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Evaluating the efficacy of financial distress prediction models in Malaysian public listed companies

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ABSTRACT

This research critically examines the precision of financial distress prediction models, with a particular focus on their applicability to Malaysian publicly listed companies under Practice Note 17 (PN17) from 2017 to 2021. Financial distress, defined as the imminent risk of bankruptcy evidenced by an inability to satisfy creditor demands, presents a significant challenge in corporate finance management. The study underscores the necessity of an efficient prediction model to strategize preemptive measures against financial crises. Unlike prior research, which predominantly compared prediction models without assessing their accuracy, this study incorporates an accuracy analysis to discern the most effective model. Utilizing the Grover and Zmijerski models, it assesses whether companies listed under PN17 are experiencing financial distress. A noteworthy finding is the substantial correlation between the return on assets (ROA) and the prediction of financial distress in these companies. Furthermore, the Grover model demonstrates a remarkable 100% accuracy rate, indicating its exceptional efficiency in forecasting financial distress. This research not only contributes to the existing body of knowledge on financial distress prediction but also offers practical insights for companies and stakeholders in the Malaysian financial market.

1. Introduction

The financial crisis significantly impacts every company's stakeholders, affecting them both directly and indirectly. Abdullah et al. (2016) explained that main stakeholders might lose their invested money, whereas lenders will pay back only the amount the company owes. According to Bruynseels and Willekens (2012), financial problems can vary in severity. They describe this as sometimes being temporary issues with cash flow, covering terms like insolvency and default. Sun et al. (2014) argued that the most severe consequence is known as business failure or bankruptcy, which results in the company stopping its operations.

The Securities Commission, established in 1993, aims to support the growth of Malaysia's securities market, following the guidelines of the Malaysian Securities Law 1993, as noted by Sanaa (2009). Bursa Malaysia, the national stock exchange, operates with approval from the Securities Commission under the Capital Markets and Services Act 2007. This exchange adheres strictly to both the Malaysian Stock Exchange Rules and Listing Requirements. Companies that are publicly listed trade on Bursa Malaysia and are categorized into Main or ACE markets based on their profiles. However, companies facing financial difficulties are marked under PN17 (Practice Note 17), indicating they are in financial distress. PN17, introduced by the Malaysian Stock Exchange in 2005, labels companies that are financially troubled lack a core business, or fail to meet minimum capital requirements and shareholder fund levels as PN17 companies, following the Stock Exchange of Malaysia's Listing Requirements and Rules.

Poor decisions made by financial institutions can have serious implications that can lead to credit risk,

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financial crisis, or bankruptcy. Since the outbreak of the coronavirus disease 2019 (COVID-19) at the end of 2019, industries have encountered severe challenges, as stated by Hao et al. (2020). In the years 1985, 1997, and 2008, with the largest in 2008, Malaysia was hit by a financial crisis, and the current financial crisis, exacerbated by the COVID-19 pandemic, has resulted in an increase in the number of business closures.

2. Literature review

Recently, forecasting financial distress has emerged as a significant challenge, prompting extensive research into developing models for predicting company bankruptcy. Various methods exist for anticipating a company's financial troubles, each critical for investors and financial institutions when making investment decisions. Predictions often rely on income statements and the company's historical performance. The accuracy of these methods has been evaluated against other approaches in past research. Saragih et al. (2019) studied to determine and analyze the prediction of bankruptcy in telecommunication companies listed on the Indonesia Stock Exchange by using the Grover method. It is found that the number of telecommunication companies predicted to experience bankruptcy continued to increase in the last five years. Ditasari et al. (2019) compared the model between the Altman, Springate, Zmijewski, and Grover models in predicting financial distress. It is found that the different classifications of financial distress between the Altman models with Springate models, Altman models with Grover models, Altman models with Zmijewski models, Springate models with Grover models, Springate models with Zmijewski models and no difference in financial distress classification between the Grover models and the Zmijewski models. Financial distress analysis using the Zmijewski method study by Ramdani (2020) on three companies listed on the Indonesia Stock Exchange found that the three companies are in good condition, with no financial distress, but received a warning due to late financial reporting.

