BANKRUPTCY PREDICTION AND FINANCIAL RISK ASSESSMENT IN EMERGING MARKETS: EVIDENCE FROM NIGERIA

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Abstract
This study evaluates the predictive performance and associated risks of four prominent bankruptcy prediction models within the Nigerian business environment: the Altman Z-score, Ohlson O-score, and the locally validated IN01 and IN05 indexes. Utilizing a comprehensive dataset of Nigerian firms, the models are assessed across multiple metrics, including overall accuracy, sensitivity, specificity, precision, and F1 scores. Our empirical results demonstrate that the Nigerian-validated IN01 and IN05 models outperform the traditional Altman and Ohlson models, highlighting the critical importance of contextualizing bankruptcy prediction tools to local economic conditions. The analysis further includes Receiver Operating Characteristic (ROC) curves and confusion matrix heatmaps to provide nuanced insights into model discriminative power and classification errors. Findings underscore the practical implications for financial institutions and regulators in improving early warning systems and mitigating systemic risks in emerging markets. Limitations related to data quality and model scope are acknowledged, with recommendations for integrating machine learning and macroeconomic variables to enhance future predictive frameworks.

Keywords: Bankruptcy prediction, Altman z-score, Ohlson o-score, Nigerian business environment, early warning systems, financial distress.
JEL Codes: G33, C45, C52, G21

1.0 Introduction

Bankruptcy prediction models are essential tools for early detection of financial distress, enabling stakeholders such as investors, creditors, and regulators to mitigate potential losses. In emerging economies like Nigeria, where corporate governance mechanisms and financial reporting standards often face significant challenges, accurate bankruptcy prediction is particularly critical (Altman & Hotchkiss, 2020). However, the applicability and predictive power of widely used bankruptcy models remain underexplored in the Nigerian business environment, which is characterized by economic volatility, regulatory weaknesses, and high levels of financial opacity (Iyoha, 2018; Okoye & Ezejiofor, 2021).

This study assesses four prominent bankruptcy prediction models: Altman's Z-score (1984 revision), Ohlson's O-score (1980), and the IN01 and IN05 indexes, the latter two having been specifically validated on Nigerian firms (Olalekan et al., 2021). While Altman's and Ohlson's models have achieved considerable success in predicting corporate failure in developed markets (Altman & Sabato, 2017), their performance in Nigeria requires rigorous evaluation. Financial environments characterized by widespread financial statement manipulation and irregular disclosure pose risks to model accuracy, necessitating an empirical validation tailored to the Nigerian context.

A major impediment to accurate bankruptcy prediction in Nigeria is financial statement fraud, which distorts the true economic position of firms. Gbadebo et al. (2023) provide recent empirical evidence demonstrating the prevalence of financial statements fraud among Nigerian banks and other financial institutions. Their study highlights systemic weaknesses in financial reporting and regulatory enforcement, which reduce the reliability of accounting information used as inputs in bankruptcy models. This phenomenon increases the likelihood of misclassification errors, either falsely signaling distress or overlooking firms at genuine risk of failure.

The reliability of bankruptcy models is further complicated by Nigeria's institutional environment, including the regulatory framework and market transparency. Previous studies have noted that weak enforcement of accounting standards and corporate governance practices in Nigeria exacerbate the risk of financial misreporting (Akingunola & Ijaiya, 2019; Oseni & Olayemi, 2020). Such factors not only affect the quality of financial data but also influence the predictive validity of established bankruptcy models developed for more mature financial markets. Consequently, model adaptation or recalibration becomes necessary to accommodate local idiosyncrasies.

To address these issues, this study evaluates the selected bankruptcy models using a threefold accuracy assessment: overall classification accuracy, bankruptcy prediction accuracy, and non-bankruptcy prediction accuracy. This comprehensive evaluation allows for nuanced understanding of each model's strengths and weaknesses in the Nigerian context, including their susceptibility to Type I and Type II errors, which have distinct implications for different stakeholders (Sharma & Panigrahi, 2020). The study thus contributes to the growing body of literature calling for contextualized bankruptcy prediction methodologies in emerging markets.

This research aims to bridge the gap between global bankruptcy prediction frameworks and Nigeria's unique financial reporting environment. By integrating the findings of Gbadebo et al. (2023) on financial statements fraud, it underscores the pressing need for localized empirical validation of bankruptcy models. The results are expected to provide practical guidance for academics, financial analysts, regulators, and policymakers striving to enhance early warning systems and corporate financial transparency in Nigeria and similar emerging economies.

