FORENSIC ACCOUNTING PREDICTIVE ANALYTICS AND CORPORATE FINANCIAL DISTRESS: A STUDY OF LISTED MANUFACTURING FIRMS IN NIGERIA

Damilola Peace Babalola[a]
Damilola Gabriel Fagboro[b]
Imoleayo Foyeke Obigbemi[c]
[a,b,c] *Department of Accounting, University of Lagos, Lagos, Nigeria*

Abstract

The current research study centres on predictive analytics of financial distress in listed manufacturing firms in Nigeria. Using a six-year period, from 2018 to 2023 financial statements of selected firms; the study adopted the ex-post facto research design. The data source for the study was secondary in nature. Logistic regression distress prediction models, correlation analysis and descriptive statistical tools were enlisted to analyse the data. Empirical results show that application of forensic accounting predictive analytics is a potent means of early detection of financial distress, making it easier to work on the improved financial stability. This further presents new knowledge of how financial forensics data mining and analytics, and link analysis can be useful tools in detection of corporate distress. The study concludes that financial metrics and link analysis play a significant role in identifying financial instability of firms. Non-financial analysis and financial net worth analysis might not be reliable techniques but should not be however ignored as they can serve as red flag signals.

Key Words: *Forensic Accounting, Predictive Analytics, Financial Link Analysis, Financial Forensics Data Mining, Financial Metrics, Non-financial Metrics, Financial Distress*

INTRODUCTION

The event of cheating and unfaithful financial acts is increasing all over the world, which is a threat for fraud purposes of companies (PwC, 2022). As such, this trend has increased the demand for forensic accounting, which is demonstrated by the increased number of business scandals around the world. Forensic accounting can, in a nutshell, be viewed as the financial aspect of the crime scene. Predictive analytics is a branch of advanced analytics that uses historical data combined with statistical modeling, data mining techniques, and machine learning to make predictions about future outcomes. It applies many data mining, predictive modeling, and analytical techniques to bind the management, information technology, and modeling business process toward forecasting the future (Altman & Hotchkiss, 2010). By applying predictive analytics successfully, the businesses can interpret big data for their betterment. It has been extensively embraced in the field of forensic accounting since it helps to identify early warnings of potential financial distress before escalations happen (Adesina, 2019). Even in terms of advanced data analysis techniques, predictive analytics can detect patterns and abnormalities in financial data indicating upcoming financial distress (Bomey, 2020).

As Ikpesu, et al. (2020) argued that most of the top firms that were icons in their respective sector of operations have now found themselves financially distressed. For instance, the Asian financial crisis of 1997 and the global financial crisis between 2007 and 2008,which made many big firms become financially distressed as cash flow and profit declined, causing the firms to default on their financial obligations. In this regard, forensic accounting predictive analysis may play a major role in unveiling the root causes of the financial difficulties of the company in the context of financial distress.

More recently, in 2020, the past spiral of financial distress was further aggravated by the occurrence of the COVID-19 pandemic, pushing Hertz Global Holdings, a major player in the rental car business, into filing for bankruptcy due to this event (Bomey, 2020). The listed manufacturing sector in Nigeria plays an important role in the nation's economy, providing huge employment, industrial growth, and economic diversification. However, in the case of these large and highly visible publicly traded firms, no company is ever safe from experiencing financial distress, be it brought on by economic instability, currency fluctuations, poor infrastructure, or a myriad of other factors (Adebayo & Ajayi, 2022).

Despite such high-profile cases, there lies a lack of empirical studies to validate the role of forensic accounting predictive analytics in early identification and mitigation of financial distress in listed manufacturing firms. This gap is very crucial, as early detection of financial distress can help the firm institute measures that will avoid its state of bankruptcy and guarantee long-term survival. The study fills this gap by looking at the efficacy of forensic accounting predictive analytics in predicting financial distress among selected listed manufacturing firms in Nigeria. The research focused on financial metrics, including liquidity ratios, profitability ratios, and capital structure; non-financial metrics that include the director's and auditor's report; advanced statistical techniques that include the Altman Z-score and logit regression analysis; financial forensics with data mining and financial link analysis in its quest to arrive at elaborate answers for "how these firms can better manage financial risks and avoid distress". Thus, the study aims at the improvement of the detection of financial distress in listed manufacturing firms in Nigeria.

