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Research paper

Assessing The Impact of Covid-19 on Financial Distress: A Comparative Study Across Diverse Industries in Malaysia

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Abstract

This study examines the impact of the COVID-19 pandemic on financial distress across nine industries in Malaysia, using the Altman Z-score as the primary measure of financial health. A content analysis was conducted on the annual reports of 80 companies from 2018 to 2021, with a focus on 2021 to capture the extended effects of the pandemic. ANOVA was used to identify significant differences in mean Z-scores between industries, followed by post hoc tests to determine which sectors exhibited the most significant variation. Paired-samples t-tests were used to examine intra-industry changes over time. The average Z-score across all companies was 5.81, indicating generally low bankruptcy risk. However, sectoral differences were evident. The healthcare industry emerged as the most resilient, with a high average Z-score of 10.76, driven by increased demand, government support, and investor confidence. Conversely, the telecommunications sector recorded the lowest score of 3.83, indicating moderate risk. The results highlight the uneven financial impact of the pandemic and emphasize the need for industry-specific financial strategies. The findings contribute to the existing literature on financial distress in emerging markets and provide practical insights for policymakers and business leaders to improve financial resilience in preparation for future crises.

***Keywords**: Bankruptcy, financial crisis, accounting, Covid-19, Altman Z-score.*

1. Introduction

COVID-19 surfaced in early 2020 and has infected almost every nation globally (Ghani, Mohd Ali, Musa & Omonov, 2022). The onset of the COVID-19 pandemic in early 2020 has resulted in considerable economic strain globally, especially in Malaysia. The Malaysian government has implemented a series of Movement Control Orders (MCOs) requiring the suspension of operations across most industries, except critical services and certain industries. The COVID-19 epidemic has adversely affected the world economy, especially that of Malaysia. The hotel, restaurant, and tourist industries are among the industries most impacted by the COVID-19 pandemic (Rahmah & Novianty, 2021). The International Monetary Fund (IMF) forecasts that 95% of nations would see economic contraction or negative growth due to the global economic crisis (Rahmah & Noviaty, 2021). This situation has adversely affected numerous industries, and to compound the problem, some have been forced to cease operations due to the severe consequences. Nevertheless, a select few continue to prosper and devise strategies to optimize the company's profits to maintain competitiveness within the industry. Despite the challenging circumstances the company faces, certain managers strive to showcase the positive performance of their businesses, even though corporations are required to publish a financial report at the end of the fiscal year (Bui & Krajcsak, 2024).

This study aims to assess the impact of COVID-19 on the financial distress of Malaysian companies, as measured by the modified Altman Z-score. The financial statements of 80 companies listed on Bursa Malaysia from 2018 to 2021 serve as the primary data source for this analysis. Financial statements play a vital role in disseminating financial information about a firm, enabling stakeholders to make informed decisions. Its primary purpose is to provide financial information that helps current and potential investors, lenders, and other creditors allocate resources efficiently (Rahmah & Noviati, 2021). Beyond its functional role, financial reporting has become a key tool for managing relationships with stakeholders and establishing business credibility.

Publicly traded companies, especially large ones, are increasingly required to disclose a wide range of performance indicators, including economic, social, and environmental factors (Hua, Hla, & Md. Isa, 2016). Therefore, investors and stakeholders must rely on high-quality financial reporting practices that align with the overall objective of financial reporting. This practice helps evaluate an organization's performance and serves as a communication channel by providing both quantitative and qualitative data to internal and external stakeholders for decision-making (Blessing & Onoja, 2015). The financial statements are the main instrument for financial disclosure, offering vital information for various decision-making processes. However, even in cases of potential underperformance, managers often use accrual-based earnings management to present a more favorable view of their achievements (Hamid, Akter, & Rab, 2016). This involves manipulating financial reports to mislead stakeholders about the company's financial health or to influence contractual outcomes based on reported financial data (Healy & Wahlen, 1999).

This study places particular emphasis on the financial position and Z-score of companies in 2021. It is a critical year to reflect on the true financial situation after COVID-19, as companies struggled with the long-term economic impacts of the pandemic. Many firms faced financial instability due to disruptions in operations, supply chains, and market demand, making 2021 a crucial period for assessing the pandemic's full effect on corporate financial health.

The results of this study offer significant insights for regulators aiming to formulate strategies that assist publicly traded companies in managing future pandemic-related challenges, as poor financial health can result in substantial and enduring distress, potentially restricting investment, capital flows, and business performance, thereby hindering the nation's advancement towards developed status.

It is also important to recognize that the accuracy of financial distress prediction models, such as the Altman Z-Score, depends heavily on the quality of the underlying financial data. During periods of crisis, firms may engage in earnings management practices, such as discretionary accruals or accounting choices, to smooth earnings and present financial stability (Healy & Wahlen, 1999). Such behavior can temporarily inflate profitability, reduce apparent leverage, or distort liquidity ratios, all of which directly affect the Z-Score components. Consequently, while the Z-Score remains a reliable benchmark for detecting financial distress, analysts must interpret unusually high or stable scores during turbulent periods with caution, as these may partly reflect accounting adjustments rather than true economic resilience (Bui & Krajcsak, 2024; Hamid et al., 2016).

Comprehending financial crises is essential for stakeholders, including investors, creditors, and managers. The next section, Section 2, presents a comprehensive examination of the existing literature relevant to this study. Section 3 subsequently delineates the research methodology. Section 4 delineates the findings of the investigation and the ensuing analysis. Section 5, the concluding section, concludes this study.

2. Literature Review

A review of financial reporting literature shows that there are several definitions of financial distress. One of the earliest definitions is by Donaldson (1969). In his seminal 1969 book, Donaldson defined financial distress as a condition characterized by a lack of financial flexibility. Septiani, Siswantini, and Murtatik (2021) define financial distress as a state of deteriorating financial performance when a company does not have sufficient financial resources to operate its business and can manifest itself in different types of businesses and urging management to be cautious as the organization may be heading towards insolvency. Bringham and Daves (2003) assert that financial distress emerges even before a company files for bankruptcy or insolvency, specifically when the company is unable to meet its payment schedule or when the expected cash flow indicates that it will be unable to meet its financial obligations. Similarly, Purbayati and Afgani (2020) found in their study that financial distress is a period of deterioration in a company's financial condition before bankruptcy or liquidation. Financial distress is a condition in which an individual or organization is unable to generate revenue or income because of an inability to fulfil or pay its financial obligations (Roslan, Muhammad, Ghani, & Omonov, 2023). It is a period of deterioration in a company's financial condition before insolvency or liquidation (Hashim, Muhammad, Ghani, & Azis). According to Carolina et al. (2017), information about the status of companies in financial distress is crucial for investors seeking to allocate their capital, as they are wary of a company's financial difficulties.