Financial distress could be influenced by liquidity, leverage, profitability, and firm efficiency, which may affect the financial distress experienced by the PN17 companies in Bursa Malaysia. A study by Yadiati (2017) found that there is no significant relationship between profitability and financial distress because it does not influence the financial distress of companies. Meanwhile, according to Waqas and Md-Rus (2018), financial crisis predictions have been widely studied by companies and stakeholders, including investors, lenders, and capital market participants. They found a negative relationship between profitability ratios, as represented by net income, total assets ratio, and financial distress. Several factors studied by Jaafar et al. (2018), which are Profitability, Leverage, Liquidity, Growth of Sales, and size of the company, can lead to the failure of a company to determine financial distress among the PN17 companies listed in Bursa Malaysia. It is found that leverage and profitability are significant factors of financial distress. Examined the relationship between corporate governance mechanisms in a board of directors' characteristics (board size, board activity, CEO duality, and board independence) and financially distressed companies in Malaysia studied by Ali and Nasir (2018) and found that the board activity has a significant relationship with financially distressed companies. The study on the influence of liquidity, leverage, and profitability ratio on financial distress by Fatimah et al. (2019) found liquidity did not affect financial distress, while leverage had a positive and significant effect on financial distress. Manaf et al. (2020) investigated the factors that contribute to financial distress among the PN17 companies in Bursa Malaysia. The study found that liquidity, firm size, and leverage had a significant impact on financial distress, while profitability and sales growth had the opposite effect. A study by Rafatnia et al. (2020) explained that profitability is positively related to financial distress. A higher profitability will result in a higher probability in order to stay in a good financial state and vice versa. They concluded that profitability is an important financial ratio in determining financial distress as it is linked to fewer chances of financial distress. Firdaus (2023) studied to determine the effect of liquidity, leverage, and firm value as a predictor of financial distress in the case of Hotel Restaurant and Tourism companies. The results show that liquidity has a positive and significant effect, while leverage and firm value have no effect as a predictor of financial distress. Bozkurt and Kaya (2023) investigated the foremost firm-specific factors having an impact on financial distress and bankruptcy in the acute stage of the Covid-19 crisis. They found that the size of the firm and the years of experience of its managers also have an impact on financial failure.

The comparison analysis of the financial prediction was widely used by the previous researcher. Klieštik et al. (2015) compared the probit and logit model to analyze the company's health. They found these two models are similar to each other, but the logit model has more advantages in predicting the prediction. A review by Ul Hassan et al. (2017) for early prediction of financial bankruptcy between Logistic Regression and Multivariate Discriminant Analysis found that the logit regression model is more advantageous than multivariate discriminant analysis for better prediction of financial bankruptcy. A study to determine the financial covariates that can distinguish distressed firms from healthy ones by comparing the partial least squares discriminant analysis (PLS-DA) and logit model study by Abdul Rahim et al. (2014). The results showed that both Logistic Regression and PLS-DA performed similarly in classifying distressed firms from healthy ones. Similarly, Nayan et al. (2015) conducted a study to compare the effectiveness of the logit model in predicting failed and non-failed industrial product firms in Malaysia. The study measured the performance of the two models using accuracy rate, type I error, and type II error and concluded that the logit model performed better with a higher accuracy rate and lower type I and type II error values. The study by Hanafi et al. (2021), which examined the effect of financial distress on stock returns using firms listed on Bursa Malaysia and a logit model, found that the risk of financial distress had no significant impact on pricing stock returns across all tested models. Horváthová and Mokrišová (2020) used the data envelopment analysis (DEA) model and verified the estimation accuracy of this model in comparison with the logit model. They concluded that the DEA method is suitable for assessing the financial health of businesses even though the logit model achieved higher estimation accuracy. The accuracy model of prediction of financial distress studied by Zizi et al. (2021) found that the logistic regression models obtained by stepwise selection outperform the other models with an overall accuracy of 93.33% two years before financial distress and 95.00% one year prior to financial distress. Abidin et al. (2021) conducted a study to identify the critical factors influencing bankruptcy risk among SMEs in Malaysia's hospitality sector over a three-year period, utilizing logistic regression analysis. The findings revealed that return on assets and the age of the firm were consistently significant factors throughout all periods examined, whereas other factors were not deemed significant. Doğan et al. (2022) studied an effective prediction model by comparing the Support Vector Machine and Logistic Regression Analysis. As a result, they found both methods achieve a good prediction model. The comparison of the accuracy between Logit and Artificial Neural Networks (ANN) in corporate distress prediction by Muparuri and Gumbo (2022) found that the Logit model outperformed the ANN by an overall accuracy of 92.21% compared to ANN with 85.8%.