LITERATURE REVIEW

Financial distress is a serious problem in itself and can ooze out in the form of insolvency and bankruptcy if not properly addressed. Studies have been conducted using predictive analysis and also on the causes of financial distress, its impacts, and remedies for such as, Eze and Nwogu (2023), evaluated the role of forensic accounting and predictive analytics in mitigating financial distress in Nigerian manufacturing firms, the performance of the machine learning techniques in predicting financial distress by some manufacturing firms in Nigeria was also tested in the work of Chukwuma and Adeoye (2022).

Similarly, Nwankwo, et al. (2021) evaluated financial ratio as a predicting power in establishing financial distress among the listed Nigerian manufacturing firms. Likewise, Oluwaseun and Ogundele (2020) assessed the impact of forensic accounting on the resolution of financial distress in Nigerian manufacturing firms, while Ogunleye and Ajayi (2019) assessed the role of forensic accounting in detecting financial mismanagement and fraud in Nigerian listed manufacturing companies, Olaniyi and Olayinka (2024) analyzed the application of predictive analytics in the improvement of corporate governance of Nigerian Manufacturing Companies.

These empirical studies place forensic accounting and predictive analytics at the heart of finding a solution to the problem of financial distress among listed manufacturing firms in Nigeria. Forensic accounting helps detect financial irregularities, fraud, and mismanagement, which are the major causes of financial distress. On the other hand, predictive analytics helps firms project the impending distress using machine learning algorithms for the analysis of financial ratios, corporate governance practices, and other relevant indicators.

The studies reviewed confirm that mitigating financial distress requires a multidimensional approach, including financial monitoring, forensic investigations, improvement in governance, and advanced analytics. This would provide a channel to assist firms in detecting the starting point of financial distress, after which they would carry out corrective measures to ensure sustainable financial health. The findings provide useful insights into ways to promote the resilience and sustainability of the manufacturing sector in Nigeria for managers, auditors, and policymakers. Conclusively, the study examined the relationship between Forensic Accounting Predictive Analytics and Financial Distress guided by the agency theory (Jensen & Meckling, 1976), stakeholder theory (Freeman & Reed, 1983) and the signalling theory (Spence, 1973).
On the basis of the aforementioned discussion, the study hypothesizes that:

H_0: Forensic Accounting and Corporate Performance cannot serve as Predictive Analytics for Financial Distress

METHODOLOGY

This study adopts an ex-post facto research design, which allows for the analysis of existing secondary data without researcher intervention. By comparing the independent and dependent variables, the study aims to establish a causal relationship. A mixed-method approach was utilized, integrating both qualitative and quantitative techniques to maximize the strengths of each method. The population of the study consists of 39 listed manufacturing firms in Nigeria, as recorded by the Nigerian Exchange Group (NGX) as of August 2024. These firms belong to three main sectors: consumer goods, industrial goods, and agriculture. To ensure a representative and relevant sample, the study employs a purposive sampling technique, selecting firms based on specific criteria. The selected firms must have been continuously listed on NGX from 2018 to 2023, have audited financial statements (in naira) for the same period, and be officially registered with the Corporate Affairs Commission (CAC). Applying these criteria resulted in a final sample of 28 manufacturing firms, ensuring the availability of reliable financial data for the study.
The study examines the impact of forensic accounting predictive analytics on financial distress in Nigerian manufacturing firms. It employs descriptive and inferential statistical analyses to examine the relationship between forensic accounting predictive analytics and financial distress. Descriptive analysis was conducted to summarize the data, evaluating key characteristics which provide insights into the distribution and variability of the dataset. While for inferential statistics, ordinary least squares (OLS) linear regression analysis was applied to

determine the extent to which independent variables influence the dependent variable. These methods ensure the robustness of the findings by minimizing bias and improving estimation accuracy.

The model specification follows a multiple linear regression framework, where the dependent variable (Financial Distress Status - FDS) is expressed as a function of the independent variables: Financial Metrics (FMT), Non-Financial Metrics (NFM), Statistical Techniques (STQ), Financial Forensic Data Mining (FFD), and Financial Link Analysis (FLA), with the variable measurements provided in Table 1.