Roslan, Muhammad, Ghani, and Omonov (2023) further emphasized that financial distress in Malaysian firms can be triggered by both internal management weaknesses and external economic shocks, such as the COVID-19 pandemic. In Malaysia, the unique circumstances of the pandemic, particularly the enforcement of several Movement Control Orders (MCOs) between March 2020 and October 2021, had distinct sectoral impacts. Sectors such as tourism, hospitality, and transportation experienced prolonged shutdowns, while technology, logistics, and healthcare saw accelerated growth. The Malaysian government introduced multiple fiscal and monetary packages, including the Prihatin Rakyat Economic Stimulus Package (PRIHATIN) and Pelan Jana Semula Ekonomi Negara (PENJANA), to stabilize the economy and support business liquidity (Bank Negara Malaysia, 2022). Studies by Halim et al. (2022) and Hashim et al. (2024) noted that these interventions reduced the severity of financial distress among publicly listed firms, though smaller firms continued to face credit access issues. In the post-pandemic era, researchers have renewed their focus on financial distress and recovery dynamics. According to Bui and Krajcsak (2024), corporate governance mechanisms and managerial adaptability significantly influenced firm survival during COVID-19. Similarly, Habib and Kayani (2022) found that firms with effective working capital management had greater financial resilience during economic downturns.

Financial distress may serve as a preliminary indicator of internal issues within the company (Rahmah & Noviati, 2021). Newton (1975) identified four phases of decline that firms in financial trouble typically undergo prior to declaring bankruptcy. The first phase is the incubation stage. At this stage, a firm may encounter operational or financial challenges, but these issues are not yet critical. Initial warning indicators, such as declining sales, escalating debt, or surging expenditures, may already be evident. Nonetheless, these issues may remain undetected or deemed tolerable at this juncture. The next stage is the cash shortage. During this period, cash inflows are inadequate to meet short-term commitments, necessitating reliance on external funding, loans, or deferred payments to suppliers. The liquidity deficit indicates that the firm is struggling to sustain its daily operations. The third stage is financial bankruptcy. During this period, the firm is unable to fulfill its financial commitments when they become due. Liabilities exceed assets, making the acquisition of additional funding more challenging. The corporation may default on loans, omit payments, or engage in discussions with creditors to reorganize its obligations. The last stage is total insolvency. In this final phase, the company's financial condition deteriorates to a point where it is no longer capable of sustaining operations. Bankruptcy becomes inevitable, prompting the corporation to seek bankruptcy protection or liquidation. At this stage, the stakeholders must suffer substantial losses.

A body of the financial reporting literature has attempted to examine the factors influencing the financial distress of companies. According to Chan, Yap, and Chai (2011), financial distress can result from several factors, including improper allocation of resources, poor financial structure, poor corporate governance, and unfavorable macroeconomic circumstances. Financial distress can result from a company's failure to anticipate global events, leading to a decline in business volume and eventual bankruptcy (Ratna & Marwati, 2018). Similarly, ineffective management can lead to the failure of a company, which in turn can lead to bankruptcy. Furthermore, poor management leads to persistent financial losses, which in turn make it impossible for the company to fulfill its obligations (Fauzia, 2017). Astuti, Damayanti, Chasbiandani, and Rizal (2020) state that outsiders may perceive several signs of financial distress, including: a decline in dividend payments to shareholders over several consecutive periods; a continuous decline in earnings to the point where the company is actually losing money. The company may also cease operations of one or more business units. Other indications include dismissal of many employees and a continuous fall in prices on the share market.

Another body of the financial reporting literature has examined the importance of early diagnosis of financial distress to prevent it from escalating into uncontrollable bankruptcy (Hashim et al., 2024). Analyzing a company's financial statements is a technique for forecasting financial difficulties. Financial ratios evaluate financial statements by reflecting a corporation's advantageous or unfavorable financial condition, including instances of financial difficulty (Fadillah & Susilowati, 2019). Financial distress for the pre- and post-COVID period can be measured using financial earnings and financial leverage (Ding et al., 2023). Organizations can forecast the probability of financial difficulty using many techniques, including the Beneish M-Score, working capital management, machine learning, and ratio analysis. Habib and Kayani's (2022) study investigates the possible influence of working capital management on the probability of a financial crisis. Conversely, Halim, Shuhidan, and Sanusi (2021) use a machine learning approach to forecast the incidence of financial hardship in corporations. Research on predicting financial difficulty has shown that this methodology enhances accuracy. Other studies have used the Altman Z-score model. Roslan et al. (2023) and Muda, Hassan, Aziz, and Bakar (2017) used the Altman Z-score in their study on the banking industry in Malaysia. The research indicated that Islamic banks exhibit more resistance to bankruptcy risk than traditional banks, particularly during economic recessions.

In the accounting literature, the Altman Z-score is widely acknowledged as an exceptional model for predicting financial distress (Rahmah & Noviati, 2021; Hashim et al., 2024). The Altman model has been employed in numerous studies to forecast a company's financial distress (such as Hussain, Ali, Ullah, & Ali, 2014; Swalih, Adarsh, & Sulphey, 2021; Hashim et al., 2024). The Altman Z-score model has been demonstrated to be highly accurate in predicting corporate bankruptcies, with a lead time of up to four years, in these studies. Rahmah and Noviati (2021) used the Altman Z-Score as a predictive instrument for a company's financial distress. This score is based on five critical factors that correspond to five ratios. The initial ratio is the working capital-to-total assets ratio, a liquidity ratio that measures the amount of net working capital a company has at its disposal in relation to its total assets to sustain its operations. The second ratio is the ratio of retained earnings to total assets, which is a metric that indicates the profits that the company has accumulated over its existence. The EBIT ratio in relation to the total assets is the third critical figure. It represents the ratio of the total number of operational assets a company possesses to the amount of profit it generates. The fourth critical figure is the book value of equity in relation to the book value of total debt. By dividing the book value of equity by the book value of total assets, this ratio can be employed to ascertain the extent to which debt contributes to the overall decline in a company's asset value. The final critical figure is the ratio of sales to total assets, which represents the efficiency with which a company employs its total assets to generate sales.