Considering the literature reviewed, this study aims to explore the use of financial indicators to predict financial distress in PN17-listed companies in Bursa Malaysia. To our knowledge, our research uniquely analyzes data from Bursa Malaysia to predict financial distress. The objective is to identify the most impactful financial ratio affecting financial distress. Furthermore, we aim to assess the prediction accuracy of financial distress models, specifically comparing the Grover G-Score and Zmijewski ZM-Score. The findings of this study offer further empirical support for financial distress prediction models, providing valuable insights for those analyzing company performance and seeking the most accurate financial distress prediction model.

3. Methodology

This research utilizes secondary data from companies listed under PN17 from 2017 to 2021. The data spans various sectors, including consumer products and services, industrial products and services, telecommunications and media, transportation and logistics, technology, construction, property, and energy.

Fig. 1 presents the research framework for this study, which involves data from PN17-listed firms on Bursa Malaysia. It uses the Grover G-Score and Zmijewski ZM-Score models to classify the firms into those experiencing financial distress (indicated by 1) and those not in distress (indicated by 0). Following this classification, the study employs logistic regression analysis to identify which financial ratio and model are most accurate in predicting financial distress among PN17 firms.

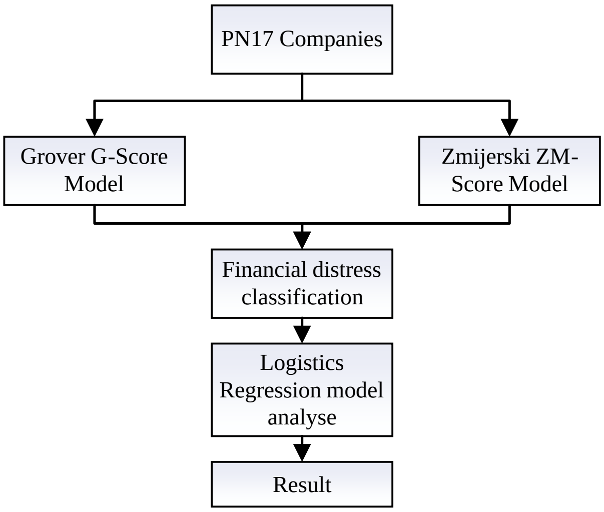

Fig. 1: Research framework

In this study, financial ratios were selected as independent variables, with the status of firms as either being PN17-listed (indicating financial distress) serving as the dependent variable. The analysis utilized data from financial reports, including balance sheets, income statements, and sales reports. The financial ratios examined were categorized into liquidity (working capital to total assets), profitability (return on assets, EBIT to total assets), liquidity again (current ratio), and leverage (debt ratio). The Grover G-Score model used financial metrics such as (current assets - current liabilities)/total assets, earnings before interest and taxes (EBIT)/total assets, and return on assets (X1, X3, and ROA). Meanwhile, the Zmijewski ZM-Score model employed variables including return on assets (ROA), debt ratio (DR), and current ratio (CR) to differentiate between distressed and non-distressed firms based on their respective scoring criteria discussed in the mathematical equations section.