Table 1

Variable Measurement Table

Variables	**Measurement**	**References**
<u>Dependent:</u> Financial Distress Status (**FDS**)	FDS = 0,717X1 + 0,847X2 + 3,107X3 + 0,420X4 + 0,998X5 Where X1 = (Current Asset - Current Liabilities) / Total Asset X2 = Retained Earning / Total Asset X3 = EBIT / Total Asset X4 = Market Value Equity / book value of Total Debt X5 = Sales / Total Asset **Z-Score Indication** < 1.81 Bankrupt =1.81 – 2.99 Gray Area / zone of ignorance > 2.99 Not Bankrupt	Altman Z-score model (1968)
<u>Independent variables:</u> Financial Metrics (**FMT**)	Ratio of market value of firm to book value of assets i.e (Market Value of Equity + Book Value of Debts)/ Book value of total assets. Liquidity ratio = Current asset/Current Liability	(Singh et al., 2018.) Kontus & Mihanovic, (2019)
Non-financial Metrics (**NFM**)	A statement indicating a threat to the going concern of the business in the Auditor’s report is scored 1 and 0 if otherwise A statement indicating an inability to settle due liabilities in the Director’s report is scored 1 and 0 if otherwise	Maria F. Oliveira (2020) Lawrence A. Gordon (2019)

Statistical Technique (**STQ**)	ST = (Ri− R) / σR Where: Ri = Financial ratio value for firm (e.g. Working Capital/Current Liability) R = Mean value of the financial ratio across all firms σR = Standard deviation of the financial ratio across all firms.	Alnoor Bhimani & Michael Bromwich (2018)
Financial Forensics Data Mining (**FFD**)	FFDM = (Y_i) - (Y^i) Where: ● Y_i = Observed value for each row ● Y^i = Predicted value for each row using regression analysis with the independent variable as CA/CL (Current Asset/Current Liability) and the dependent variable being ROA (Return on Asset)	Edward I. Altman, (2017).
Financial Link Analysis (**FLA)**	FLA = −1.32 − 0.407log(A) + 6.03LA -1.43W + 0.0757CA − 1.72X - 2.37NT - 1.83FL + 0.285Y - 0.521NI Where A = Total Assets/GNP LA = Total Liabilities / Total Assets W = Working Capital/Total Asset CA = Current Liabilities/Current Assets X = 1 if Total Liabilities > Total Assets, 0 otherwise NT= Net income/Total Asset FL = Cash Flow from Operations / Total Liabilities Y = 1 if a net loss for the last two years, 0 otherwise NI (Net income) = $\frac{NI_t - NI_{t-1}}{/NI_t/ + /NI_{t-1}/}$	Alassane Bah & Adel B. Abdallah. (2021)

Source: Author’s Compilation (2024)

The model of the study allows for an empirical examination of how forensic accounting predictive analytics influences financial distress among Nigerian listed manufacturing firms. The regression equation is specified as:

$$FDS_{it} = \alpha + \beta_1 FMT_{it} + \beta_2 NFM_{it} + \beta_3 STQ_{it} + \beta_4 FFD_{it} + \beta_5 FLA_{it} + \mathcal{E}_{it}$$

Where:

FDS = Financial Distress Status
α = intercept or constant of the equation
β_{1-5} = coefficients of the independent variables/ regression parameter.
$\mathcal{E}$ = error term
FMT = Financial Metrics
NFM = Non-Financial Metrics
STQ = Statistical Techniques
FFD = Financial Forensics Data Mining
FLA = Financial Link Analysis

However, despite the strengths of the methodology, certain limitations exist. The study covers a six-year observation period (2018–2023), which, while relevant, may yield different results if extended. Additionally, only the Altman Z-score model was used to assess financial distress, whereas other models might provide alternative perspectives. The non-financial metrics were measured using a researcher-developed scale using the dichotomous approach of scoring 0 if financial distress is not observed and 1 if observed which is tailored to the study, though may introduce subjectivity. Nonetheless, these limitations were carefully managed to ensure the study's reliability and validity.

Result and Discussion

This section presents and analyzes the data collected from secondary sources identified in the methodology section of this study. All data used were analysed using descriptive statistics via the EViews 11 software. The regression analysis was employed in testing the hypothesis formulated and tables were used to display and interpret the results.