Edward Altman introduced the Altman Z-Score in 1968, which was primarily derived from data from US enterprises in the manufacturing industry (Altman, 2002). Altman, in turn, applied his Z-score to US companies, which poses the issue of its applicability to non-US companies and emerging markets, such as those in Malaysia. The applicability of this formula to non-US companies is called into doubt for three reasons. First, the global economy has undergone a substantial transformation since Altman's initial research. Second, the data for this model is nearly 50 years old. Third, the US economy may not accurately reflect market conditions in other countries, and industries are not always comparable to manufacturing (the industry that was utilized in the development of the original Altman Z-score). Consequently, organizations that are not located in the United States implement an altered variation of the formula known as the "Z" score. To evaluate a company's financial distress, the modified Altman Z-score model employs multiple discriminant analysis (MDA) to analyze numerous financial ratios simultaneously (Lord, Landry, Savage, & Weech-Maldonado, 2020). The Z-score is a statistical technique that is a part of multiple discriminant analysis and integrates ratios into a multivariate framework (Rim & Roy, 2014). The original and modified Altman Z-scores are compared in Table 1.

Table 1: Original and Modified Altman Z-scores

Altman Z Score	Formula	Indications
Original: Z-Score (1968)	Z = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E	Z > 2.99 (Safe Zone) 2.99 > Z > 1.81 (Grey Zone) Z < 1.81 (Distress Zone)
Modified for Emerging Markets: Malaysian Companies Z"-Score (1995)	Z" = 6.56 (A) + 3.26 (B) + 6.72 (C) + 1.05 (D) + 3.25	Z > 2.99 (Safe Zone) 2.99 > Z > 1.81 (Grey Zone) Z < 1.81 (Distress Zone)

Where:
A = Working Capital / Total Assets
B = Retained Earnings / Total Assets
C = EBIT / Total Assets
D = Market Value of Equity / Book Value of Total Liabilities
E = Sales / Total Assets

The modification of the Z-score serves to take account of the different financial structures and risk profiles in different industries and countries, e.g. in the manufacturing and non-manufacturing industries. Manufacturing companies generally rely heavily on physical assets, which are not as crucial in other industries, such as the service industry. In addition, emerging markets such as Malaysia face higher economic volatility and different financial dynamics, requiring adjustments to the original Altman Z-score. Therefore, the formulas differ to ensure that the Z-score accurately reflects the bankruptcy risk for different types of companies, considering their specific financial characteristics.

3. Research Methodology

3.1 Sample Selection

In the field of research, determining an appropriate sample size is a crucial step in ensuring the reliability and validity of the study's findings. One of the widely used methods for sample size estimation is the Krejcie and Morgan (1970) table, which provides a guideline for determining the sample size based on a given population size. The Krejcie and Morgan (1970) table suggests that for a population of 100 companies, the recommended sample size is 80 companies. This sample size is considered adequate to draw reliable inferences about the population and to avoid sampling errors or biases. (Nanjundeswaraswamy & Divakar, 2021). Consequently, of the 100 top listed companies on Bursa Malaysia, 80 were considered as the sample for this study.

Although this study used the Krejcie and Morgan (1970) table to determine an appropriate total sample size (80 companies), it is acknowledged that the distribution of companies across industries was uneven. For example, the healthcare and transportation industries were each represented by only five companies, while the consumer products industry included twenty-one companies. This variation reflects the actual composition of Bursa Malaysia's main market, where certain industries (e.g., consumer products, industrial products) have a significantly larger number of listed firms compared to more specialized sectors such as healthcare and telecommunications.

While the uneven sample sizes may affect the comparative statistical power between industries, this study mitigated potential bias by employing ANOVA with post hoc tests (Tukey's HSD), which are robust to moderately unequal sample sizes when variance homogeneity is satisfied (as confirmed by the Brown-Forsythe test, $p > 0.05$). Moreover, the aim of this study is not to generalize across all firms uniformly but to capture inter-industry trends and highlight how different sectors experienced financial distress during and after the pandemic. Therefore, the results should be interpreted as indicative of relative patterns across industries rather than absolute generalizations applicable to all companies in each sector.

3.2 Research Instrument and Data Collection

The research tool used in this study is content analysis, utilizing four years of financial data from 80 listed companies in the main market of Bursa Malaysia. The data was sourced from Refinitiv® Datastream® and the corporate websites of the respective companies, which provide secondary data in the form of audited annual financial reports for the years 2018 to 2021. Banks and financial institutions were excluded from the sample as they are subject to different regulatory and reporting requirements that could lead to inconsistencies compared to other industries. In addition, companies providing airline services were excluded due to outliers in the data, as the implementation of the Movement Control Order (MCO) during the COVID-19 pandemic led to a ban on all flights, which significantly distorted their financial data.

3.3 Data Analysis

Malaysia is classified as an emerging market due to several key characteristics. The country has experienced consistent economic growth and has successfully transitioned from an agriculture-based economy to one driven by industrialization and services. In recent years, Malaysia has also attracted substantial foreign direct investment (FDI) and demonstrated significant progress in financial system reforms and political modernization. However, it remains a middle-income economy, which is a common trait among emerging markets. These factors collectively position Malaysia as an emerging market with strong growth potential.

For the reasons outlined above, with Malaysia being classified as an emerging market, this study collects a total of 320 data points (80 companies across 4 years of financial data). These data were then utilized to calculate the modified Altman Z-Score, using the following adjusted formula:

Altman Z-Score: $Z'' = 6.56\,(A) + 3.26\,(B) + 6.72\,(C) + 1.05\,(D) + 3.25$

Where:

A = working capital / total assets

B = retained earnings / total assets

C = earnings before interest and tax / total assets

D = market value of equity / total liabilities

E = sales / total assets

Altman and Hotchkiss (2006) made important adjustments to the original Altman Z-score formula to better fit the realities of emerging markets. One important change was the introduction of the constant 3.25, which helps address the unique financial risks and economic conditions to which these markets are exposed. Unlike developed economies, emerging markets often experience higher volatility, have less mature capital markets, and are more sensitive to external economic surprises. By including the constant 3.25, the modified formula is designed to offset the additional risks and structural differences present in emerging markets, making the Z-score more accurate for these contexts. Without this adjustment, companies in these markets would appear to have a higher risk of bankruptcy than is the case.

The Altman Z-score is divided into three categories, with higher scores indicating a lower likelihood of bankruptcy or financial distress (safe zone with a Z-score of more than 3), as shown in Table 2. In this study, the mean values of the Altman Z-scores are calculated, as previously stated above.