3.1. Mathematical equation

3.1.1. Grover model

The Grover method is a method used to predict bankruptcy. Jeffrey S. Grover created this method by designing and reassessing the Altman Z-Score method. Jeffrey S. Grover used samples according to the Altman Z-Score model in 1968. Grover has applied these financial ratios to predict a company's bankruptcy. The G-Score equation is as follows (Aminian, 2016):

$$\mathrm{G-Score} = 1.650\mathrm{X}_1 + 3.403\mathrm{X}_3 + 0.016\mathrm{ROA} + 0.057$$

where, X represents the variables listed, which are; X_1 = (current asset-current liability)/total assets; X_3 = Earning before interest and tax (EBIT)/Total Assets; ROA = Return on assets.

Based on the Grover model formula, the firm is classified into three categories with the following descriptor zones:

G ≤ -0.02 = bankrupt
G ≥ 0.01 = non-bankrupt
0.02 ≤ G ≤ 0.01 = grey area

3.1.2. Zmijewski model

The financial distress model produced by Zmijewski (1983) uses liquidity ratio analysis, leverage, and measures the performance of a company. The ZM-Score equation is as follows:

$$\mathrm{ZM-Score} = -4.3 - 4.5\mathrm{ROA} + 5.7\mathrm{DR} + 0.004\mathrm{CR}$$

where, the variables listed represents are; ROA = Return on assets; DR = Debt ratio; CR = Current ratio.

Based on the Zmijewski model formula, the firm is classified into a category with the following descriptor zones:

G > 0 = bankrupt
G < 0 = non-bankrupt

As such, the proposed hypothesis to predict the financial distress model in the context of PN17 firms is as follows;

H1: The Grover G-score model has the highest accuracy rate compared with the Springate S-score model in predicting the financial distress of PN17 companies in Bursa Malaysia in the period 2017-2021.

3.1.3. Logistic regression model

Logistic regression has found two broad applications in applied research: classification (predicting group relationships) and profiling (differentiating between two groups based on certain factors). Let event Y be the financial distress's emergence (marked as Y=1) and the non-emergence (marked as Y=0). In general, the logistic regression model has the form (Lawrence and Kleinman, 2009);

$$\log\frac{\mathrm{P}}{1-\mathrm{P}} = \beta_0 + \beta_1\mathrm{X}_1 + \beta_2\mathrm{X}_2 + \cdots + \beta_n\mathrm{X}_n \quad (1)$$

where, p is the probability of the outcome of interest, β_0 an intercept term, β_i the coefficient associated with the corresponding dependent (explanatory) variable

$$X_i, X = (1, X_1, X_2, \dots, X_n)$$

and

$$\beta = (\beta_0, \beta_1, \beta_2, \dots, \beta_n)'.$$

The probability of the outcome of interest, p, is expressed as a non-linear function of the predictors in the for

$$P = \frac{1}{1+e^{-(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}} \quad (2)$$

Eq. 2 ensures that the right-hand side will always lead to values within the interval [0, 1]. This is called the logistic response function. In Eq. 1, the expression

$$\log\frac{P}{1-P} = odds,$$

which can be written as

$$P = \frac{odds}{1+odds} \quad (3)$$

Hence, in logistic regression, one estimates the log of probability odds, also known as the logit, by a linear combination of the predictor variables. The logit takes on values from $-\infty$ to $+\infty$.

Taking exponentials of both sides of Eq. 1 leads to

$$P = \frac{e^{X\beta}}{1+e^{X\beta}} \quad (4)$$

4. Results and discussion

The results of the study above can be found in Table 1.

Table 1: Financial distress prediction model

	Distress	Non-distress
Grover model	70	40
Zmijewski model	87	23

The results are presented in Table 1, which shows the Financial Distress Prediction Model classified based on Grover G-Score and Zmijewski ZM-Score models. Table 1 shows that out of the 110 firms studied in the period 2017-2021, the Grover G-

The score model predicts financial distress for 70 firms, while the Zmijewski ZM-Score model predicts financial stress for 87 firms.