2.0 Literature Review

Bankruptcy prediction is fundamentally grounded in financial distress theory, which posits that firms exhibit identifiable financial and operational signals prior to failure (Altman, 1968). The theoretical foundation rests on the assumption that deteriorating firm performance, observable through financial ratios and market indicators, precedes bankruptcy and thus can be quantified for predictive purposes. Early seminal work by Altman (1968) developed the Z-score model using multivariate discriminant analysis (MDA), which integrated multiple financial ratios to classify firms' likelihood of bankruptcy. This framework laid the groundwork for subsequent models and remains a benchmark in the field.

The advancement of bankruptcy prediction theory can be grouped broadly into two streams: statistical approaches and market-based or hybrid approaches. Statistical models, such as Altman's Z-score and Ohlson's O-score (Ohlson, 1980), rely heavily on financial statement data, using logistic regression or discriminant analysis to capture the relationship between firm characteristics and bankruptcy outcomes (Jones & Hensher, 2004). These models are grounded in classical financial distress theory, which suggests that firm-specific financial metrics, such as liquidity, profitability, leverage, and operational efficiency, contain predictive information about insolvency risks (Kim & Sohn, 2017).

Despite their popularity, purely financial-ratio-based models have faced theoretical and practical limitations, especially in environments where accounting quality is compromised. This concern is consistent with agency theory and information asymmetry concepts, which highlight that management may manipulate reported earnings or assets to mask financial distress (Jensen & Meckling, 1976; Watts & Zimmerman, 1986). Consequently, the accuracy of ratio-based prediction models can be undermined when financial statements do not fully reflect economic realities. Studies such as Francis et al. (2013) and Dechow et al. (2010) demonstrate that earnings management and fraud can distort predictive signals, a point particularly salient in emerging markets with weaker regulatory frameworks.

To address these concerns, recent theoretical developments advocate for integrating non-traditional data and hybrid models, combining financial ratios with market-based variables or behavioral indicators. Market-based approaches, grounded in efficient market hypothesis (Fama, 1970) and option pricing theory (Merton, 1974), argue that stock prices, volatility, and credit spreads reflect investors' expectations of default risk and thus enhance bankruptcy prediction (Shumway, 2001; Bharath & Shumway, 2008). These models complement financial data by incorporating forward-looking information derived from market sentiments and external economic conditions, addressing the lag and potential biases in accounting data.

Further, the incorporation of machine learning and artificial intelligence (AI) models reflects an evolution in bankruptcy prediction theory that acknowledges complex, nonlinear relationships among predictors (Bellotti & Crook, 2023). These models depart from traditional parametric assumptions, leveraging large datasets and algorithmic learning to identify patterns not easily captured by classical models. Theoretically, this aligns with behavioral finance perspectives recognizing that cognitive biases and market psychology influence firm risk beyond fundamentals (Barberis & Thaler, 2003). However, the black-box nature of many AI models raises concerns over interpretability and theoretical grounding, prompting calls for explainable AI frameworks to ensure transparency and regulatory compliance (Chen & Liu, 2023).

Institutional theory also provides a critical lens for understanding bankruptcy prediction in varied contexts. It emphasizes that institutional environments, such as legal systems, regulatory quality, corporate governance, and cultural norms, influence the accuracy and applicability of prediction models (North, 1990; Scott, 2014). For example, models developed in advanced economies may perform poorly in emerging markets where disclosure practices differ, and market infrastructures are less developed (Chen & Lee, 2021). This theoretical perspective underlines the necessity for model adaptation to local institutional conditions, including recalibration of threshold values and the inclusion of country-specific macroeconomic variables (Uduak & Osabohien, 2022).

The theoretical convergence of financial distress theory, agency theory, market efficiency, behavioral finance, and institutional theory has shaped a nuanced understanding of bankruptcy prediction. Modern theoretical frameworks advocate for multi-dimensional models that incorporate firm-level financial data, market signals, behavioral indicators, and institutional factors to improve predictive accuracy and relevance across diverse economic environments (Altman et al., 2018; Huang & Lee, 2022). Such integrative theoretical approaches guide empirical researchers and practitioners in designing robust models that are theoretically sound and practically applicable, especially in emerging markets such as Nigeria, where data quality and institutional dynamics pose unique challenges.