Table 2. Descriptive Statistics

Variable	Mean	Min.	Max.	Std. Dev.	Skewness	Kurtosis	Observations
FDS	0.6821	0.0000	1.0000	0.2951	-0.3882	2.4272	168
FMT	0.6273	-9.2737	2.0617	1.4052	-5.0614	29.3846	168
NFM	0.0179	0.0000	0.5000	0.0931	5.0037	26.0370	168
STQ	0.0000	-1.8617	3.8684	0.9833	0.6108	4.2107	168
FFD	0.0949	-0.9635	6.2041	0.5127	10.1089	121.7821	168
FLA	5.6621	-3.7525	152.4695	19.2214	5.4694	33.8211	168

Source: Author's Computation using E-views (2024)

The descriptive statistics table provides insights into the distribution and characteristics of the study variables. Each variable is based on 168 observations, ensuring a consistent sample size across the dataset. The FDS (Financial Distress Status) variable has a mean of 0.6821, with values ranging from 0.0000 to 1.0000 due to content measurement metric approach used. A standard deviation of 0.2951 indicates moderate variability around the mean. Its slight negative skewness (-0.3882) suggests that the distribution has a small tail to the left, and a kurtosis of 2.4272 implies a relatively normal peak and tail weight. FMT (Financial Metrics) shows a mean of 0.6273; however, the extreme minimum of -9.2737 and a maximum of 2.0617 result in a high standard deviation of 1.4052. The pronounced negative skewness (-5.0614) and very high kurtosis (29.3846) indicate that the distribution is heavily left-skewed with outliers causing fat tails.

For NFM (Non-Financial Metrics), the mean is 0.0179 with a narrow range (0.0000 to 0.5000) and a low standard deviation (0.0931). The strong positive skewness (5.0037) and high kurtosis (26.0370) suggest that most values are clustered at the lower end, with a long right tail indicating the presence of extreme values. The STQ (Statistical Techniques) variable has a mean of 0.0000, with values from -1.8617 to 3.8684 and a standard deviation of 0.9833. Its moderate positive skewness (0.6108) and kurtosis (4.2107) imply a slight right-tail elongation and a somewhat peaked distribution

FFD (Financial Forensic Data Mining) presents a mean of 0.0949 and ranges from -0.9635 to 6.2041. The standard deviation of 0.5127 shows moderate spread, but the very high skewness (10.1089) and kurtosis (121.7821) indicate an extremely right-skewed distribution with significant outliers. Finally, FLA (Financial Link Analysis) has a mean of 5.6621, with a wide range from -3.7525 to 152.4695 and a high standard deviation of 19.2214. The skewness

(5.4694) and kurtosis (33.8211) further reveal that this variable is highly right-skewed and exhibits heavy tails.

Table 3. Regression Analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FMT	0.3030	0.1392	2.1772	0.0309
NFM	0.6129	0.8177	0.7496	0.4546
STQ	-0.2285	0.0388	-5.8845	0.0000
FFD	0.0164	0.0483	0.3399	0.7344
FLA	0.0178	0.0084	2.1137	0.0361
R^2				0.3205
Adj. R^2				0.2996
F-stat				15.2844
Prob.				0.0000

Source: Author's Computation using E-views (2024)

The model's R-squared value of 0.3205 suggests that the independent variables explain approximately 32.05% of the variation in financial distress, indicating moderate explanatory power The adjusted R^2 0.2996 further confirms the model's goodness of fit after adjusting for the number of predictors. The F-statistic of 15.2844 confirmed that the model, as a whole, is valid and p value of 0.0000 confirms the overall model's statistical significance, meaning that at least one predictor significantly affects financial distress.

The regression results revealed significant insights into the relationship between financial distress (FDS) and its predictors. Financial Metrics (FMT) have a positive and statistically significant effect on FDS with a coefficient of 0.3030 and p value of 0.0309, suggesting that effective financial management reduces financial distress. A one-unit increase in FMT is associated with a 0.30 unit increase in FDS, and this effect is statistically significant. This implies that variations in financial metrics have a meaningful positive impact on financial distress levels. Thus, as financial metrics increases, financial distress increases and if financial metrics reduces, financial distress lessens. The result replicates and extends previous research carried out by Adebayo (2018) and Yusuf and Olakunle (2021) while being in contrast to the findings of Johnson and Timothy (2015) where it was indicated that financial metrics used in the detection of financial distress did not have a substantial effect.

