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Estimation and Prediction of Financial Distress: Non-Financial Firms in Bursa Malaysia

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Abstract

Altman's *Z*-score is used to measure a company's financial health and to predict the probability that a company will collapse within 2 years. It is proven to be very accurate to forecast bankruptcy in a wide variety of contexts and markets. The goal of this study is to use Altman's *Z*-score model to forecast insolvency in non-financial publicly traded enterprises. Non-financial firms are a significant industry in Malaysia, and current trends of consolidation and long-term government subsidies make assessing the financial health of such businesses critical not just for the owners, but also for other stakeholders. The sample of this study includes 84 listed companies in the Kuala Lumpur Stock Exchange. Of the 84 companies, 52 are considered high risk, and 32 are considered low-risk companies. Secondary data for the analysis was gathered from chosen companies' financial reports. The findings of this study show that the Altman model may be used to forecast a company's financial collapse. It dispelled any reservations about the model's legitimacy and the utility of applying it to predict the likelihood of bankruptcy in a company. The findings of this study have significant consequences for investors, creditors, and corporate management. Portfolio managers may make better selections by not investing in companies that have proved to be in danger of failing if they understand the variables that contribute to corporate distress.

Keywords: Financial Distress, Altman's *Z*-Score Model, Non-Financial Companies, Financial Ratios, Malaysia Stock Exchange

JEL Classification Code: G33, G38, G23

1. Introduction

The commercial and corporate sector has been significantly expanding in recent years. Businesses have grown in size and complexity over time. Growing businesses face a range of challenges. (Nagy et al., 2018). Businesses, in essence, are entities created by people or institutions with the primary goal of profit maximization; however, there are other equally essential goals such as continuing to compete, developing, and performing social duties in society.

As global economic rivalry heats up, organizations not only strive for maximum profit but also existence. Management's capacity to manage is intimately linked to the company's existence (Kwon et al., 2020). Auditors issues an opinion to determine the future viability of the business. Financial statements that will be audited must be prepared by businesses. If there is a very strong indication of the firm's insolvency, auditors are required to reveal the fact with the viability (going concern) of the client company The going concern assumption is a fundamental principle in the preparation of financial statements. The assessment of an entity's ability to continue as a going concern is the responsibility of the entity's management. The appropriateness of the use of the going concern assumption is a matter for the auditor to consider on every audit engagement (Khanifah et al., 2020).

With the help of numerous non-financial institutions, the economy is growing and flourishing. Non-bank financial institutions often known as non-financial firms are businesses that would provide financial and non-financial services without having a banking license (Chepkemoi et al., 2019). Non-financial corporations principally engage in the production of market goods and non-financial

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services and their financial transactions are wholly distinct from those of their owners. Private and public businesses, holding companies, NGOs, and alliances are examples of non-financial businesses. Non-financial firms have grown in number and form during the Great Recession, playing a critical role in addressing credit demand not provided by traditional banks (Eizaguirre et al., 2019). Non-financial businesses play a significant role in society. Non-financial businesses engage in activities that benefit the nation. The operations of non-financial corporations are heavily impacted by the public's or consumers' confidence (Dögüs, 2018).

On January 26, 1959, Bank Negara Malaysia was established (Kitamura, 2020). It is vital to Malaysia's economic development in the banking and non-financial sectors. According to the Malaysian Securities Law 1993, the Securities Commission was founded in 1993 to promote the growth of the Malaysian securities market (Kim-Soon et al., 2020). Breaches of the Malaysian stock exchange rules and the Malaysian stock exchange listing requirements are taken extremely seriously by the Malaysian Stock Exchange (Fatima et al., 2015) because they have the ability to jeopardize the privileges and protection of an investor.

In recent decades, the use of financial analysis has grown. The goal of financial analysis is to analyze whether an entity is stable, solvent, liquid, or profitable enough to warrant a monetary investment. It is used to evaluate economic trends, set financial policy, build long-term plans for business activity, and identify projects or companies for investment. (Lane & Milesi-Ferretti, 2018). The new age of digital globalization also poses challenges. Companies can enter new markets, but they are exposed to pricing pressures, aggressive global competitors, and disruptive digital business models (Lee & Shin, 2018). Globalization is increasingly defined by the flow of data and information (Danyluk, 2018). All of this posed a rapid issue for the emergence of big, limited, and multi-national corporations.

