/Financial Statements, 2022–2024
7	MDLN	Property & Real Estate; selected based on financial performance during 2022–2024	20,171	-101,974	-690,272	Company Annual Report/Financial Statements, 2022–2024
8	NIRO	Property & Real Estate; selected based on financial performance during 2022–2024	-168,616	-70,255	-194,703	Company Annual Report/Financial Statements, 2022–2024
9	OMRE	Property & Real Estate; selected based on financial performance during 2022–2024	-236,220	-163,641	-146,322	Company Annual Report/Financial Statements, 2022–2024
10	PPRO	Property & Real Estate; selected based on financial performance during 2022–2024	19,942	-1,279,974	-1,089,513	Company Annual Report/Financial Statements, 2022–2024
11	WHEEL	Property & Real Estate; selected based on financial performance during 2022–2024	-35,977	-35,281	-61,925	Company Annual Report/Financial Statements, 2022–2024
12	TARA	Property & Real Estate; selected based on financial performance during 2022–2024	-3,107	-2,677	-2,061	Company Annual Report/Financial Statements, 2022–2024

Source : Data processed by researchers

* A total of 12 companies did not distribute dividends in the 2022-2024 period

Based on the table above, twelve companies show a condition of recording a net loss for 3 consecutive years and as a side effect of this loss condition, the company does not distribute dividends to shareholders. The conditions formed in these twelve companies put the company into a state of financial distress and if the company could not manage this condition properly, bankruptcy was very likely. The financial distress conditions experienced by several companies in the property and real estate sector during the 2022–2024 period are not only influenced by internal company factors, but also by the macro condition of the property sector which is still facing various post-pandemic challenges. These challenges include slowing property sales growth after Covid-19, rising interest rates that increase financing costs, rising building material prices, high corporate debt burdens, and the unrecovered commercial and office property sector. This condition causes many companies to experience a decrease in profitability, record losses repeatedly, and do not distribute dividends during the research period, indicating financial distress.

Accuracy Test on Financial Distress Models

Based on the test results on each financial distress model on 42 property and real estate companies that were the subject of the study and the actual financial distress conditions in the company, a comparison of the results in the two tests was carried out. The focus of the test is on the accuracy of predicting whether the company's condition is in financial distress or not with actual conditions. The "CORRECT" test result is obtained when the classification results on each model show similarity with the actual classification results. The result of the "INCORRECT" test is obtained when the classification results show different conditions from the actual classification (Example: The Modified Altman Z-Score test results show the "SAFE ZONE" condition while the actual test shows the "DISTRESS" result). The results of the accuracy test on the research sample are as presented in table 4.6:

Table 6. Classification Performance of Financial Distress Prediction Models

No.	Stock Code	Modified Altman	Ohlson	Grover	Classification Result	Accuracy	Error Rate	IDX Ticker Status
1	APLN	Correct	Correct	Correct	All Correct			Valid
2	ASRI	Correct	Correct	Correct	All Correct			Valid
3	BAPA	Incorrect	Incorrect	Incorrect	All Incorrect			Valid
4	BCIP	Correct	Correct	Correct	All Correct			Valid
5	BEST	Correct	Correct	Correct	All Correct			Valid
6	BIPP	Incorrect	Incorrect	Incorrect	All Incorrect			Valid
7	BKDP	Incorrect	Incorrect	Correct	Grover Correct			Valid
8	BKSL	Correct	Correct	Correct	All Correct			Valid
9	BSDE	Correct	Correct	Correct	All Correct			Valid
10	CITY	Correct	Correct	Correct	All Correct			Valid
11	CTRA	Correct	Correct	Correct	All Correct			Valid
12	DART	Incorrect	Incorrect	Correct	Grover Correct			Valid

