Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-1 | Jan 2026
Original Researcher Article

Detecting Financial Manipulations Of Nigerian Electricity Distribution Companies Using The Altman Z-Score Model

Celestine Chukwutem Ebogbue[1], Ahmad Bukola Uthman[2], Lucky Otsoge Onmonya[3], Yemisi Funmilayo Bosun-Fakunle[4]
[1]*Department of Accounting, Nile University of Nigeria, Abuja, https://orcid.org/0009-0008-6524-9102
[2]Department of Accounting, Nile University of Nigeria, Abuja, https://orcid.org/0000-0002-4272-5574
[3]Department of Accounting, Nile University of Nigeria, Abuja, https://orcid.org/0000-0003-1081-270X
[4]Accounting Department, Igbinedion University, Okada, Edo State, Nigeria, https://orcid.org/0000-0001-6002-3755
***Corresponding Author:**
Department of Accounting, Nile University of Nigeria, Abuja,
https://orcid.org/0009-0008-6524-9102

ABSTRACT
The study examines the detection of financial distress of Nigerian DisCos using the Altman Z-score model. An ex post facto research design was adopted for the study to assess the effectiveness and adequacy of the independent variables of the Altman Z-Score model in influencing the result of the dependent variable, regardless of the direction it is skewed, which is a determinant of whether a firm could be classified as being engaged in fraudulent financial statement practices or not. The study's sample is drawn from the financial statements of the 11 successor companies from 2014 to 2023, available on their respective websites. A panel regression model was used in testing the hypotheses. The findings show that the Altman Z-score model effectively detects financial statement manipulations in DisCos, and there is a significant correlation between the model's independent variables and the detection of financial distress, leading to the conclusion that the Altman Z-score model is a reliable and efficient method for detecting an organisation's financial distress. The study recommended that, by applying the Altman Z-score model and considering its limitations, stakeholders can make more informed decisions and take proactive measures to mitigate financial distress
Keywords: DisCos, Altman Model, Manipulation, Electricity, Fraud, Detecting...

1. .INTRODUCTION

The Nigerian power generation began in 1898 with the Colonial Government (Thomas et al., 2023). This was followed, in 1923, by the installation of a 2 MW power generation system at the Kwali River (near Abuja) to support local mining operations. In 1929, the Nigerian Electricity Supply Company (NESCO) installed a 25MW hydroelectric power system in Kura, a mining town near Jos, at the initiative of local miners. The African Timber and Plywood (AT&P) power generation project in Ogorode, Sapele (present-day Delta State), undertaken by the then United African Company (UAC), was born in 1969 (Aideyan, 2023). There was also the government's investments in the power sector between 1950 and 1969, beginning with the Power Works Department (PWD) in Lagos, which became the Electricity Corporation of Nigeria (ECN) in 1950, and commissioned the country's first Transmission lines in 1961, linking major commercial hubs (Abanihi et al., 2018). The first Government Hydro Power Plant (Kainji Dam) was commissioned in 1969, followed by pockets of government-controlled power plants in the country until 1972, when the National Electric Power Authority (NEPA) was established, which operated until 1995, and was transformed into the Power Holding Company of Nigeria (PHCN) (Ajumogobia & Okeke, 2015). Given its perennial challenges, the Electric Power Sector Reform Act (EPSRA, 2005) was enacted to prepare for the sector's unbundling and privatisation, which commenced in earnest in 2013 with the establishment of six successor GenCos, one TCN, and eleven DisCos. Today, in Nigeria, over 23 Generation (GenCos) and 12 Distribution Companies (DisCos) are operational.

In several studies, various fraud detection models were adopted to study the implications of fraudulent reporting for an organisation, including the Altman Z-score to estimate the likelihood of bankruptcy and failure. Such research includes MacCarthy (2017), Liodorova and Voronova (2019), Cindik and Armutlutu (2021), and Saleh et al. (2021), among others. These studies, centred on the use of Z-scores to detect fraud and distress in organisations, were conducted in other countries and industries, and none was conducted in Nigeria. These industries include Enron (MacCarthy, 2017), ICT and Media analytics (Kukreja et al., 2020), among others. This research, focuses on using the Altman Z-score model (a financial distress prediction model formulated by Professor Edward Altman in 1968, with the purpose of predicting an organisational bankruptcy within two years, and used today, as a red flag indicator for potential financial statement manipulations), to determine fraudulent financial statement reporting in the Nigerian Electricity Distribution Companies (DisCos), utilising data from audited financial statements for 2014–2023, where available. With the Z-score model (rather than the traditional ratios), the researchers intend to show the likely benefits and probable disadvantages of using the model in performing a detailed analysis of financial statements of companies, for the benefit of the current and potential investors, not just in the power sector, but also in other industries.