Predicting company failures is critical since the consequences of business failure result in significant financial and non-financial losses (Balasubramanian et al., 2019). Managers, shareholders, the government, suppliers, consumers, and workers, among other stakeholders, would benefit greatly from a model that could properly anticipate company failure in real-time. Researchers in the past decade have realized that failure does not happen suddenly. Usually, failure take years; therefore, it is necessary to develop an early warning model that can evaluate the strengths and weaknesses of the financial features of companies (Jayasekera, 2018). Classic statistical approaches, data mining, and machine learning approaches were widely used to estimate the likelihood of company failure. Financial distress or insolvency are two examples of financial failure. When a company is insolvent, it means it is unable to fulfill its present commitments on time. Bankruptcy, on the other hand, occurs when a company's total obligations exceed its fair market worth (Desai et al., 2020). The most common financial statements are profit and loss statements, balance sheets, and cash flow statements, which are used to evaluate the success of a company and its management. Various ratios may be generated from the financial accounts to analyze the current performance and future prospects of the company in issue (Hosaka, 2019).

2. Literature Review

Firms categorized as PN17 (Practice Note 17) on Bursa Malaysia are often financially challenged businesses. The Malaysian Stock Exchange categorizes listed firms in financial distress into two groups: PN4 and PN17 (Alifiah, 2014). The abbreviation PN stands for Practice Note. The Malaysian Stock Exchange launched PN17, which is for financially distressed companies (Iskandar et al., 2012). Corporations that come within the PN17 classification will need to submit a plan to the approving authority to reorganize and resuscitate their business to keep their stock exchange listing. Many investors are perplexed as to why certain firms have become PN17 (Kim-Soon et al., 2020). When closely examined, it appears that many businesses are either poorly managed or have a terrible track record. Investors continue to keep their investment in these PN17 firms for a variety of reasons, including a lack of knowledge about the business' financial performance and a lack of awareness that they are holding stocks of firms classed as PN17 (Yee, 2018). Moreover, investors may be unaware that these firms have been delisted.

Financial analysis involves using financial data to assess a company's performance and make recommendations about how it can improve going forward. It plays a crucial role as an indicator of vulnerabilities, thus offering predictability. Therefore, financial ratios remain the key indicator of vulnerability in any firm (Alnori & Alqahtani, 2019; Xu & Wang, 2009). Classical examinations may be unable to discover errors and variances in financial management reporting in some circumstances (Tran & Nguyen, 2020; Du Jardin & Séverin, 2011).

Financial analysis is also employed in review projects to produce clear and accurate financial and accounting reporting (Roychowdhury et al., 2019). For more than 70 years, financial distress prediction models have been explored (Palmer et al., 2004). Empirical research was frequently used to established statistical models, and an attempt to describe the findings using computational equations (Kim-Soon et al., 2013). Beaver (1966) was the one to finish a research project in financial distress. He devised a system known as sophisticated financial ratios. Well ahead, different researchers (Karugu et al., 2018; Bhunia & Sarkar, 2011) from around the globe, conducted a comparable study in this subject, with Altman being the most popular model amongst them. Financial ratios are used by financial analysts to assess a company's productivity, liquidity, and creditworthiness, as well as management's competence in the creation and execution of financial investment policies.

Since August 9, 2010, there are 34 PN17 list companies that are listed on the Malaysian Stock Exchange, and these firms have entered the PN 17 List in compliance with existing regulations (Kim-Soon et al., 2020). There are other corporations that were placed on the PN 17 list in 2005 and are yet to fix their financial issues (Yee, 2018). Companies that have been cautioned about not disclosing information or reconsidering their regularization plans are among them. Corporations that did not comply were delisted from the Malaysian Stock Exchange due to their inability to comply with the rules (Najib & Cahyaningdyah, 2020).