Strategic Techniques (STQ) exhibit a highly significant negative impact with a coefficient of -0.2285 and p-value of 0.0000, indicating that strategic planning significantly mitigates financial distress. This indicates that improvements in the application of statistical techniques are associated with reduced financial distress. Conversely, Financial Leverage Assessment (FLA) has a significant positive effect with a coefficient of 0.0178 and p value of 0.0361, implying that increased financial leverage heightens financial distress. This small but statistically significant positive effect, means that higher levels of financial link analysis are associated with an increase in financial distress. This may be the case since most of the complexities and assumptions in the statistical models cannot fully capture real-world financial scenarios of distress. This therefore confirms Bamidele's (2020) results, that indeed overreliance on the statistical models without consideration for qualitative factors results in the underestimation. However, it is opposed to Sodiq and Kazeem (2022), who discovered that using statistical techniques is significantly adding value to distress detection.

However, Non-Financial Metrics (NFM) and Financial Fraud Detection Mechanisms (FFD) with coefficients of 0.6129 & 0.0164 as well as p values of 0.4546 & 0.7344 respectively do not show a significant relationship with FDS, as their p-values exceed 0.05. Consequently, Although NFM has a positive coefficient, its effect on FDS is not statistically significant, suggesting that changes in non-financial metrics do not reliably predict financial distress. Also, FFD with a positive coefficient and a non-significant p-value, does not appear to have a significant impact on financial distress.

The NFM result means that even though such a non-financial instance like a going threat statement in the firm's auditor and director report would enhance the ability to identify distress, it is by a small percentage. This is in line with findings by Adeolu & Ogunde (2017) who had argued that the non-financial metrics play a less role in detecting distress compared to financial metrics. Conversely, the study presents a contradiction to the findings from Osakwe & Nkereuwem (2019), which reported that the non-financial metrics in their study had a significant effect. While, the FFD result suggests that although financial forensic data mining would be anticipated to provide insights towards detection of anomalies, within the context of Nigerian listed manufacturing firms, their performance could not be expected to an acceptable degree. This is supported by the study that was conducted by Chukwuma & Obasi (2016), where similar results were reached, proving therefore that the use of data mining techniques themselves could not dramatically enhance the identification of distress. This research finding is quite contradictory to the study by Oladipo & Afolabi (2019), who once again supports the fact that there exists a strong positive significant relationship between forensic data mining and distress detection. Since this is a new area of testing.

In summary, FMT and FLA have significant positive impacts on financial distress, whereas STQ significantly reduces financial distress. Non-financial metrics and financial forensic data mining do not have statistically significant effects on financial distress in this model. Thus, effective strategic techniques (STQ) play a crucial role in reducing financial distress, while high financial leverage increases risk. Although the model is statistically significant, there may be some external factors not captured in the regression contribute to financial distress, warranting further investigation.

Conclusions

In this study, emphasis was put on how forensic accounting techniques and various metrics play a role in forecasting financial distress among the listed manufacturing firms in Nigeria. The conclusions in respect of this study have been made on the premise that financial metrics showed a significant positive impact on distress detection. This alludes to the relevance in the early warning systems of the firms in financial distress. Non-financial metrics, howbeit positive, displayed insignificant effects. This outcome, in a Nigerian context, could be an indication that the non-financial indicators are not as effective as financial metrics in detecting distress.

It is important to note that a negative impact was revealed by the interaction with the statistical techniques, and a much more careful and modulated use of them seemed in order to prevent the derivation of incorrect predictions. Also, the interaction with financial forensic data mining and analytics is not significant, which means that data mining techniques would be of use for better clues that will materially improve the possibility for distress prediction in the case of Nigerian manufacturing industry. Financial link analysis proved to be highly value-enriched, with a positive and significant effect on the detection of distress, showing the importance of analysis in corporate relationships with respect to the prediction of financial risks.

Overall, the findings of this study underscore the need to maximize the use of financial metrics and analytical tools so that the ability to detect distress is enhanced. The research also indicated that non-financial metrics and forensic data mining further required fine-tuning before they can become effective devices in the Nigerian setting.

References

Adebayo, A. (2018). The Role of Financial Ratios in Predicting Financial Distress of Manufacturing Firms in Nigeria. *Journal of Finance and Accounting, 5(3),* 112-125.

Adebayo, O., & Ajayi, F. (2022). Financial distress and its impact on listed manufacturing firms in Nigeria. *Journal of Finance and Economics*, 14(3), 178-190.

Adeolu, O., & Ogunde, S. (2017). Non-Financial Metrics and Their Impact on Corporate Performance: Evidence from Nigerian Listed Firms. *International Journal of Business and Economic Development, 5(2),* 88-97.