Section 2 of this research presents a detailed review of the literature on the concept of fraud and the Altman Z-score fraud model (a tool for potential fraud detection). The methods and materials of the study will be discussed in Section 3, while the results from the analysed data will be presented in Section 4, including the findings. Section 5 presents the study's conclusions and recommendations, along with potential directions for future research.

2. LITERATURE REVIEW

Fraud Concept

The financial statements record the financial operations and activities of entities. However, there have been instances of financial scandals within organisations, despite statements being certified by auditors. Examples are the Waste Management Scandals (1998), Enron (2001), WorldCom and Tyco (2002), among others, resulting in jobs lost, economies nosediving, and potential income or GDP lost, while the governments have introduced stricter financial reporting regulatory measures, including corporate governance (Gbadebo et al., 2023). In Nigeria, there were Cadbury's overstated profitability of ₦13 billion (Okaro & Okafor, 2011), the AfriBank and Lever Brothers scandals (Ajayi, 2006), among others. Fraud implications could be severe, including financial losses and reputational damage from media reports (Burnaby et al., 2011), as well as bankruptcy reports and organisational winding-up. It signifies “peril to the sustainability” and challenges the trust shareholders have in the organisations (Miharsi et al., 2024). It is a misstatement of fact in financial reporting, an unethical practice that prioritises personal advantage and the misuse of organisational resources over the credibility and judicious use of resources (Saleh et al., 2021; Akbar et al., 2022). The intricacy of manipulating financial data to mask the line between optimistic “reporting and fraudulent activities” creates identification challenges for such activities (Miharsi et al., 2024), making the antecedent losses from such activities unquantifiable. As opined by Omar et al. (2014), it is deliberately intended to misrepresent an entity's financial health by misrepresenting figures and data.

The Nigerian power sector positions itself as an easy target for fraud, despite a lack of proven evidence. The DisCos' operations are often susceptible to fraud in customers' connections to the grid, as evidenced by reports in the Consumer Fraud Index (Stakeholder Democracy Network, 2018). Electricity theft is also a significant hole in the fraudulent report, as these are not quantified in the annual financial statements.

The gravity of information misrepresentation in financial statements has necessitated the use of various early-detection tools or models, including the Altman Z-Score and others, each with its own strengths and limitations (Miharsi et al., 2024). However, with the misrepresentation of facts, it becomes possible to detect alternatives and expose the basis of unprincipled infections that have become a reality over time, driven by greed and the possibility of failure (Pedneault et al., 2012; Hossain, 2020). Financial statement fraud detection is typically analysed from the perspectives of auditors, financial analysts, lenders, and investors, for their respective and intended benefits, using various prediction and detection models (Rasa & Zivile, 2015). This prompts the use of the Altman Z-Score model, as presented herein, to predict and identify the potential failures or bankruptcies of organisations within the next two years.

Altman Z-Score Model (1968)

21st-century organisations are consistently striving to achieve sustainable profitability in their operations, under external pressures to maintain an outstanding image, remain relevant in the competitive sector, and avoid unnecessary bankruptcy and takeover challenges (Ranjbar & Amanollahi, 2018). With financing arrangements becoming a frontline issue and businesses attempting to meet market obligations, concerns are overemphasised on the risk of losing both current and future investors and being delisted as beneficiaries of the government's extensive interventions. Stakeholders may assist the company in its plan to recruit and close other deals for revenue, investment, development, and projects. However, operational targets are achievable with businesses maintaining positive “relationships with their stakeholders and exchange favourable financial expectations” with a super-claim on boosting performances (Kamaluddin et al., 2024). Achieving consistency in performance can be difficult amid fluctuations in revenue and profits over time (Munjal et al., 2021; Repousis et al., 2021), as management may resort to aggressive financial statement manipulation to avoid the danger zone of financial distress (Kamaluddin et al., 2024).