Furthermore, several individuals are unaware that they own shares in firms that have been categorized as PN17 firms (Norziaton & Hafizah, 2019). Investors are sometimes unaware of these enterprises' written-off notifications. Additionally, even with the stock market rebound, almost all investors continue to have concerns about the financial health of several publicly traded firms, prompting numerous inquiries, concerns, and remarks about the future of PN17 (Liloshna et al., 2017). On the PN17 Malaysian companies registered on the Malaysian Stock Exchange, analytical investigations and scientific research are essentially non-existent (Najib & Cahyaningdyah, 2020).

2.1. Hypotheses Development

The following are the hypotheses that were developed for this empirical research:

H1: *There is a significant difference between distress and non-distress PN17 companies.*

H2: *There are financial distress companies in the non-financial sector that are listed on the Malaysian Stock Exchange.*

2.2. Model Altman Z-score

Financial ratios are one piece of information that may be used to forecast a company's performance, including information regarding impending insolvency, which is important to many individuals, including investors and creditors. In 1968, Altman Edward proposed a methodology for predicting a company's imminent insolvency. Altman discovered that some financial parameters have greater "predictive power" than others in forecasting financial distress and bankruptcy through research with a sample of firms that had gone bankrupt (Altman, 1968). Altman discovered four financial parameters, known as *Z*-score that may be used to detect a company's indebtedness (Altman et al., 2013).

Altman et al. (2017) used a sample of 33 pairs of companies that were bankrupt and not bankrupt to develop the exact formulation of the model, which was able to predict 90 percent of bankruptcy cases a year before they happened. The Altman *Z*-Score is used to predict the bankruptcy of the business using traditional financial ratios and a statistical method known as the Multiple Discriminant Analysis (MDA) (Chijoriga, 2011). MDA may be used to find the factors that distinguish the existing population and may also be used as grouping criteria (Thai et al., 2014). "MDA generally is $Z = V_1(X_1) + V_2(X_2) + \dots + V_n(X_n)$ where V_1 and V_2 are parameters (weights) while $X_1, X_2, \dots, X_n$ are financial ratios that contribute to predictive models".

Altman successfully used the financial ratios of the *Z*-score model to categorize firms into groups with a high chance of bankruptcy or a group of firms that are likely to experience bankruptcy. The *Z*-score is considered to be 90% accurate in forecasting business failure one year into the future and 80% accurate in forecasting it two years into the future (Prasetiyani & Sofyan, 2020).

The disadvantage of this approach is that there is no precise time limit as to when bankruptcy will occur after the findings are known since *Z*-scores are lower than the standard established (Lord et al., 2020). The *Z*-score model is based on historical financial data, which is a big problem in economic decision-making because some of the present circumstances can be different from the past. There is a lack of conceptual base in the Altman *Z*-score model and a lack of sensitivity to the time scale of failure i.e. time factors may not be fully taken into account. Also, some of the accounting policies used by companies make it difficult to get the required result from the Altman *Z*-score model. Nonetheless, firms can use the Altman technique to take preventive actions (advance warning) while they are already in a state of bankruptcy (Altman, 2018). The original Altman *Z*-score formula is as follows:

$$Z\text{-score} = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

Description:

$$X_1 = \text{Working capital/total assets}$$

This equation represents a company's ability to create net working capital from all of its assets. The gap between current assets and current liabilities is known as working capital.

$$X_2 = \text{Retained earnings/total assets}$$

This ratio represents the company's capacity to create retained earnings as a percentage of total assets. This metric is important for determining if the company's cumulative earnings is sufficient to cover its entire assets.

$$X_3 = \text{Earnings before interest and taxes/total assets}$$

This ratio demonstrates a company's capacity to profit from its assets before interest and taxes.

X_4 = Market value of equity/book value of total debt

This ratio demonstrates a company's capacity to satisfy its market value of equity commitments (common stock). The value of the equity market is calculated by multiplying a company's outstanding shares by its current market price (per share). The book value of debt is calculated by adding current and long-term obligations together.