Table 2: Z-Score Range

Z-Score Range	Indications
Z-Score < 1.81	Distress Zone (High risk of bankruptcy)
1.81 < Z-Score <2.99	Grey Zone (Moderate risk)
Z-Score > 2.99	Safe Zone (Low risk of bankruptcy)

To compare the financial distress across industries, the researchers collected financial data and calculated Altman Z-scores for companies from nine different industries. An ANOVA test was then performed to determine whether there were statistically significant differences in Z-scores between these industries. A post-hoc test (Tukey's HSD) was then conducted to determine which specific industries showed differences from one another. Finally, the researchers conducted a paired-samples t-test to determine the mean differences in Z-scores before and after the COVID-19 pandemic for the most affected industry. This test is particularly useful for comparing two related groups, as it helps to determine whether there is a significant change in financial distress over time. However, before conducting comparative mean analyses, it is important to check the normality of the data. This ensures that parametric tests, such as ANOVA and t-tests, can be applied appropriately, as these tests assume a normal distribution of the data. If the data deviate significantly from normality, non-parametric tests or data transformations may be required to compare means between groups or over time accurately.

4. Finding and Discussion

4.1 Descriptive Statistics

This section contains the descriptive statistics for 80 companies with 320 data sets, categorized into nine industries. The industries included in the analysis are construction, consumer products, energy and utilities, healthcare, industrial products, plantations, technology, telecommunications, and transport. Table 3 and Figure 1 summarize the descriptive statistics of the Altman Z-score by industry for four years from 2018 to 2021.

Table 3: Descriptive Statistics of Atman Z-score by Industries

Industries	No of companies in each industry	%	Average Z-Score			
			2018	2019	2020	2021
Construction	8	10.0	5.10	5.09	4.93	5.26
Consumer product	21	26.3	6.11	6.08	5.16	5.38
Energy & Utilities	10	12.5	4.33	4.60	4.80	4.79
Healthcare	5	6.3	6.46	6.10	7.78	10.76
Industrial product	8	10.0	4.89	5.30	5.34	5.23
Plantation	9	11.3	6.35	6.04	6.20	6.32
Technology	8	10.0	6.46	6.63	6.61	7.10
Telecommunications	6	7.5	4.20	3.28	3.80	3.83
Transportation	5	6.3	7.04	6.80	7.10	5.92
Total	**80**	**100.0**				

This analysis sheds light on the financial health and stability of companies across different industries, highlighting key trends and areas of concern. The consumer product is the most represented with 21 companies (26.3%), followed by energy and utilities with 10 companies (12.5%), and plantations with 9 companies (11.3%). The industries with the lowest number of companies are healthcare and transportation, with 5 companies (6.3%), respectively.

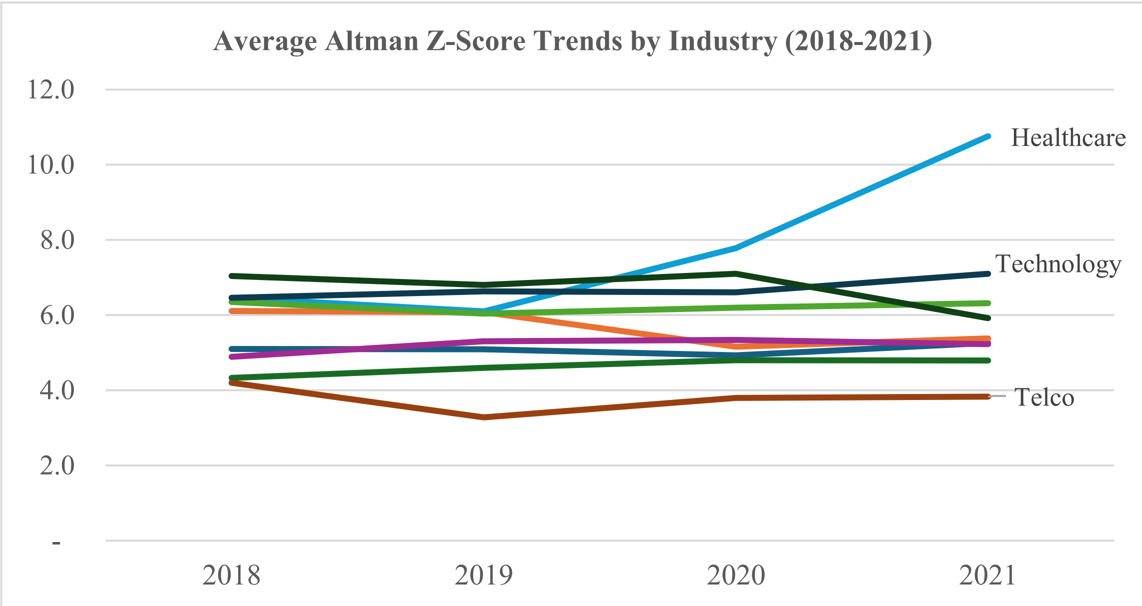

Fig. 1: Average Altman Z-Score Trends by Industry (2018–2021)

As shown in the table and figure, the highest average Z-Scores were observed in the Healthcare (10.76) and Technology (7.10) industries, particularly in 2021, while Telecommunications (3.83) and Energy & Utilities (4.79) displayed weaker scores, indicating potential financial distress. The healthcare and technology industries show an upward trend, reflecting strong pandemic-related demand. In contrast, consumer products and telecommunications experienced fluctuations, with moderate recovery post-2020. The overall pattern indicates that sectors that are essential and innovation-driven were more resilient to financial distress during and after the COVID-19 pandemic. The data reflects the impact of economic conditions over the years, particularly with noticeable declines in Consumer Products and Transportation during 2020, likely linked to the pandemic's effects, followed by mixed recoveries in subsequent years. The varied performance across industries highlights the different impacts of market conditions and economic factors, emphasizing the importance of industry-specific analysis when assessing financial health.

This study also examines the impact of COVID-19 on the Altman Z-score of individual industries. To do that, this study used 2021 as the base year for the analysis due to several factors. In 2021, many countries, including Malaysia, continued to face restrictions and lockdowns due to COVID-19, which significantly affected business operations, consumer behavior, and overall economic activity. In addition, by 2021, many government support programs and financial assistance that had initially helped businesses weather the pandemic had either been scaled back or expired, forcing companies to rely more heavily on their operational resilience and financial stability.