To detect or predict potential distress and bankruptcy challenges in organisations, Edward Altman (1968) developed a model based on statistical methods, primarily focused on manufacturing organisations. Maccarthy (2017) emphatically stated the model’s ability in identifying “a very high degree” of capacity in predicting the financial recklessness of organisations, as evidenced by distress in both developed and emerging markets, while classifying the variables into five independent variables, providing the chances to forecast the possibilities of a firm going bankrupt in future (Kamaluddin et al., 2024). Over time, the model has become a viable predictor of failure and is commonly used to assess a company’s insolvency level (Kulkarni & Kothari, 2020), with its 5-variable analysis that encompasses all aspects of the financial statement to measure a firm's performance or competence.

Based on the research, Figure 1 presents the conceptual framework, illustrating the independent and dependent variables of Altman’s Z-score model. The dependent variables serve as proxies for financial distress or manipulation (as demonstrated in modern times).

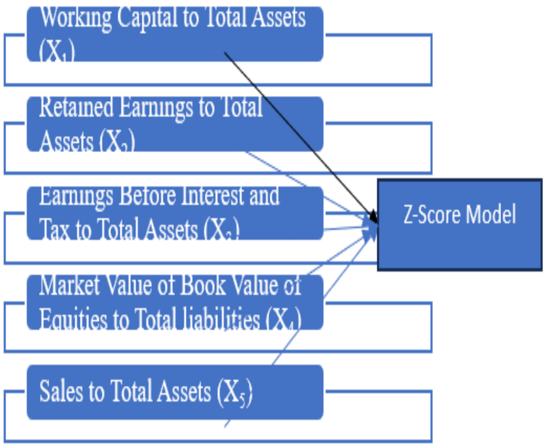

Figure 1: Research Framework

Figure 1: Research Framework

$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5$

Decision criterion: >2.99 (Safe Zone), 1.81<Z<2.99 (Grey Zone), and <1.81 (Distress Zone).

The model is positioned as a "warning tool" for firms, before they slide into bankruptcy (Singh & Singla, 2023). The model utilises information from the audited financial statements to assess a company's financial health in a linear combination of independent variables. However, MacCarthy (2017) noted that, despite the model's near-perfection, it remains industry or geographic-specific, as its application may not be suitable for all industries due to their differing characteristics. Having been obtained from the financial statement, the model assumes the accuracy of the ratios. However, it could be argued that distressed companies may manipulate their financial statements to present themselves as performing well to prospective investors.

The Altman Z-score model is positioned as a powerful warning tool for firms' operations at risk of bankruptcy, ensuring that they remain vigilant in their financial reporting to avoid manipulative practices that could result in reputational damage. Using the model to predict firms' failure probability, Singh and Singla (2023) examined the Indian steel sector, employing regression analysis, and found that size is inversely related to the probability of failure. However, the study failed to examine whether size and fraudulent financial statement reporting could be positively correlated. Using the Pearson Correlation Matrix (PCM), Elia et al. (2021) examined the impact of independent variables on the model's dependent variable across the ten Alpha Banks in Lebanon between 2009 and 2018, with results indicating that some entities exhibited signs of distress during the period examined. The study recommended the use of the Z-score model for any external or internal decision-making by auditors, financial managers, investors, and lenders regarding organisations' distress and manipulative conditions.

3. Theoretical Framework

Fraud Triangle Theory

Donald Cressey, on the fraud triangle theory, identified pressure, opportunity, and rationalisation as indicative of the risk of fraud (Repousis, 2016; Omar et al., 2017; Drábková, 2018; Mohammed et al., 2021), and the obvious motivations behind those who commit fraud, including engaging in financial statement manipulations (Kamaluddin et al., 2024). With the pressure to meet the company's financial and other objectives, management is challenged to devise alternatives to business performance for various stakeholders, including financial statement analysts. (Huang et al., 2017; Aviantara, 2021), and may resort to opportunities or techniques, with flaws or gaps in any aspect of management and internal control, to influence their reports (Kamaluddin et al., 2024), providing justifications for their actions under the guise of best intentions to benefit their firm. This aligns with the notion that companies in financial distress often manipulate their financial statements to meet the expectations of pundits, as high performers, and to protect debt covenants that are crucial to the company's sustainability and competitiveness in the global marketplace.