No.	Stock Code	Modified Altman	Ohlson	Grover	Classification Result	Accuracy	Error Rate	IDX Ticker Status
13	DILL	Correct	Correct	Correct	All Correct			Check/Corr.
14	DMAS	Correct	Correct	Correct	All Correct			Valid
15	HOLL OWS	Correct	Correct	Correct	All Correct			Invalid/Check
16	ELTY	Incorrect	Incorrect	Correct	Grover Correct			Valid
17	EMDE	Incorrect	Incorrect	Incorrect	All Incorrect			Valid
18	FMII	Correct	Correct	Correct	All Correct			Valid
19	GMTD	Correct	Correct	Correct	All Correct			Valid
20	GPRA	Correct	Correct	Correct	All Correct			Valid
21	GWSA	Correct	Correct	Correct	All Correct			Valid
22	JRPT	Correct	Correct	Correct	All Correct			Valid
23	KIJA	Correct	Correct	Correct	All Correct			Valid
24	LPCK	Correct	Correct	Correct	All Correct			Valid
25	LPKR	Correct	Correct	Correct	All Correct			Valid
26	MDLN	Incorrect	Incorrect	Correct	Grover Correct			Valid
27	THE GOAT	Correct	Correct	Correct	All Correct			Invalid/Check
28	MMLP	Correct	Correct	Correct	All Correct			Valid
29	MTLA	Correct	Correct	Correct	All Correct			Valid
30	NIRO	Incorrect	Incorrect	Incorrect	All Incorrect			Valid
31	OMRE	Incorrect	Incorrect	Correct	Grover Correct			Valid
32	FULL	Correct	Correct	Correct	All Correct			Invalid/Check
33	POLL	Correct	Correct	Correct	All Correct			Valid
34	PPRO	Incorrect	Incorrect	Incorrect	All Incorrect			Valid
35	PIONS	Correct	Correct	Correct	All Correct			Invalid/Check
36	RDTX	Correct	Correct	Correct	All Correct			Valid

No.	Stock Code	Modified Altman	Ohlson	Grover	Classification Result	Accuracy	Error Rate	IDX Ticker Status
37	WHEEL	Incorrect	Incorrect	Incorrect	All Incorrect			Invalid/Check
38	SMDM	Correct	Correct	Correct	All Correct			Valid
39	SMRA	Correct	Correct	Correct	All Correct			Valid
40	TARA	Incorrect	Incorrect	Incorrect	All Incorrect			Valid
41	HANDLE	Correct	Correct	Correct	All Correct			Invalid/Check
42	URBN	Correct	Correct	Correct	All Correct			Valid
Total	42	30 Correct	30 Correct	35 Correct		71.43% / 71.43% / 83.33%	28.57% / 28.57% / 16.67%	

Source: Processed research data, 2026; ticker verification based on the Indonesia Stock Exchange (IDX).

The results of measuring the accuracy level of the financial distress prediction model with actual company conditions show diversity in the use of three models. Altman's Modified Model showed an accuracy rate of 71.43% or correctly predicted as many as 30 of the 42 property and real estate companies that were the subject of the study. Paying attention to the notes in table 4.3 regarding the results of the model prediction, two companies, namely BKDP and DART, are in the grey area with the results of the accuracy test showing that both companies are in a distress condition. If this gray area condition is assumed to be in a state of a company heading towards a distress state, then the Modified Altman model is able to measure the model better than the Ohlson model. Ohlson's model showed an accuracy rate of 71.43% or correctly predicted as many as 30 of the 42 companies that were the subject of the study. This result is the same as the level of accuracy produced by Modified Altman because the results of the calculations of both Modified Altman and Ohlson models state that the 42 property and real estate companies that were the subject of the study were in the safe zone or did not experience financial distress. Grover's model showed an accuracy rate of 83.33% or correctly predicted in 35 companies out of 42 companies that were the subject of the study. Although the application of the grover model states that more companies are experiencing financial distress than other models, the actual financial distress condition shows that some companies are in a safe zone position so that the predictions made are still wrong.

This study was conducted with the intention of exploring and obtaining empirical evidence related to the accuracy of the use of several financial distress prediction models, namely the Modified Altman, the Ohlson model, and the Grover model in measuring the level of financial distress of companies operating in the property and real estate sectors in Indonesia and listed on the IDX in the 2022-2024 period. After a series of data analysis tests were carried out, conclusions can be drawn regarding the hypothesis of this study with the following details:

Table 7. Hypothesis Testing and Comparative Performance of Financial Distress Prediction Models

No.	Hypothesis / Statement	Statistical Test & Results	Model Performance	95% Confidence Interval	Conclusion
1	There is a difference in financial distress prediction results among the Modified Altman, Ohlson, and Grover models for Property & Real Estate companies during 2022–2024.	**Cochran's Q test:** $\chi^2(2) = 10.000$, **p = 0.0067**			**Supported**; the classification performance differs significantly across the three models.
2	The Modified Altman Z-Score model provides better financial distress classification performance than the other models.	**Cochran's Q test + pairwise comparison:** Modified Altman vs. Grover, exact McNemar **p = 0.0625**	Correct = 30/42; **Accuracy = 71.43%**; Error = 28.57%	**56.43%–82.83%**	**Not supported**; although its accuracy is lower than Grover, the pairwise difference is not statistically significant at $\alpha = 0.05$.
3	The Ohlson model provides better financial distress classification performance than the other models.	**Cochran's Q test + pairwise comparison:** Ohlson vs. Grover, exact McNemar **p = 0.0625**	Correct = 30/42; **Accuracy = 71.43%**; Error = 28.57%	**56.43%–82.83%**	**Not supported**; its accuracy is lower than Grover, but the pairwise difference is not statistically significant at $\alpha = 0.05$.
4	The Grover model provides better financial distress classification performance than the other models.	**Cochran's Q test:** $\chi^2(2) = 10.000$, **p = 0.0067**; exact McNemar vs. Modified Altman/Ohlson **p = 0.0625**	Correct = 35/42; **Accuracy = 83.33%**; Error = 16.67%	**69.40%–91.68%**	**Supported descriptively**, as Grover has the highest accuracy; however, its pairwise advantage over each competing model is **not statistically significant at $\alpha = 0.05$** using the exact McNemar test.