The combination of continued restrictions and reduced government support meant that the 2021 financial data reflected the true impact of COVID-19 on companies. In contrast to 2020, when many companies benefited from temporary relief measures, 2021 is a year in which operational and financial challenges became more pronounced and sustained. Using 2021 as a base year also allows for more effective comparisons with previous years (2018 to 2020), which illustrate how the pandemic has changed financial health indicators across industries and make it easier to recognize the long-term impact of COVID-19 on individual industries. Thus, 2021 is a crucial year to understand the impact of the pandemic on the Altman Z-Score. Table 4 provides descriptive statistics of the Altman Z-Score by industry in 2021.

Table 4: Descriptive Statistics of Altman Z-score by Industries in 2021

Industries	N	%	Average Z-Score (2021)	SD	Min	Max	Indications (Min-Max)
Telecommunication	6	7.50	3.83	1.03	2.30	5.00	Grey - Safe
Energy & Utility	10	12.50	4.79	0.99	3.30	6.60	Safe
Industrial product	8	10.00	5.23	1.65	3.40	7.60	Safe
Construction	8	10.00	5.26	1.36	3.50	7.40	Safe
Consumer product	21	26.25	5.38	2.73	2.10	10.80	Distress - Safe
Transportation	5	6.25	5.92	1.34	4.60	7.70	Safe
Plantation	9	11.25	6.32	1.42	4.00	9.00	Safe
Technology	8	10.00	7.10	2.24	3.90	9.60	Safe
Healthcare	5	6.25	10.76	6.35	3.70	17.40	Safe
Total	**80**	**100.00**	**5.81**	**2.75**	**2.10**	**17.40**	

The average value of the Altman Z-score of 80 observations is 5.81, and the standard deviation is 2.75. The score values range from a minimum of -2.10 to a maximum of 17.40. The healthcare industry stands out with the highest average Z-Score (10.76), while the telecommunications industry has the lowest average Z-Score (3.83). Although all industries have an average Z-score above 2.99, which is in the safe zone or low bankruptcy risk, some companies are in the distress zone (high bankruptcy risk), i.e., a company from the consumer product industry with a Z-score of -2.10. There is also a company from the telecommunications industry in the grey zone with a Z-score of 2.30.

4.2 Validity and Reliability

To ensure reliable results, the data collection was randomized. This approach helps to ensure that the sample adequately represents the population, making it easier to generalize the results. In this study, the researcher has analyzed the 2021 data of the 80 listed companies in Malaysia, categorized by industry, indicating that the sample adequately reflects the overall population. Furthermore, scoring the dependent variable on an interval or ratio scale means that it should be continuous and have equal intervals. For this study, the researchers focused on independent variables consisting of two or more categorical groups.

The analysis of variance (ANOVA) is a statistical method that makes it possible to determine significant differences between the mean values of three or more groups. Before performing an ANOVA test, the data must fulfill several critical assumptions to ensure the reliability and validity of the test results. The first aspect is observer independence. The data collected from one subject should not influence the data collected from another subject, and each observation should be independent of the others. This study has confirmed this hypothesis.

The residuals (errors) of the data should be normally distributed. There are several methods to test for normality, including graphical methods and statistical tests. Both approaches should be used together to make an informed decision about the normality of your data. In this study, we used the statistical test, i.e., the Shapiro-Wilk test. Table 5 shows that the p-value of the Shapiro-Wilk test is greater than 0.05 for all industries, which means that the data fulfill the normality assumption.

Table 5: Normality Tests on 2021 Data (**Shapiro-Wilk)**

	Statistic	df	Sig.
Construction	0.948	8	0.686
Consumer products	0.935	21	0.176
Energy & utility	0.935	10	0.495
Healthcare	0.826	5	0.130
Industrial products	0.888	8	0.226
Plantation	0.970	9	0.896
Technology	0.881	8	0.191
Telecommunication	0.903	6	0.389
Transportation	0.905	5	0.437

The variances within each category should also be approximately equal. The Brown-Forsythe test was used to test this assumption, which is crucial for the validity of the F-test used in the ANOVA. As shown in Table 6, the p-value is greater than 0.05, which indicates that the variances in the categories are equivalent.

Table 6: Robust Tests of Equality of Metrics

	Statistic	df1	df2	Sig.
Brown-Forsythe	3.164	8	8.987	0.053

4.3 ANOVA Test

The main aim of ANOVA is to determine whether there are statistically significant differences between the means of three or more independent groups. Using this method, researchers can evaluate the null hypothesis, which states that all group means are equal, against the alternative hypothesis, which states that at least one group mean is different. In this study, the alternative hypothesis states that in 2021, the means of Altman Z-scores are significantly different across industries in Malaysia. As shown in Table 7, the hypothesis was supported by an F-statistic of 3.872 and a p-value of less than 0.001, which means that there was a significant difference in the Altman Z-scores between the nine industries.

Table 7: ANOVA test (2021)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	181.096	9	22.637	3.872	0.001
Within Groups	415.104	71	5.847		
Total	**596.200**	**79**			

4.4 POST HOC Test

Following a significant ANOVA result, which indicates that in 2021, at least one group mean differs, post hoc tests such as the Bonferroni correction or Tukey's HSD (Honestly Significant Difference) are used to determine which industry means differ. Tukey's HSD was used in this study, as this is a widely used method for multiple comparisons in ANOVA. This approach is particularly effective for comparing all possible pairs of group means while controlling for Type I error. The results show that in 2021, only the healthcare industry had a significant difference in mean Altman Z-scores compared to the construction, consumer goods, energy, industrial products, plantation, and telecommunications industries, as shown in Table 8. In particular, the difference in mean score between healthcare and telecommunications is the largest at 6.92667 ($p < 0.05$). Subsequently, the mean value of healthcare is significantly different from energy and utilities (5.97000, $p < 0.05$), consumer products (5.37905, $p < 0.05$), construction (5.49750, $p < 0.05$), industrial products (5.53500, $p < 0.05$), and plantations (4.43778, $p < 0.05$). This suggests that the Altman Z-scores of healthcare companies reflect the impact of the COVID-19 pandemic more accurately than those of other industries, as all variances in the means are positive. However, there are no significant differences between the healthcare, technology, and transport industries, nor between the other industries analyzed.