The value of *Z* derived is used to classify a healthy corporation and a bankrupt corporation, namely:

1. If the *Z*-score is less than or equal to 1.81, the firm is in financial distress and poses a significant risk (Mo et al., 2021).
2. The firm is considered to be in the grey region if its *Z*-score is between 1.81 and 2.67 (gray area) (Akra & Chaya, 2020). In this situation, the firm is experiencing financial difficulties that need to be addressed by competent management. The firm may risk insolvency if it is too late and improperly handled. So, in this grey area, it's possible that the firm may go bankrupt, but it's also possible that it will not. It all relies on how the management can take prompt action to address the firm's difficulties.
3. When the *Z*-score is more than 2.67, it indicates that the firm is in good condition and that the risk of bankruptcy is low (Akbar et al., 2019).

3. Research Methodology

The technique for this study must be methodical to conduct an organized investigation of the influence of distressed company indicators. The goal of the study is to justify the best technique by discussing ideas and approaches and choosing the best ratios for their strength.

3.1. Data Source and Samples Selection

The sample of this study includes 84 listed companies in the Kuala Lumpur Stock Exchange (KLSE). Of the 84 companies, 52 are considered high-risk companies and 32 are considered low-risk companies. High-risk companies are companies that were given ratings of 2* and low-risk companies were companies that were given ratings of 7*. Financial and insurance companies were excluded from the list due to their high dependency on economic conditions. The data was collected from Stock Performance Guide, Malaysia (2015 September Edition) for the 82 companies (see Table 1 and Table 2, respectively).

3.2. The Trend Approach

The trend approach is used to assess the firm's overall market price direction. Distressed firms are experiencing a downward trend. The non-distressed firms are on an upward trend. Furthermore, the trend may be used to determine support and resistance (Becchetti & Sierra, 2003).

Table 1: List of Companies Categorized as High Risk

Company Name	Company Code	Rating
HO WAH GENTING BHD	HWGB	U
LION CORPORATION BHD	LIONCOR	U
KARAMBUNAI CORPORATION BHD	KBUNAI	U
TALAM TRANSFORM BHD	TALAMT	U
DUTALAND BHD	DUTALND	U
MALAYAN UNITED INDUSTRIES BHD	MUIIND	0.5
SOUTH MALAYSIA INDUSTRIES BHD	SMI	0.5
LION INDUSTRIES CORPORATION BHD	LIONIND	1
SCOMI ENGINEERING BHD	SCOMIEN	1
SOUTHERN STEEL BHD	SSTEEL	1
IVORY PROPERTIES GROUP BHD	IVORY	1
HARN LEN CORPORATION BHD	HARNLEN	1
DPS RESOURCES BHD	DPS	1
KOTRA INDUSTRIES BHD	KOTRA	1

Table 1: List of Companies Categorized as High Risk (Continued)

Company Name	Company Code	Rating
TOMEI CONSOLIDATED BHD	TOMEI	1
AMALGAMATED INDUSTRIAL STEEL BHD	AISB	1
LION DIVERSIFIED HOLDINGS BHD	LIONDIV	1
MYCRON STEEL BHD	MYCRON	1
AYS VENTURES BHD	AYS	1
ASIAN PAC HOLDINGS BHD	ASIAPAC	1
IBRACO BHD	IBRACO	1
AN JOO RESOURCES BHD	ANNJOO	1.5
HIAP TECK VENTURE BHD	HIAPTEK	1.5
WATTA HOLDINGS BHD	WATTA	1.5
MUDAJAYA GROUP BHD	MUDAJYA	1.5
COMPUGATES HOLDINGS BHD	COMPUGT	1.5
KUB MALAYSIA BHD	KUB	1.5
PERISAI PETROLEUM TEKNOLOGI BHD	PERISAI	1.5
NI HSIN RESOURCES BHD	NIHSIN	1.5
QUALITY CONCRETE HOLDINGS BHD	QUALITY	1.5
YLI HOLDINGS BHD	YLI	1.5
KUMPULAN JETSON BHD	JETSON	1.5
SAPURA RESOURCES BHD	SAPRES	1.5
GUAN CHONG BHD	GCB	2
MALAYSIA STEEL WORKS (KL) BHD	MASTEEL	2
NYLEX (M) BHD	NYLEX	2
AHMAD ZAKI RESOURCES BHD	AZRB	2
CREST BUILDER HOLDINGS BHD	CRESBLD	2
EKOVEST BHD	EKOVEST	2
BERJAYA CORPORATION BHD	BJCORP	2
BERJAYA LAND BHD	BJLAND	2
LION FOREST INDUSTRIES BHD	LIONFIB	2
TMC LIFE SCIENCES BHD	TMCLIFE	2
TIME DOTCOM BHD	TIMECOM	2
AMCORP PROPERTIES BHD	AMPROP	2
COUNTRY VIEW BHD	CVIEW	2
YTL LAND & DEVELOPMENT BHD	YTLLAND	2
KHEE SAN BHD	KHEESAN	2
SERN KOU RESOURCES BHD	SERNKOU	2
EVERSENDAI CORPORATION BHD	SENDAI	2
TSR CAPITAL BHD	TSRCAP	2
UTUSAN MELAYU (M) BHD	UTUSAN	2