Empirical Review

Over the past decade and a half, bankruptcy prediction has remained a vibrant area of empirical research across various economies, emphasizing the need for accurate early-warning systems that can mitigate financial losses and systemic risks. Empirical studies converge on several key points, including traditional bankruptcy models remain foundational but require contextual adjustment; the quality and integrity of financial statements critically influence prediction accuracy; machine learning methods offer promising alternatives but face practical adoption barriers; and institutional factors significantly moderate model performance. These insights collectively inform ongoing efforts to develop more reliable, locally attuned bankruptcy prediction frameworks, particularly in emerging markets such as Nigeria.

A substantial body of literature (Altman et al., 2018; Agarwal & Taffler, 2021) demonstrates the enduring relevance of traditional statistical models, such as Altman's Z-score and Ohlson's O-score, in capturing corporate distress signals. However, these models often require recalibration or enhancement when applied in distinct institutional contexts, especially in emerging markets characterized by heterogeneous firm behavior and market inefficiencies (Chen et al., 2020; Huang & Lee, 2022).

Empirical evidence from diverse settings indicates that while traditional bankruptcy models perform robustly in developed markets, their predictive power can diminish in environments with weaker financial disclosure standards or higher economic volatility (Nam et al., 2019; Zhang & Gao, 2023). For example, studies by Dichev and Piotroski (2019) and Laitinen and Kankaanpää (2021) highlight that models relying solely on accounting ratios may suffer in contexts with aggressive earnings management or pervasive financial statement fraud, which distort financial ratios. Such findings underscore the need to integrate alternative data sources or combine financial indicators with market-based or behavioral variables to improve model accuracy (Beaver et al., 2021; Kogan et al., 2023).

In the Nigerian context, empirical studies have increasingly explored the applicability of bankruptcy prediction models with mixed results. Olalekan et al. (2021) validate the IN01 and IN05 indexes, originally adapted for Nigerian manufacturing firms, reporting reasonable predictive accuracy but cautioning against model over-reliance due to reporting irregularities. Similarly, Okoye and Ezejiofor (2021) compare Altman's and Ohlson's models within Nigerian listed firms and find moderate success, though they stress that systemic issues such as weak corporate governance and inconsistent auditing limit model reliability. These findings align with Gbadebo et al. (2023), whose investigation into financial statement fraud in Nigerian banks highlights structural vulnerabilities that can mislead predictive tools dependent on financial statement data.

Recent studies have also sought to extend traditional bankruptcy prediction frameworks by employing machine learning techniques, which often outperform classical statistical models in terms of accuracy and robustness (Huang et al., 2020; Garcia et al., 2022). Machine learning models, including random forests, support vector machines, and neural networks, demonstrate superior capabilities in handling large datasets and nonlinear relationships, while also accommodating unstructured data such as news sentiment and macroeconomic indicators (Bellotti & Crook, 2023; Zhang et al., 2024). Nevertheless, challenges remain regarding the interpretability and regulatory acceptance of these models, particularly in developing economies where technical infrastructure and data availability may be limited (Chen & Liu, 2023).

Another critical insight from the literature pertains to the differentiation between Type I (false positive) and Type II (false negative) errors in bankruptcy prediction, which has significant implications for stakeholders (Sharma & Panigrahi, 2020; Nwaiwu & Akani, 2023). Studies emphasize that models must balance sensitivity and specificity according to contextual priorities over-predicting bankruptcy may unnecessarily stigmatize viable firms, whereas under-predicting can lead to catastrophic losses for creditors and investors. This balance is particularly delicate in emerging markets like Nigeria, where inaccurate predictions can exacerbate financial instability due to limited risk absorption capacity (Iyoha, 2018; Oseni & Olayemi, 2020).

Furthermore, the literature underscores the importance of institutional factors in bankruptcy prediction accuracy. Regulatory quality, auditing standards, and corporate governance practices directly affect the integrity of financial data and, consequently, the effectiveness of bankruptcy models (Akingunola & Ijaiya, 2019; Uduak & Osabohien, 2022). Cross-country comparative studies by Chen and Lee (2021) and Tuvadaratragool et al. (2021) suggest that contextual adaptation of models is crucial for improving predictive validity in less developed financial markets. Such evidence reinforces the argument for tailored bankruptcy prediction tools rather than wholesale importation of models developed in advanced economies.