Table 8: Post Hoc Test (Tukey HSD) (2021)

		Mean Difference	Std. Error	Sig.
Construction	Consumer products	-0.11845	1.00460	1.000
	Energy	0.47250	1.14694	1.000
	Healthcare	**-5.49750***	**1.37845**	**0.005**
	Industrial products	0.03750	1.20898	1.000
	Plantation	-1.05972	1.17492	0.992
	Technology	-1.83750	1.20898	0.842
	Telecommunication	1.42917	1.30585	0.973
	Transportation	-0.65750	1.37845	1.000
Consumer products	Construction	0.11845	1.00460	1.000
	Energy	0.59095	0.92901	0.999
	Healthcare	**-5.37905***	**1.20321**	**0.001**
	Industrial products	0.15595	1.00460	1.000
	Plantation	-0.94127	0.96334	0.987
	Technology	-1.71905	1.00460	0.738
	Telecommunication	1.54762	1.11930	0.901
	Transportation	-0.53905	1.20321	1.000
Energy	Construction	-0.47250	1.14694	1.000
	Consumer products	-0.59095	0.92901	0.999
	Healthcare	**-5.97000***	**1.32437**	**0.001**
	Industrial products	-0.43500	1.14694	1.000
	Plantation	-1.53222	1.11098	0.902
	Technology	-2.31000	1.14694	0.539
	Telecommunication	0.95667	1.24863	0.997
	Transportation	-1.13000	1.32437	0.995
Healthcare	**Construction**	**5.49750***	**1.37845**	**0.005**
	Consumer products	**5.37905***	**1.20321**	**0.001**
	Energy	**5.97000***	**1.32437**	**0.001**
	Industrial products	**5.53500***	**1.37845**	**0.004**
	Plantation	**4.43778***	**1.34867**	**0.039**
	Technology	3.66000	1.37845	0.183
	Telecommunication	**6.92667***	**1.46415**	**0.000**
	Transportation	4.84000	1.52925	0.055
Industrial products	Construction	-0.03750	1.20898	1.000
	Consumer products	-0.15595	1.00460	1.000
	Energy	0.43500	1.14694	1.000
	Healthcare	**-5.53500***	**1.37845**	**0.004**
	Plantation	-1.09722	1.17492	0.990
	Technology	-1.87500	1.20898	0.827
	Telecommunication	1.39167	1.30585	0.977
	Transportation	-0.69500	1.37845	1.000
Plantation	Construction	1.05972	1.17492	0.992
	Consumer products	0.94127	0.96334	0.987
	Energy	1.53222	1.11098	0.902
	Healthcare	**-4.43778***	**1.34867**	**0.039**
	Industrial products	1.09722	1.17492	0.990
	Technology	-0.77778	1.17492	0.999
	Telecommunication	2.48889	1.27438	0.580
	Transportation	0.40222	1.34867	1.000
Technology	Construction	1.83750	1.20898	0.842
	Consumer products	1.71905	1.00460	0.738
	Energy	2.31000	1.14694	0.539
	Healthcare	-3.66000	1.37845	0.183
	Industrial products	1.87500	1.20898	0.827
	Plantation	0.77778	1.17492	0.999
	Telecommunication	3.26667	1.30585	0.249
	Transportation	1.18000	1.37845	0.994
Telecommunication	Construction	-1.42917	1.30585	0.973
	Consumer products	-1.54762	1.11930	0.901
	Energy	-0.95667	1.24863	0.997
	Healthcare	**-6.92667***	**1.46415**	**0.000**
	Industrial products	-1.39167	1.30585	0.977
	Plantation	-2.48889	1.27438	0.580

		Mean Difference	Std. Error	Sig.
	Technology	-3.26667	1.30585	0.249
	Transportation	-2.08667	1.46415	0.884
Transportation	Construction	0.65750	1.37845	1.000
	Consumer products	0.53905	1.20321	1.000
	Energy	1.13000	1.32437	0.995
	Healthcare	-4.84000	1.52925	0.055
	Industrial products	0.69500	1.37845	1.000
	Plantation	-0.40222	1.34867	1.000
	Technology	-1.18000	1.37845	0.994
	Telecommunication	2.08667	1.46415	0.884

Interestingly, the post-hoc results also show that the technology and transportation industries did not exhibit significant differences in financial distress compared to the healthcare industry. This outcome can be attributed to several economic factors during Malaysia's COVID-19 period. First, both industries experienced increased demand due to digital transformation and logistical needs during lockdowns. The technology sector benefited from greater adoption of e-commerce, remote working systems, and digital payments, which enhanced revenue and investor confidence (Tan, Ong, & Low, 2023). Similarly, while passenger travel declined abruptly, the transportation sector—particularly logistics, courier services, and supply chain operators—saw growth in freight demand driven by online retail and healthcare supply distribution (Bank Negara Malaysia, 2022).

During the COVID-19 crisis, the healthcare industry has performed better than many other industries for several reasons. The pandemic led to a surge in demand for essential healthcare services and products, as well as increased government support in the form of grants and subsidies. Public health awareness led to increased spending on healthcare goods, while pharmaceutical companies involved in the development and distribution of COVID-19 vaccines experienced significant sales growth. These factors are well documented in the literature. Overall, healthcare companies performed significantly better financially than many other industries that faced severe disruptions and downturns during the pandemic. They benefited from increased demand, government support, their status as a vital service, and innovation.

4.5 Paired Samples T-Test Analysis on the Healthcare Industry

A further analysis of the Altman Z-scores for the healthcare industry was conducted, as the post-hoc test revealed that the Z-scores of this industry differ significantly from those of the other industries. There are only five companies in this industry, resulting in a total of 20 Altman Z-score data points (10 data points before the pandemic and 10 data points during the pandemic), as shown in Table 9. The mean Altman Z-score was 6.28 before the pandemic and increased to 9.27 during the pandemic. This increase indicates that, on average, these companies maintained a solid financial position during and after the pandemic. A higher Altman Z-score correlates with a lower probability of bankruptcy and a better financial position.

Table 9: Descriptive Statistics of the Atman Z-score of the Healthcare Industry

	Years	N	Minimum	Maximum	Mean	SD
Before	2018-2019	10	3.90	9.90	6.28	2.15241
During	2020-2021	10	3.70	17.40	9.27	5.11470
Total		**20**				

The Altman Z-scores of the healthcare industry for the two periods were then compared to determine whether the mean difference between them was significantly different from zero. To assess this difference, a paired-samples t-test was conducted to compare the financial distress of healthcare companies between the two time periods. The mean difference in Altman Z-scores before and after the pandemic was -2.990, as shown in Table 10. The negative value indicates that the mean score before the pandemic was lower than during the pandemic, suggesting that the financial health of healthcare companies improved on average during this period. With a p-value of 0.044 (t-value of -2.343), the mean difference in Altman Z-scores is statistically significant as it is below the 0.05 significance level.