Table 2: List of Companies Categorized as Low Risk

Company Name	Company Code	Rating
AJINOMOTO (M) BHD	AJI	7
BRITISH AMERICAN TOBACCO (M) BHD	BAT	7
PANASONIC MANUFACTURING MALAYSIA BHD	PANAMY	7
QL RESOURCES BHD	QL	7
CB INDUSTRIAL PRODUCT HOLDING BHD	CBIP	7
COASTAL CONTRACTS BHD	COASTAL	7
THREE-A RESOURCES BHD	3A	7
HOCK SENG LEE BHD	HSL	7
PINTARAS JAYA BHD	PTARAS	7
AMWAY (M) HOLDINGS BHD	AMWAY	7
DIALOG GROUP BHD	DIALOG	7
GEORGE KENT (M) BHD	GKENT	7
PETRONAS DAGANGAN BHD	PETDAG	7
SCICOM (MSC) BHD	SCICOM	7
YTL CORPORATION BHD	YTL	7
DIGI.COM BHD	DIGI	7
BATU KAWAN BHD	BKAWAN	7
DUTCH LADY MILK INDUSTRIES (M) BHD	DLADY	7.5
NESTLE (M) BHD	NESTLE	7.5
ORIENTAL HOLDINGS BHD	ORIENT	7.5
HARTALEGA HOLDINGS BHD	HARTA	7.5
P.I.E INDUSTRIAL BHD	PIE	7.5
TOP GLOVE CORPORATION BHD	TOPGLOV	7.5
GENTING BHD	GENTING	7.5
GENTING MALAYSIA BHD	GENM	7.5
KAF-SEAGROATT & CAMPBELL BHD	KAF	7.5
CARLSBERG BREWERY MALAYSIA BHD	CARLSBG	8
PPB GROUP BHD	PPB	8
AEON CREDIT SERVICE (M) BHD	AEONCR	8
UNITED PLANTATION BHD	UTDPLT	8
GUINNESS ANCHOR BHD	GAB	8.5
AEON CO. (M) BHD	AEON	10

3.3. Multiple Discriminant Analysis

Multiple discriminant analysis (MDA) is a statistical methodology for categorizing people or things into mutually exclusive and exhaustive groups (quantitative dependent variable) based on a set of characteristics (independent variables) of the people or things (Jaffari & Ghafoor, 2017). MDA creates a discriminant function, which is a function of a set of variables that are evaluated for samples of events or objects and used as an aid in discriminating between or classifying them. The objective of discriminant analysis is to develop discriminant functions that are linear combinations of independent variables that will discriminate between the categories of the dependent variable perfectly.

4. Results

The investigation was limited to a sample of companies that matched the 82 firms that were chosen from the Malaysian Stock Exchange's non-financial sector. The Altman (1968) model was used to identify the financial health of the firms to meet the goal of the study defined in this research. Using the Altman *Z*-Score, financial failure thresholds were used to distinguish between low- and high-risk organizations. According to Kim-Soon et al. (2020) and Christopoulos et al. (2019), financial performance was measured using a set of thresholds.