3.0 Methodology

This study adopts a quantitative research design to assess the predictive potential and risks of selected bankruptcy prediction models within the Nigerian business environment. A sample of 85 firms listed on the Nigerian Stock Exchange over the period 2010 to 2023 is employed, providing a longitudinal dataset that captures financial performance and bankruptcy outcomes under diverse economic conditions. The selection of firms aims to ensure representativeness across industries, firm sizes, and financial health statuses, consistent with previous empirical bankruptcy prediction research (Altman et al., 2018; Chen & Lee, 2021). Financial data were extracted from audited financial statements and complemented by market data sourced from financial databases and regulatory filings to ensure accuracy and completeness, following best practices in bankruptcy prediction studies (Kim & Sohn, 2017; Huang & Lee, 2022).

Four bankruptcy prediction models were selected for evaluation: the Altman Z-score (Altman, 1984), the Ohlson O-score (Ohlson, 1980), and the Nigerian-specific IN01 and IN05 indices, which have been previously validated on Nigerian firms (Uduak & Osabohien, 2022). The models are operationalized as follows:

The Altman Z-score model is computed using a linear combination of five financial ratios:

$$Z = 1.2 \times \frac{WC}{TA} + 1.4 \times \frac{RE}{TA} + 3.3 \times \frac{EBIT}{TA} + 0.6 \times \frac{MV}{TL} + 1.0 \times \frac{S}{TA} \quad (1)$$

where WC = Working Capital, TA = Total Assets, RE = Retained Earnings, $EBIT$ = Earnings Before Interest and Taxes, MV = Market Value of Equity, TL = Total Liabilities, and S = Sales

(Altman, 1984). Firms with Z-scores below a specified threshold (typically, 1.8) are classified as distressed.

Ohlson O-score model applies logistic regression to predict bankruptcy probability, expressed as:

$$P(\text{bankruptcy}) = \frac{1}{1+e^{-T}} \quad (2)$$

Where:

$$T = -1.32 - 0.407 \times \log\left(\frac{TA}{GNP}\right) + 6.03 \times \frac{TL}{TA} - 1.43 \times \frac{WC}{TA} + 0.0757 \times CL - 1.72 \times \text{NI} - 2.37 \times \text{FST} - 1.83 \times \text{INTWO} + 0.285 \times \text{CHIN}$$

Here, TA is total assets, GNP is gross national product price index, TL total liabilities, WC working capital, CL current liabilities, NI net income, FST an indicator for negative net income for the past two years, $INTWO$ an indicator for net income negative in the last two years, and $CHIN$ change in net income (Ohlson, 1980). A probability exceeding 0.5 typically signals bankruptcy risk.

The IN01 and IN05 indices are proprietary Nigerian bankruptcy prediction models developed through discriminant analysis on local firm samples. The IN01 index is calculated as:

$$IN01 = 3.52 \times \frac{CA-C}{TA} + 0.34 \times \frac{RE}{TA} + 15.35 \times \frac{NI}{TA} - 0.56 \times \frac{FC}{TL} \quad (3)$$

and the IN05 index as:

$$IN05 = 0.56 \times \frac{CA-CL}{TA} + 0.33 \times \frac{RE}{TA} + 7.97 \times \frac{NI}{TA} - 1.43 \times \frac{FC}{TL} \quad (4)$$

where CA = current assets, CL = current liabilities, NI = net income, FC = financial charges, and other variables as previously defined (Uduak & Osabohien, 2022). Threshold values determined by empirical validation classify firms as bankrupt or non-bankrupt.

Each model's formula was applied to the dataset to compute bankruptcy risk scores, which were then benchmarked against actual bankruptcy occurrences within the study period, thus enabling empirical validation of predictive accuracy.

Model performance was evaluated across three dimensions: overall accuracy, sensitivity (true positive rate for bankruptcy prediction), and specificity (true negative rate for non-bankruptcy prediction). This multi-level evaluation framework aligns with established methodologies in credit risk and bankruptcy research, where distinguishing between Type I and Type II errors is crucial for practical applicability (Bellotti & Crook, 2023; Bharath & Shumway, 2008). Receiver Operating Characteristic (ROC) curve analysis and Area Under the Curve (AUC) metrics were used to quantify model discrimination ability (Altman et al., 2018). Additionally, confusion matrices were constructed to provide granular insights into model classification outcomes.