In Table 2, the Omnibus Tests of the Model Coefficients showed that the significance value for both models is 0.000, which is less than the threshold of 0.05 for the three independent variables in the Grover G-Score model and Zmijewski ZM-Score model. Therefore, the regression models are deemed fit for use, and the independent variables have a significant influence on the dependent variable to predict the financial distress of the firms in this study.

Table 2: Omnibus tests of model coefficients

Model	G-score	ZM-score
Chi-square	144.206	81.692
df	3	3
Sig.	0.000	0.000

Table 3 shows the summary of the descriptive statistics that comprise the measures of variables' tendency. The highest standard deviation is indicated by ROA (return on asset), which indicates that the data has the highest variability since the standard deviation is higher than the mean. The ROA has the highest standard deviation, suggesting that a higher ROA will lead to higher financial distress. A lower ROA in the mean can lead to higher debt or financial distress. This is because lower profitability (ROA) means that the companies' performance is in an unhealthy financial condition (Alifiah et al., 2013). The average in CR (current ratio) is 0.01 minimum to 4.28% maximum. The result shows that there is a high risk in the PN17 companies because there is insufficient CR.

Table 4 presents the Model Summary for both models. The Nagelkerke R Square is a goodness of fit measure that describes how well the statistical models fit the data. The results show that the Nagelkerke R Square value is 1.000 for the Grover G-Score model, indicating that 100% of the financial distress variable cases are explained by the three independent variables (X_1, X_3, and ROA) used in this study. For the Zmijewski ZM-Score model, the Model Summary shows that the Nagelkerke R Square value is 0.780, indicating that only 78% of the financial distress variable cases are explained by the three independent variables (ROA, Debt Ratio, and Current Ratio) used in this study. The remaining 22% are explained by other external factors. These results suggest that the Grover G-Score model performs better than the Zmijewski ZM-Score model.

Table 3: Descriptive statistics

	X_1	X_3	ROA	CR	DR
Mean	-0.309091	-0.331527	-8.830673	0.994855	1.788491
Minimum	-13.7280	-12.7860	-184.7800	0.0100	0.0690
Maximum	0.5950	0.6570	46.8100	4.2800	6.8210
Std. deviation	1.4842024	1.5895637	23.8369718	0.7936026	1.1763769
N			110		

Table 4: Model summary

	-2 Log likelihood	Cox and Snell R square	Nagelkerke R square
G-Score	0.000	0.730	1.000
ZM-Score	40.911	0.524	0.780

Table 5 presents the Hosmer and Lemeshow Test for both models. The Hosmer and Lemeshow Test determines if the observed values align with the predicted values to assess the goodness of fit for the model. According to Table 5, the Hosmer and Lemeshow Test results show a significance value of 1.000 for G-Score and 0.002 for ZM-Score. This indicates that the logistic regression approach can anticipate the value of observations since the significance value is greater than 0.05. A significance value above 0.05 suggests that the expected and perceived values are close, indicating a good fit for the model. As a result, the Grover G-Score model is accepted since it matches the observational data.

Table 5: Hosmer and Lemeshow test

	G-score	ZM-score
Chi-square	0.000	24.119
df	4	8
Sig.	1.000	0.002

Table 6 presents the classification table for both models. For the Grover G-Score model, the logistic regression approach resulted in an overall Percentage Correct of 100%, indicating that the model correctly predicts financial distress values.

For the Zmijewski ZM-Score model, the logistic regression approach resulted in an overall Percentage Correct of 95.5%, indicating that the model can predict 95.5% of financial distress values correctly. The proportion of 92.6% represents classification correctness for non-financial distress companies. There are two observation errors in the financial distress group and 25 observations that can be accurately forecasted. The proportion of 96.4% represents the classification correctness for financially distressed companies, with three observation errors and 80 observations that can be accurately forecasted.