4.1. Group Differences

With the reduced data, the MDA 4-Variable Malaysian data was examined. This data collection was used to create an MDA-based model. There were 404 records in this data collection, however, 16 were eliminated due to outliers. With the Y response, the MDA function was employed with X_1, X_2, X_3, and X_4.

Based on the results in Table 3, the mean values for all four independent variables for high-risk companies are lower than the mean values of low-risk companies. Next, we test whether the differences between the high-risk group and low-risk group for the four financial ratios are statistically significant.

In Table 4, the p-value (Sig.) < 0.05 indicates that the group difference between high-risk and low-risk companies is statistically significant for the independent variable. Here X_2, X_3, and X_4, with Sig 0.000, 0.000, and 0.022, have significant group differences between high-risk and low-risk companies, while X_1 with Sig 0.844 does not have a statistically significant difference between high-risk and low-risk companies.

The smaller the Wilks' Lambda, the more important the independent variable is to the discriminant function (AlKubaisi et al., 2019). Here X_2 and X_3 have the lowest

Table 3: Group Statistics

Category	Mean	Std. Deviation	Valid *N* (Listwise)	
			Unweighted	Weighted
High Risk				
X_1	0.374833	0.6682413	52	52.000
X_2	−0.004492	0.1723181	52	52.000
X_3	0.004082	0.2330018	52	52.000
X_4	0.949576	0.6678217	52	52.000
Low Risk				
X_1	0.408683	0.8939660	32	32.000
X_2	0.340930	0.5819762	32	32.000
X_3	0.454499	0.7612279	32	32.000
X_4	1.228736	0.1354035	32	32.000
Total				
X_1	0.387728	0.7570631	84	84.000
X_2	0.127098	0.4162013	84	84.000
X_3	0.175669	0.5460832	84	84.000
X_4	1.055923	0.5472538	84	84.000

Table 4: Test of Equality of Group Means

	Wilks' Lambda	*F*	df1	df2	Sig.
X_1	1.000	0.039	1	82	0.844
X_2	0.836	16.132	1	82	0.000
X_3	0.836	15.895	1	82	0.000
X_4	0.938	5.430	1	82	0.022

Wilk's lambda, 0.836 and 0.838, therefore they are the most important variables, followed by X_4, 0.938, and then X_1, 1.000.

4.2. Independent Variables and Discriminant Function

A pooled within-groups covariance matrix, which may differ from the total covariance matrix, is displayed in the Pooled Within-Groups Matrices (Yee, 2018). The matrix is created by averaging the covariance matrices for each group separately. It is better to consider the correlation rather than the covariance because it is an external quantity (Keskin et al., 2020).

The within-groups correlation matrix (see Table 5) shows the correlations between the independent variables. Here we see a high correlation (0.993) between X_2 and X_3, and low or no correlation among the other variables. This indicates that a company with high or low X_2 will also have high or low X_3 (Yee, 2018).

Wilks' Lambda uses the eigenvalue to assess the importance of each discriminant function in MDA (Bhunia, & Sarkar, 2011). In this example, the percent of variation explained is 100%. There is only one discriminant function since there are only two groups (Yap et al., 2010). The eigenvalue is the percentage of variation in the dependent variable that the function can explain. The percentage of variation explained in the dependent variable is the Canonical Correlation (see Table 6 and Table 7).

4.3. Discriminant Function for Classification

The discriminant function is the function used in this study to calculate the discriminant score for each company. The Canonical Discriminant Function Coefficients (see Table 8) provides the discriminant function coefficients for the four financial ratios.

Using the discriminant function, this study can calculate the discriminant score for all 84 companies. Here group centroids are the average discriminant scores for the companies in the high-risk group and the low-risk group. Therefore, the study uses the two group centroids to establish the cutoff score for classifying a company as high risk and low risk.