The framework for the fraud detection is depicted below:

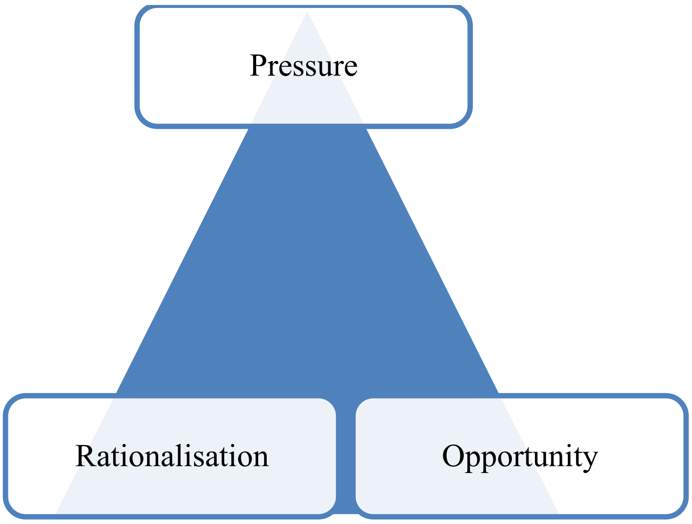

Figure 2: Donald Cressey's Fraud Triangle (1953)

4. Empirical Review

Detecting Financial Statement Fraud

The DisCos in Nigeria are suspected of compromising their operational integrity, and this may also be reflected in their financial statements. The activities of these DisCos have significant implications not only for the economy but also for all their stakeholders, including regulators (financial and industry-wise), prospective and current investors, and customers, considering the industry's role in national economic development. With concerns over financial misstatements in DisCos intensifying between 2014 and 2023, this research analysis utilises a proven fraud prediction and detection model, the Altman Z-Score, to examine DisCos' performance over the years. The financial statements are prepared with utmost care to minimise errors, while ensuring that the information presented is fair and accurate regarding the company's operating performance and financial position (Rasa & Zivile, 2015), thereby enabling users to make informed decisions or judgements about the company. However, that does not prevent fraud, as management under distress may attempt to take undue advantage of various opportunities, including manipulating figures to show a better performance or concealing losses.

Liodorova and Voronova (2019), in the exposures of construction companies in Latvia, proposed that the Altman Z-Score model can accurately predict more than 80% of cases involving manipulated financial statements. Miharsi et al. (2024) in a contemporary literature review stated that the “Altman Z-Score, synthesising financial ratios, has demonstrated efficacy in discerning financial fraud.” Accordingly, the model demonstrates adaptability in evaluating different companies and sectoral risks related to financial statement manipulations, utilising various ratios, including liquidity, profitability, leverage, solvency, and productivity, to assess the robustness of a company’s financial performance (Kukreja et al., 2020). The model is acknowledged for its capacity to mitigate certain shortcomings of financial ratios while yielding highly dependable results for measuring organisational financial performance, highlighting activities that are fraudulently projective in nature (Miharsi et al., 2024). However, in contemporary accounting research, Jones et al. (2008) stated that models could have a significant positive association with both the occurrence and magnitude of fraud.

While adopting the use of models in studying the possibilities of fraudulent financial reporting in the Jordanian manufacturing environment, Saleh et al. (2021) utilised the Z-Score and F-Score models in their research study with data from 2015 to 2019 (5 years), which confirmed the validity and accuracy of these models in detecting financial statement fraud. The study employed a methodological model based on multiple regression analysis to evaluate various fraud theories and the factors that contribute to their perpetration. In a similar study, Kukreja et al. (2020) utilised the Beneish M-score and Altman Z-score as indicators of corporate fraud. The study analysis was conducted using Comscore Inc.'s financial statements (2012-2018) to detect early signs of fraud. The study found the Altman Z-score to be highly effective at predicting early signs of fraudulent activity in an organisation’s financial statement reporting. The study results also pointed to the influence of geography or region on the use of fraud detection models.

Poor organisational performance could result from financial distress and signal that management is involved in financial statement manipulation, seeking to sustain the organisational image while projecting themselves as better performing. Arshad et al. (2015) suggested that strong governance, scrutiny, and disciplining of management are necessary to prevent involvement in fraudulent financial reporting. This will include establishing a robust, resilient control environment that prevents systems from being compromised or manipulated (Kamaluddin et al., 2024). From the above, the following hypothesis is proposed:

H_1: The Altman Z-score model could not effectively detect financial statement manipulations in the Nigerian Electricity Distribution Companies (DisCos).