Table 10: Paired Samples T-Test

	Paired differences Mean	Std. Deviation	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
			Lower	Upper			
Before - During	-2.99000	4.03470	-5.87625	-0.10375	-2.343	9	0.044

These results indicate that there is a significant difference in the financial distress of Malaysian healthcare organizations between the two periods, showing that the COVID-19 pandemic has had a significant positive impact on their financial health. The statistical significance of this improvement, as shown by the t-test results, confirms that the observed changes are not merely random but rather reflect factors related to the pandemic.

5. Conclusion

The focus of this study is to analyze the impact of the COVID-19 pandemic on the financial distress of the industry in Malaysia. The content analysis was conducted using the annual reports of 80 different companies from various industries from 2018 to 2021. The methodology of the study, which included data collection and appropriate analysis techniques, ensured the reliability of the results. By applying the Krejcie and Morgan sample size and conducting thorough tests for normality and equality of variance, the study provided a robust framework for understanding the financial impact of the pandemic on the Malaysian industry.

The result of this study has provided valuable insights into the financial distress of Malaysian companies across various industries in the wake of the COVID-19 pandemic, using the Altman Z-score as a key metric. The analysis revealed that the average Z-score for the sample was 5.81, indicating a generally low risk of bankruptcy, although there were significant differences between industries. The healthcare sector was exceptionally resilient, with the highest average Z-score of 10.76, indicating robust financial health amid the challenges of the pandemic. The following factors can be seen as the main reasons for the healthy financial position of companies in the healthcare industry. Firstly, the pandemic has significantly increased the demand for healthcare services, including testing, treatment, and vaccination.

Companies involved in the production of vaccines, medical equipment, and telemedicine services have seen significant growth. This surge in demand led to higher revenues for many healthcare companies, which positively impacted their financial position. Secondly, many governments, including the Malaysian government, provided significant financial support and resources to the healthcare industry to combat the pandemic. This inflow of funds helped stabilize and improve healthcare companies' financial position. Thirdly, investor confidence in these companies increased as the healthcare industry played a crucial role during the pandemic. This led to higher share prices and better capital access, further strengthening the companies' financial health. Finally, the crisis encouraged rapid innovation and expansion in the healthcare industry. This not only improved their financial situation but also positioned them for long-term success.

In contrast, the telecommunications sector had the lowest average Z-score of 3.83, placing it in the grey zone, indicating moderate risk. These results emphasize the varying impact of economic disruption on different sectors and highlight the importance of sector-specific assessments when evaluating financial stability in times of crisis. In addition, ANOVA results confirmed statistically significant differences in the degree of financial distress among the nine industries, with a particular focus on the healthcare sector. Post-hoc tests revealed that the healthcare industry performed significantly better than other sectors, particularly telecommunications, energy, and consumer goods, which faced greater challenges during the pandemic. This suggests that the financial health of healthcare companies enabled them to manage the uncertainties of COVID-19 more effectively than their counterparts in less resilient industries.

The non-significant differences between healthcare, technology, and transportation industries further indicate that digitalization and essential-service sectors were key drivers of financial resilience during the pandemic. These industries adapted promptly to new market demands, supported by Malaysia's digital economy initiatives and logistics expansion under post-MCO recovery strategies. This explains why their financial health remained strong, mirroring the performance of the healthcare sector during the same period.

Despite the robustness of the analysis, the study has several limitations. One key limitation is the uneven distribution of sample firms across industries, which may affect the representativeness of certain sectors, particularly healthcare and transportation. This imbalance reflects the actual structure of Malaysia's capital market, where the number of listed healthcare firms is relatively small compared to other sectors, such as consumer products or industrial goods. Future research could enhance generalizability by employing a stratified sampling approach or including a broader dataset that covers small and medium enterprises (SMEs) or unlisted firms, thereby providing more balanced sectoral insights.

The study shows that certain industries, such as telecommunications, energy, and consumer products, remain vulnerable to financial shocks. Therefore, targeted measures are needed to strengthen their financial resilience. First, Bursa Malaysia can enhance its monitoring of company health by requiring firms in high-risk sectors to provide regular financial updates. This would help detect financial problems early and increase transparency. Second, the Securities Commission (SC) can offer incentives to companies that maintain strong governance and accurate reporting. For example, firms with robust internal controls could receive faster approvals or lower listing fees. Third, Bank Negara Malaysia (BNM) and the Ministry of Finance could introduce special financial aid for capital-intensive industries during crises, similar to the recovery and financial facilities provided during COVID-19. This could include loan guarantees or temporary interest relief to help firms remain operational. Finally, all regulators could establish a Financial Resilience Index (FRI), such as the Altman Z-Score, to track early warning signs of financial distress and enable authorities to act quickly to support struggling industries.

The study emphasizes the urgent need for targeted financial strategies and support measures tailored to the specific conditions and challenges of different sectors, especially in times of economic disruption. The findings not only contribute to the existing literature on financial distress in emerging markets but also provide practical insights for stakeholders, including policymakers and business leaders, to improve financial resilience and prepare for future crises. Overall, this study provides a foundation for further research on the long-term effects of COVID-19 on various sectors in Malaysia and beyond.