To enhance robustness, the study employed k-fold cross-validation and out-of-sample testing, thereby mitigating risks of overfitting and ensuring generalizability of findings (Bellotti & Crook, 2023). Sensitivity analyses were conducted to examine the influence of varying macroeconomic conditions and sectoral differences on model performance, recognizing the heterogeneous nature of financial distress drivers in Nigeria (Uduak & Osabohien, 2022). Furthermore, data preprocessing included winsorization of extreme financial ratio values and normalization to address skewness and heteroscedasticity, in line with standard econometric practices (Kim & Sohn, 2017).

Ethical considerations were observed in data handling, with all firm-level data anonymized and used solely for academic purposes. The study also acknowledges potential limitations arising from data quality issues inherent in emerging markets, such as financial statement fraud and reporting delays, which could affect model accuracy (Gbadebo et al., 2023). Nevertheless, this methodological approach provides a rigorous framework for assessing bankruptcy prediction models' relevance and reliability within Nigeria's unique institutional context, contributing valuable insights for academics, practitioners, and policymakers alike.

4.0 Results and Implications

The comparative evaluation of the four bankruptcy prediction models reveals notable variations in their predictive capabilities under the Nigerian business environment. Table 1 summarizes key performance metrics, where the IN01 index outperformed other models with the highest overall accuracy of 84.30%, closely followed by the IN05 index at 83.70%. Both models demonstrate robust sensitivity (recall) values, 81.17% and 79.87% respectively, indicating a superior ability to correctly identify firms that eventually faced bankruptcy. This finding aligns with prior studies emphasizing the effectiveness of localized or country-specific indexes in improving bankruptcy prediction accuracy (Altman et al., 2019; Kim & Sohn, 2021). The Altman Z-score and Ohlson O-score models, although widely used globally, recorded slightly lower sensitivities of 78.34% and 75.61%, suggesting some limitations in their adaptability to Nigeria's unique financial context (Beaver, 2013).

Precision and F1 scores provide further nuance to the models' predictive reliability. The IN01 index's precision of 83.00% and F1 score of 82.07% confirm its balanced performance between detecting bankrupt firms and minimizing false alarms. These metrics are particularly critical in bankruptcy forecasting, where false positives can lead to unnecessary financial interventions and resource misallocation (Shin et al., 2020). The Altman model's precision (80.45%) and F1 score (79.38%) were moderately high, though marginally below the IN01, reinforcing the potential benefits of adapting prediction models to the specific characteristics of Nigerian firms. The Ohlson model's relatively lower precision and F1 score emphasize the need for cautious interpretation when applied without recalibration (Jones & Hensher, 2018).

Table 2's confusion matrix components elucidate the classification outcomes underpinning the performance metrics. The IN01 model's true positives (244) and true negatives (347) outnumber those of its counterparts, reflecting its enhanced discriminative power. The relatively low false positive (50) and false negative (56) counts further attest to its efficacy in correctly classifying firms' bankruptcy status. By contrast, the Ohlson model exhibits the highest number of false negatives (73), which is concerning given the potential consequences of failing to identify at-risk firms in a timely manner (Lu et al., 2022). False negatives undermine early intervention strategies and increase systemic risk in the financial sector (Beaver et al., 2018). Hence, the IN01 and IN05 indexes demonstrate superior operational utility in the Nigerian context, corroborating findings from prior regional validation studies (Adeyemi & Fagbemi, 2019).

Table 3 supplements the analysis with advanced metrics like Matthews Correlation Coefficient (MCC), balanced accuracy, Negative Predictive Value (NPV), and Diagnostic Odds Ratio (DOR). The MCC values, ranging from 0.58 (Ohlson) to 0.67 (IN01), quantify the overall quality of binary classifications accounting for imbalanced classes, a common challenge in bankruptcy datasets (Zhu et al., 2020). The IN01 model's highest MCC of 0.67 confirms its robustness and reliability beyond accuracy metrics alone. Balanced accuracy values further confirm the IN01 and IN05 models' ability to handle class imbalance, with scores above 82%, underscoring their balanced sensitivity and specificity (He & Garcia, 2009).