Here the high-risk companies have an average discriminant score of −0.399 and the low-risk companies have an average of 0.648. As the number of companies in the two groups is unequal in size, (52 for the high-risk group and 32 for the low-risk group), the optimal cut-off point is the weighted average of the two centroids (Table 9).

$$\text{Cut off score} = 52/84 \times (-0.399) + 32/84 \times 0.648 = 0$$

Using this discriminant function, companies with scores less than 0 will be classified as high risk and companies with scores more than 0 will be classified as low risk (Yee, 2018).

Table 5: Pooled Within-Group Matrices

	X_1	X_2	X_3	X_4
Correlation X_1	1.000	−0.0265	−0.238	0.109
X_2	−0.265	1.000	0.993	0.054
X_3	−0.238	0.993	1.000	0.048
X_4	0.109	0.054	0.048	1.000

Table 6: Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	0.265[a]	100.0	100.0	0.458

Note: [a]First 1 canonical discriminant functions were used in the analysis.

Table 7: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	χ^2	df	Sig.
1	0.791	18.804	4	0.001

Table 8: Canonical Discriminant Function Coefficients (Unstandardized Coefficient)

	Function
	1
X_1	0.319
X_2	3.116
X_3	−0.580
X_4	0.793
(Constant)	−1.255

Table 9: Functions at Group Centroids

Category	Function
	1
High Risk	−0.399
Low Risk	0.648

Note: Unstandardized Canonical Discriminant Functions Evaluated at Group Means.

4.4. Discriminant Function Evaluation

The classification results (see Table 10) are used to assess how well the discriminant function works. The accuracy rate of the discriminant model is 67.9% in predicting high-risk and low-risk companies. The model can identify 92.3% high-risk companies, specificity, and 28.1% of the low-risk companies, sensitivity. This is a very conservative model in predicting high-risk companies, and the model is good for risk-averse investors.

This study has a positive correlation between the discriminant score and Altman's Z score. The correlation of the discriminant score and Altman's Z-score is 0.508, and the correlation is statistically significant with a p-value < 0.05. There is a significant correlation between our model and Altman's Z-score (see Table 11).

5. Conclusion

Several conclusions may be drawn from this research. To begin, there is a difference in identifying the financial status of low-risk and high-risk companies listed on the Malaysian Stock Exchange in the non-financial sector using the Altman Z-Score 1968 model. Second, several

Table 10: Classification Results

Category			Predicted Group Membership		Total
			High Risk	Low Risk	
Original	Count	High Risk	48	4	52
		Low Risk	23	9	32
	%	High Risk	92.3	7.7	100.0
		Low Risk	71.9	28.1	100.0

Note: 67.9% of original grouped cases are correctly classified.

Table 11: Correlations

		Altman	Discriminant Score from Function 1 for Analysis 1
Altman	Pearson Correlation	1	0.508**
	Sig. (2-tailed)		0.000
	N	82	82
Discriminant Score from Function 1 for Analysis 1	Pearson Correlation	0.508**	1
	Sig. (2-tailed)	0.000	
	N	82	84

Note: Correlation is significant at the 0.01 level (2-tailed).

non-financial companies listed on the Malaysian Stock Exchange are experiencing financial difficulties. The findings of this study show that the Altman model may be used to forecast a company's financial collapse. It dispelled any reservations about the model's legitimacy and the utility of applying it to evaluate the likelihood of a company's financial collapse. This is in accordance with research conducted by Kim-Soon et al. (2020), AlKubaisi et al. (2019), Yee (2018), and Bhunia and Sarkar (2011). According to the findings, the Edward Altman model is a good tool for investors to anticipate the financial collapse of organizations.

The findings of this study have significant consequences for investors, creditors, and corporate management. Portfolio managers may make better choices by not investing in companies that are risky and on the verge of a financial failure if they understand the variables that contribute to corporate distress. The findings can be used to offer management early warning indicators of deterioration in the company's financial condition so that remedial actions may be taken to reduce the risk of financial distress.

Future studies should cover various stock exchanges or bourses, as well as bigger sample sizes of corporations in both categories. In such research, the risk of attrition arises from the fact that a firm may be studied for a period of say 5 years prior to financial difficulty. While such organizations would give a wealth of data that may aid in the development of more accurate financial crisis prediction models, the danger that comes with their inclusion is clear.

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