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References

[1] Altman, E. I., & Hotchkiss, E. (2006). Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt (3rd ed.). John Wiley & Sons.
[2] Altman, E.I. (2002), Revisiting Credit Scoring Models in a Basel 2 Environment. Available from: https://finbox.com/OTCPK:TGLV.Y/ explorer/altman_z_score
[3] Astuti, S. B., Damayanti, A., Chasbiandani, T., & Rizal, N. (2021). Pandemi Covid-19 dalam Penyajian Pelaporan Keuangan dan Keberlangsungan Usaha melalui Prediksi Kebangkrutan. AFRE (Accounting and Financial Review), 3(2), 165–171.
[4] Bank Negara Malaysia. (2022). Economic and monetary review 2022.
[5] Blessing, A., & Onoja, E.O., The role of financial statements on investment decision-making: A case of United Bank for Africa PLC, European Journal of Business, Economics and Accountancy, 3(2), 12-38
[6] Brigham, E.F. & Daves P.R. (2003), Intermediate Financial Management with Thomson One. United States of America: Cengage SouthWestern
[7] Bui, H., & Krajcsák, Z. (2024). The impacts of corporate governance on firms' performance: From theories and approaches to empirical findings. Journal of Financial Regulation and Compliance, 32(1), 18–46.
[8] Chan, K.T., Yap., V.C. & Chai, S.N. (2011), Factors affecting financial distress: The case of Malaysian public listed firms, Corporate Ownership and Control, 8(4), 345-352
[9] Ding, S., Cui, T., Bellotti, A. G., Abedin, M. Z., & Lucey, B. (2023). The role of feature importance in predicting corporate financial distress in pre and post COVID periods: Evidence from China. International Review of Financial Analysis, 90, 102851.
[10] Donaldson, G. (1969). "Strategy for Financial Mobility. Boston", Mass.: Harvard University Press
[11] Fadillah, M. R., & Susilowati, P. I. (2019). Faktor-faktor yang mempengaruhi financial distress pada Perusahaan manufaktur di Indonesia, 4(1), 191–192.
[12] Fauzia, I.Y. (2017), Mendeteksi Kebangkrutan Secara Dini Perspektif Ekonomi Islam. Jurnal Ekonomi Dan Keuangan, 19(1), 90.
[13] Ghani, E.K., Mohd Ali., M., Musa, M.N.R., & Omonov, A.A. (2022), The effect of perceived usefulness, reliability and COVID-19 pandemic on digital banking effectiveness: Analysis using technology acceptance model, Sustainability, 14(18), 1-16.
[14] Habib, A. M., & Kayani, U. N. (2022). Does the efficiency of working capital management affect a firm's financial distress? Evidence from UAE. Corporate Governance: The International Journal of Business in Society, 22(4), 567–589.
[15] Halim, A., Shuhidan, S. M., & Sanusi, Z. M. (2022). Predicting financial distress using machine learning: Evidence from Malaysian firms. Asian Journal of Accounting and Governance, 13(1), 45–60.

[16] Halim, Z., Shuhidan, S.M., Sanusi, Z.M. (2021), Corporation financial distress prediction with deep learning: Analysis of public listed companies in Malaysia. Business Process Management Journal, 27(4), 1163-1178.
[17] Hamid, F., Akter, S., & Rab, N. (2016). Earnings management and financial performance: Evidence from Malaysia. Management & Accounting Review, 15(2), 1–18.
[18] Hamid, T., Akter, F., & Rab, N. B. (2016). Prediction of financial distress of non-bank financial institutions of Bangladesh using Altman's Z score model. International Journal of Business and Management, 11(12), 261-272.
[19] Hashim, M., Muhammad, K., Ghani, E. K., & Azis, M. A. A. (2024). Financial distress analysis of top 100 Malaysian public listed companies during COVID-19 pandemic using Altman Z-score analysis. International Journal of Economics and Financial Issues, 14(4), 200–205.
[20] Healy, P. M., & Wahlen, J. M. (1999). A review of the earnings management literature and its implications for standard setting. Accounting Horizons, 13(4), 365–383.
[21] Hua, S.C., Hla, D.T., & Md Isa, A.H. (2016), Malaysia financial reporting practices and audit quality promote success: The case of Malaysian construction sector, UNIMAS Review of Accounting and Finance, 1(1), 36-51.
[22] Hussain, F., Ali, I., Ullah, S., Ali, M. (2014), Can Altman Z-score model predict business failures in Pakistan? Evidence from textile companies of Pakistan. Journal of Economics and Sustainable Development, 5(13), 110-115.
[23] Krejcie, R.V., Morgan, D.W. (1970), Determining sample size for study activities. Educational and Psychological Measurement, 30(2), 607-610
[24] Lord, J., Landry, A., Savage, G.T., Weech-Maldonado, R. (2020), Predicting nursing home financial distress using the Altman Z-Score. Inquiry: The Journal of Health Care Organization, Provision, and Financing, 57(1), 1-9.
[25] Muda, R., Hassan, S., Aziz, R.A., Bakar, N.A. (2017), Financial distress and economic cycle in a dual banking system: Evidence from Malaysia. ACRN Journal of Finance and Risk Perspectives, 6(3), 135-152
[26] Nanjundeswaraswamy, T. S., & Divakar, S. (2021). Determination of sample size and sampling methods in applied research. Proceedings on engineering sciences, 3(1), 25-32.
[27] Newton, G. W. (1975). Bankruptcy and insolvency accounting. New York: The Ronald Press
[28] Purbayati, R., & Afgani, K. F. (2020). Pemodelan Multiple Discriminant Analysis untuk Memprediksi Financial Distress Bank Umum Syariah di Indonesia. Ekspansi: Jurnal Ekonomi, Keuangan, Perbankan Dan Akuntansi, 12(1), 31–42
[29] Rahmah, I., Novianty, I. (2021), Comparative analysis of financial distress before and during the Covid-19 pandemic: Empirical evidence in Indonesia. International Journal of Business, Economics and Law, 24(5), 216-223
[30] Ratna, I., & Marwati, M. (2018). Analisis Faktor- Faktor Yang Mempengaruhi Kondisi Financial Distress Pada Perusahaan Yang Delisting Dari Jakarta Islamic Index Tahun 2012-2016. Jurnal Tabarru': Islamic Banking and Finance, 1(1), 51–62.
[31] Rim, E.K., Roy, A.B. (2014), Classifying manufacturing firms in Lebanon: An application of Altman's model. Procedia-Social and Behavioral Sciences, 109, 11-18.
[32] Roslan, R., Muhammad, K., Ghani, E. K., & Omonov, A. A. (2023). The effect of financial assistance, accounts receivable management and university size on financial distress. Review of Economics and Finance, 21(10), 96–104.
[33] Septiani, T. A., Siswantini, T., & Murtatik, S. (2021). pengaruh likuiditas, leverage dan profitabilitas terhadap financial distress pada sektor industri barang konsumsi yang terdaftar di BEI. Jurnal Apresiasi Ekonomi, 9(1), 100-111.
[34] Swalih, M., Adarsh, K., & Sulphey, M. (2021). A study on the financial soundness of Indian automobile industries using Altman Z-Score. Accounting, 7(2), 295-298.
[35] Tan, W. Y., Ong, C. H., & Low, K. H. (2023). A trend analysis on digital transformation resilience capability: The Malaysian experience during COVID-19. International Journal of Management and Computer Science, 1(1), 25–38.
[36] Thai, S. B., Goh, H. H., HengTeh, B., Wong, J., & San Ong, T. (2014). A revisited of Altman z-score model for companies listed in Bursa Malaysia. International Journal of Business and Social Science, 5(12).