4.1. Grover G-score

Based on Table 7, the logistic regression equation is

$$\log \frac{P}{(1-P)} = -19.107 - 480.84X_1 - 991.62X_3 - 4.090ROA$$

Considering the above information, it can be said that an increase in X_1. X_3 and ROA correspond to a decrease in the probability of bankruptcy. These estimates provide information about the relationship between the independent and dependent variables. Specifically, for every one-unit increase in X_1, there is a 480.84 decrease in the log odds of financial distress. For every one-unit increase in X_3, there is a 991.62 decrease in the log odds of financial distress. For every one-unit increase in ROA, there is a 4.090 decrease in the log odds of financial distress. Furthermore, based on Table 7, it can be concluded that there is no significant variable, which is all variables more than the p-value of 0.005.

Table 6: Classification table [a]

	G-Score			ZM-Score		
	Predicted			Predicted		
	Healthy	Distressed	Percentage correct	Healthy	Distressed	Percentage correct
Healthy	40	0	100	25	2	92.6
Distressed	0	70	100	3	80	96.4
Overall correct			100			95.5

a: The cut value is .5

Table 7: Variables in the equation

	G-score					ZM-score				
	B	S.E.	Wald	df	Sig.	B	S.E.	Wald	df	Sig.
X_1	-480.84	4966.379	.009	1	.923					
X_3	-991.62	10852.539	.008	1	.927					
ROA	-4.090	52.919	.006	1	.938	-.506	.135	14.116	1	.000
CR						-.627	1.017	.381	1	.537
DR						1.816	1.015	3.204	1	.073
Constant	-19.107	232.847	.007	1	.935	-1.326	1.076	1.518	1	.218

4.2. Zmijewski ZM-score

Based on Table 7, the logistic regression equation is

$$\log\frac{P}{(1-P)} = -1.326 - 0.506ROA - 0.627CR + 1.816DR$$

It is considered that an increase in ROA and CR (Current Ratio) corresponds to a decrease in the log odds of financial distress. For every one-unit increase in ROA and CR, there are 0.506 and 0.627 decreases in the log odds of financial distress, respectively. For every one-unit increase in DR (Debt Ratio), there is a 5.406 decrease in the log odds of financial distress. Based on Table 7, it can be concluded that the only significant variable is ROA, as its significance value is 0.000, which is less than the p-value of 0.005.

4.3. Accuracy model test

Based on the results of the evaluation, an accuracy test was employed for the Altman and Springate models to determine the accurate prediction of the firms using the following equation:

$$\text{Accuracy Test} = \frac{\text{no of prediction}}{\text{number of samples}} \times 100\%$$

Based on a study by Ditasari et al. (2019) concluded only the differences in the classification between the Altman, Springate, Zmijewski, and Grover models in predicting financial distress. Upon calculating the accuracy test using the formula above in this study, it is found that the most accurate model in predicting financial distress in the PN17 companies listed on the Bursa Malaysia is the Grover G-Score, with the highest percentage gain of 100%, compared to the Zmijewski ZM-Score, which is 95.5% as shown in Table 8.

Table 8: Accuracy model test

	Grover G-score	Zmijewski ZM-score
Accuracy model test	100%	95.5%

5. Conclusions

The statistical data from Trading Economics in 2019 shows an increasing trend in bankruptcy rates in Malaysia since 1998. This highlights the importance of predicting financial distress in PN17-listed firms in Malaysia for investors, financial managers, and creditors. It helps them make informed decisions about investing, managing funds, and lending money, respectively. Identifying financial distress early is crucial to prevent a company from being declared bankrupt. The study found that the Grover G-Score model was more accurate in predicting financial distress compared to the Zmijewski ZM-Score model. The most significant indicator of financial health was the ROA, a measure of profitability. The results suggest that the Grover G-Score model could be a valuable tool for companies to predict financial distress as a preventative measure against bankruptcy or to evaluate their performance. Investors and creditors could use predictive analysis of a company's potential bankruptcy in the coming years as a basis for their lending and investment decisions.

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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