Adesina, O. (2019). Financial Management Practices and Corporate Financial Distress in Nigeria. *Journal of Financial Management and Analysis*, *21*(4), 45–62.

Afolabi, A. (2018). Corporate governance and financial mismanagement: The case of Cadbury Nigeria. *African Journal of Business Management*, *12*(5), 120–133.

Altman, Edward I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589. doi:10.2307/2978933

Bamidele, F. (2020). The Effectiveness of Statistical Techniques in Financial Distress Detection: A Study of Nigerian Listed Firms. *Journal of Applied Economics and Business Research, 10(1),* 45-60.

Bomey, N. (2020). Hertz files for bankruptcy as car rentals evaporate in pandemic. *USA Today. Retrieved from USA Today*.

Chukwuma, E., & Adeoye, D. (2022). Machine Learning Algorithms in Predicting Financial Distress in Nigerian Manufacturing Firms. *Journal of Financial Analytics, 10(1),* 53–68.

Chukwuma, I., & Obasi, K. (2016). Data Mining Techniques in Detecting Financial Distress among Nigerian Manufacturing Companies. *Journal of Financial Crime, 23(4),* 903-918.

Eze, U., & Nwogu, C. (2023). Integrating Forensic Accounting and Predictive Analytics in Mitigating Financial Distress in Nigerian Manufacturing Firms. *Nigerian Journal of Business and Finance*, *18*(2), 110–128.

Freeman, E., & Reed, D. (1983). Stockholders and stakeholders: A new perspective on corporate governance. *California Management Review, 25(3),* 88–107.

Ikpesu, F., Vincent, O., & Dakare, O. (2020). Financial distress overview, determinants, and sustainable remedial measures. In *Corporate Governance Models and Applications in Developing Economies* (pp. 102–113). doi:10.4018/978-1-5225-9607-3.ch006

Jensen, M.C. and Meckling, W.H. (1976) Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of Financial Economics, 3*, 305-360

Johnson, S., & Timothy, R. (2015). An Investigation into the Predictive Power of Financial Ratios in Distress Detection: Evidence from Nigeria. *Journal of Corporate Finance, 21(1),* 131-147.

Nwankwo, P., Adebayo, O., & Akinyemi, S. (2021). Predictive Power of Financial Ratios in Identifying Financial Distress in Nigerian Manufacturing Firms. *African Journal of Finance and Economics*, *19*(3), 67–83.

Ogunleye, T., & Ajayi, M. (2019). The Role of Forensic Accounting in Detecting Financial Mismanagement in Nigerian Manufacturing Firms. *Journal of Financial Crime Prevention*, *14*(2), 102–115.

Olaniyi, F., & Olayinka, A. (2024). Predictive Analytics and Corporate Governance in Nigerian Manufacturing Firms: Enhancing Financial Stability. *Journal of Corporate Governance and Finance*, *12*(3), 45–60.

Oluwaseun, K., & Ogundele, J. (2020). Forensic Accounting and Financial Distress Resolution in Nigerian Manufacturing Firms: A Case Study Approach. *Journal of Accounting Research*, *22*(4), 78–94.

Osakwe, M., & Nkereuwem, U. (2019). The Impact of Non-Financial Metrics on the Financial Distress of SMEs in Nigeria. *Small Business Economics Journal, 32(3),* 145-157.

PwC. (2022). *Nigeria's manufacturing sector outlook: Navigating challenges and opportunities*. PricewaterhouseCoopers.

Skeel, D. (2011). The Chrysler and GM bankruptcies: Observations on the Chrysler and General Motors bankruptcies. *Michigan State Law Review*, 669–681.

Sodiq, R., & Kazeem, A. (2022). Enhancing Financial Distress Detection through Statistical Techniques: Insights from Nigerian Firms. *Journal of Business Analytics, 14(1),* 65-79.

Spence, M. (1973). "Job Market Signaling." *Quarterly Journal of Economics*, *87(3),* 355-374

World Bank. (2022). *Doing business 2022: Nigeria report*. World Bank Publications.

Yusuf, S., & Olakunle, B. (2021). Financial Ratios and Their Effectiveness in Predicting Financial Distress in Nigerian Listed Manufacturing Firms. *International Journal of Accounting and Finance Studies, 9(3),* 207-220.