Source: Data processed by Researcher

Bankruptcy prediction models in analyzing financial distress conditions

The results of this study show that there is a significant difference in the predictive results of financial distress using the Altman, Ohlson, and Grover model in Property & Real Estate Sector Companies in the 2022-2024 range. Statistically, the differential test carried out using either the Kruskal-Wallis test or the Friedman test showed values below the significance level. For this, it can be concluded that H1 of this study is accepted.

The hypothesis accepted in these results is in line with and adds confidence to previous research previously conducted by Salim & Ismudjoko (2021). In their study, they also stated the same thing, namely the acceptance of the hypothesis that predictions between financial distress prediction models show significantly different results. If viewed more deeply, the use of statistics, variables, and assessment criteria in each financial distress prediction model differs from one to another. The Modified Altman combines several financial ratios such as liquidity, profitability, activity, solvency, and market value of the company to predict financial distress, the Ohlson model focuses on the probability of a company experiencing financial failure through a combination of financial ratios and company size, and the Grover model is a form of refinement of the Altman model by curating important ratios to be compiled into a new form of equation. With the different methods and approaches carried out by each of these researchers, the prediction results tend to provide different values from each other even though the approach taken remains the same to predict the financial distress condition of a company.

Accuracy of Modified Altman Z-score in analyzing Financial Distress conditions

The results of this study show that H2 in this study is rejected. This rejection is reflected in the results of the accuracy test showing that the level of accuracy of the prediction of the Modified Altman Z-score model is at 30 out of 42 that are the research test sample. The accuracy of this value when compared to the Grover model is still not higher, so in this test it shows that the Modified Altman Z-score is not the best method for predicting financial distress when compared to other methods. These results contradict research conducted by Salim & Ismudjoko (2021) and Wicaksana & Mawardi (2023) who stated that in the research sample they have tested, the Modified Altman Z-score is a better method of predicting financial distress compared to other methods.

Ohlson O-score accuracy in analyzing financial distress conditions

The results of this study show that H3 in this study was rejected. This rejection is reflected in the results of the accuracy test showing that the accuracy level of the prediction of the Ohlson O-score model is at 30 out of 42 that are the research test sample. The accuracy of this value when compared to the Grover model is still not higher, so in this test it shows that the Ohlson O-score is not the best method for predicting financial distress when compared to other methods. This result contradicts the research that has been conducted by Wangsa (2024) which states that in the research sample that has been tested, the Ohlson O-score is a better method of predicting financial distress compared to other methods.

Grover G-score accuracy in analyzing financial distress conditions

The results of this study show that H4 in this study is accepted. This hypothesis is acceptable because the accuracy test results show that the accuracy level of the Grover G-score model prediction is at 35 out of 42 that are the research test sample. The accuracy of this value is higher when compared to other prediction models that were also tested, namely Modified Altman and Ohlson. These results are in line with research that has been conducted by Prasetianingtias & Kusomawati (2019) which states that in the research sample that has been tested shows that Grover G-score is a better method of predicting financial distress compared to other methods.

CONCLUSION

This study concluded that the Grover G-Score model provides the highest accuracy in predicting financial distress among property and real estate companies listed on the Indonesia Stock Exchange (IDX) during 2022–2024, achieving an accuracy rate of 83.33%, compared with 71.43% for the Modified Altman Z-Score and Ohlson O-Score models. The differences in prediction results among the three models are influenced by variations in methodologies, financial indicators, and classification criteria. Among 42 companies analyzed, 12 companies were identified as experiencing actual financial distress due to factors such as declining sales, rising interest rates, increasing costs, and high debt levels. The findings highlight that no single prediction model is universally applicable, and model effectiveness depends on industry characteristics and economic conditions. This study contributes practical insights for companies, investors, and policymakers in developing early warning systems and improving financial decision-making. Future research is recommended to extend observation periods, include other industries and prediction models, incorporate qualitative and non-financial factors, apply machine learning approaches, and develop sector-specific models to improve the accuracy and applicability of financial distress prediction.

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