The dependent variables, or the five accounting ratios of the Z-score model, evaluate a company’s liquidity and capacity to pay financial commitments (Pratiwi et al., 2022), financial distress in terms of profitability and productivity (Toly et al., 2020), identify earnings falsifications, show the efficacy of debt repayment to win over stakeholders (Pratiwi et al., 2022), and determine the utilisation of total assets to create sales(Maccarthy, 2017; Toly et al., 2020; Pratiwi et al., 2022). The results from these studies and the arguments on the geographical effects of the application of the Altman Z-score model resulted in the second hypothesis for the study using the Altman Z-score for selected companies in Nigeria:

H2: There is no significant correlation between the independent variables of the Altman Z-score model in detecting financial statement fraud in the Nigerian Electricity Distribution Companies (DisCos).

The efficacy of the Altman Z-score in detecting distress using financial statements lies in its ability to determine whether an organisation's operational activities are still within the safe zone or the grey zone, thereby indicating susceptibility to bankruptcy. Africa, as a test case from recent research, has been overlooked due to inadequate information presented in the AFS, insufficient disclosures and reporting frameworks, a lack of resources, and non-existent legal enforcement (Alastair et al., 2023; Nyakiarimi, 2022; Okiro & Otiso, 2021).

5. Methodology

The ex post facto research design is utilised in this study to assess the effectiveness and adequacy of the independent variables of the Altman Z-Score model in influencing the outcome, and to determine whether a firm is engaged in fraudulent financial statement practices. Centred on the Nigerian Electricity Distribution Companies (DisCos), the study’s sample comprises the financial statements of the 11 successor companies for the period from 2014 to 2023, available on their respective websites. Table 1 below summarises the Z-score model performance for each DisCo, based on the analysis of the audited financial statements for 2014 to 2023, and indicates the operational likelihood of data manipulation from the source.

Summary			
Company	Distress	Grey Zone	Safe
1	2014 - 2023		

2	2014 - 2023*		
3	2016 - 2018, 2022 - 2023	2015, 2019 - 2021	2014
4	2015 - 2019, 2021 - 2023	2014, 2020	
5	2016 - 2023*	2014 - 2015	
6	2015 - 2023	2014	
7	2015 - 2023*	2014	
8	2015 - 2023*		2014
9	2016 - 2023*	2015	2014
10	2014 - 2016	2017	2018 - 2023*
11	2015 - 2020, 2022 - 2023*	2014, 2021	
* denotes Management Account for the affected years			

Table 1: Summarised aggregate DisCos performance of the Altman Z-Score

Source: Author's Compilation, 2025

Results/Findings

Table 2:Descriptive Analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
zscore	110	-1.598727	3.608766	-13.97	8.07
wcta	110	-.6434545	.7300803	-3.3	.15
reta	110	-.3215455	.8378185	-3.26	1.21
ebitta	110	-.0703636	.5087815	-1.07	3.04
mvbvetl	110	.3405455	1.389224	-.76	10.72
sta	110	.5991818	.3764005	.16	3.45

Source: Author's Compilation, 2025

Table 2 above shows the characteristics of the individual variables used for the study. The total number of observations was 110 for each variable. The mean value for the z-score is -1.59, with a corresponding standard deviation of 3.60, with a minimum value of -13.97 and a maximum value of 8.07. Working capital to total assets has an average of -0.64, a standard deviation of 0.73, a minimum of -3.3, and a maximum of 0.15. Retained earnings to total assets have an average value of -0.32, a standard deviation of 0.837, a minimum value of -3.26 and a maximum value of 1.21. Earnings before interest and Tax to total assets show an average of -0.34, a standard deviation of 1.38, a minimum of -0.76, and a maximum of 10.72. Sales-to-total assets suggested an average of 0.59, with a corresponding standard deviation of 0.37, a minimum of 0.16, and a maximum of 3.45.

Table 3: Normality Test

Variable	Obs	W	V	z	Prob>z
zscore	110	0.90506	8.490	4.770	0.00000
wcta	110	0.80680	17.277	6.354	0.00000
reta	110	0.91668	7.451	4.478	0.00000
ebitta	110	0.65819	30.566	7.626	0.00000
mvbvetl	110	0.54362	40.812	8.271	0.00000
sta	110	0.67387	29.164	7.521	0.00000

Source Authors Compilation, 2025.

Table 3 shows the test for normality using the Shapiro-Swilk. The probability value for the z-statistic for the variables is 0.00, which is less than the 0.05 level of significance, implying that the data for all variables are not normally distributed. Hence, Spearman's rank correlation will be adopted for the correlation matrix.

Table 4: Correlation Matrix (Spearman's Rank)

	ZSCORE	WCTA	RETA	EBITTA	MVBVETL	STA
ZSCORE	1.0000					
WCTA	0.9288	1.0000				
RETA	0.8457	0.7390	1.0000			
EBITTA	0.4363	0.4551	0.2665	1.0000		
MVBVETL	0.9053	0.8665	0.7880	0.2611	1.0000	
STA	-0.1118	-0.2329	-0.1897	-0.0335	-0.2003	1.0000

Source: Authors Compilation, 2025.

Table 4 shows the relationship among the variables under investigation. The results show that working capital to total assets, market value of book value of equity to total liabilities, earnings before interest and tax to total assets, and retained earnings to total assets are positively correlated with z score, while sales to total assets are negatively correlated with z score, portraying the significant influence of the four independent variables on the dependent variable.

Table 5: Regression Analysis: Panel Ordinary Least Squares

Variables	Coef.	T stat.	Prob.
WCTA	3.10	1068.73	0.00
RETA	1.00	416.19	0.00
EBITTA	0.41	173.74	0.00
MVBVETL	0.71	870.49	0.00
STA	0.84	273.18	0.00
R^2			1.00
F Stat. Prob			999999.00 0.00
Vif			2.48
Random Test: Chi2 Prob.			 0.00 1.00

Table 5 shows the panel regression (Pooled Ordinary Least Squares) used for the test of the hypothesis. Pre-estimation tests were conducted, including the variance inflation factor test for multicollinearity, which yielded a value of 2.48, indicating no evidence of multicollinearity. Random Test was conducted; it reveals a p-value of 1.00, indicating that pooled ordinary least squares is more appropriate than random-effects estimation. Hence, the pooled ordinary least squares model was adopted. All the variables (WCTA, RETA, MVBVETL, STA) show a positive and significant effect (cof=3.10; p-value = 0.00, cof. =1.00; p-value = 0.00; cof = 0.41, p-value =0.00; cof. = 0.71; p-value = 0.00; cof.0.84; p-value = 0.00) on z score. This shows that an increase in any independent variable automatically increases the z-score. The R^2 value is 1.00, which implies that the model is perfect and that all independent variables perfectly determine the dependent variable (z-score). Also, the F-statistic probability was 0.00, which is significant at the 5% level, hence the model is the best fit.

From the results above, it is evident that the Altman Z-score model effectively detects financial statement manipulations in the Nigerian Electricity Distribution Companies (DisCos*)*. Hence, the null hypothesis is rejected

Also, there are significant correlation between the independent variables of the Altman Z-score model in detecting financial statement fraud in the Nigerian Electricity Distribution Companies (DisCos).

3. DISCUSSIONS OF FINDINGS

The above result shows that the Altman Z-score model effectively detected financial statement manipulations among the Nigerian Electricity Distribution Companies for the period under review, consistent with the result of Liodorova and Voronova (2019). Additionally, the study discovered a significant correlation between the independent variables of the Altman Z-score model in detecting financial statement manipulations in the Nigerian Electricity Distribution Companies (DisCos), which is in line with the finding of MacCarthy (2017), but did not strongly agree with Elia et al (2021) on the four variables of the Altman Z-score.

4. CONCLUSION AND RECOMMENDATIONS

Based on the above findings, the study demonstrates the effectiveness of the Atman z-score model in detecting financial distress. The findings suggest that the model accurately predicts financial distress and provides valuable insights for stakeholders. The model's ability to distinguish between financially healthy and distressed companies makes it a useful tool for investors, creditors, and other stakeholders. The result of the study supports the use of the Altman Z-score model as a reliable and efficient method for detecting financial distress. By applying this model, stakeholders can identify potential financial distress early on and take proactive measures to mitigate risk. The study recommended that the Altman Z-score model can be used to identify potential financial distress and provide early warning signals

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