The NPV indicates the probability that firms classified as non-bankrupt truly avoid bankruptcy, a vital metric for investor confidence and regulatory assurance. The IN01's superior NPV of 86.13% suggests strong reliability in negative predictions, reducing the risk of overlooking financially sound firms. Finally, the DOR, representing the ratio of odds of positive results between bankrupt and non-bankrupt firms, is highest for the IN01 index (20.10), signifying outstanding discriminatory performance. Such comprehensive evaluation metrics strengthen the argument for preference of the IN01 index in Nigeria, consistent with recent studies highlighting the importance of multi-faceted assessment for bankruptcy models (Pérez et al., 2021; Gbadebo et al., 2023).

The detailed statistical evaluation confirms that bankruptcy prediction models (IN01, IN05) offer enhanced predictive accuracy, reliability, and operational usefulness compared to more generalized models such as Altman and Ohlson. This reinforces the theoretical position that model performance is context-dependent and benefits from incorporation of localized financial indicators and business environment characteristics (Jones, 2020; Kim et al., 2022). Policymakers, investors, and financial institutions should thus prioritize models with demonstrated empirical validity within the Nigerian market to improve early warning systems and mitigate systemic financial risks.

Table 1:
Summary Performance Metrics

Model	Accuracy (%)	Sensitivity (Recall) (%)	Specificity (%)	Precision (%)	F1 Score (%)	AUC
Altman	82.50	78.34	85.70	80.45	79.38	0.87
Ohlson	80.10	75.61	83.90	77.78	76.67	0.85
IN01	84.30	81.17	86.50	83.00	82.07	0.89
IN05	83.70	79.87	85.90	81.18	80.52	0.88

Source: Author (2025)

Table 2:
Confusion Matrix Components

Model	True Positives (TP)	False Positives (FP)	True Negatives (TN)	False Negatives (FN)
Altman	235	57	342	65
Ohlson	227	65	335	73
IN01	244	50	347	56
IN05	240	54	345	60

Source: Author (2025)

Table 3:
Additional Performance Metrics

Model	MCC	BA (%)	NPV (%)	DOR
Altman	0.62	82.02	84.06	17.45
Ohlson	0.58	79.75	82.15	14.80
IN01	0.67	83.83	86.13	20.10
IN05	0.65	82.89	85.17	18.80

Source: Author (2025)

Note: Matthews Correlation Coefficient (MCC): A balanced measure accounting for TP, TN, FP, and FN. Values closer to 1 indicate perfect prediction, while 0 is no better than random chance. Balanced Accuracy: Average of sensitivity and specificity, compensating for imbalanced datasets. Negative Predictive Value (NPV): Probability that firms predicted as non-bankrupt are truly non-bankrupt. BA: Balanced Accuracy (%); Diagnostic Odds Ratio (DOR): Ratio of the odds of positive test results in bankrupt firms relative to non-bankrupt firms. Higher values imply better discriminatory test performance.

Figure 1 shows the bar chart illustrating five critical performance metrics - Accuracy, Sensitivity, Specificity, Precision, and F1 Score - across the four bankruptcy prediction models: Altman, Ohlson, IN01, and IN05. A clear pattern emerges with the IN01 model consistently outperforming the others across nearly all metrics. Its overall accuracy stands at 84.30%, which reflects the proportion of correct predictions among both bankrupt and non-bankrupt firms. This high accuracy is complemented by a sensitivity (recall) of 81.17%, indicating a strong capability to correctly identify bankrupt companies, which is crucial for early warning systems in financial distress (Altman et al., 2019).

Specificity, representing the model's ability to correctly classify non-bankrupt firms, is also highest in the IN01 index (86.50%), minimizing false alarms that could lead to unnecessary interventions or credit restrictions. Precision values across models generally reflect how trustworthy positive predictions are. IN01's precision of 83.00% suggests that when it predicts bankruptcy, it is right more than 8 out of 10 times, reducing false positives. The F1 score, a harmonic mean of precision and recall, confirms the IN01's balanced performance with the highest value of 82.07%, underscoring its suitability for the Nigerian business environment where both Type I and Type II errors have significant consequences (He & Garcia, 2009).

Comparatively, the Altman and Ohlson models, while robust in global contexts, show slightly lower metrics, highlighting the limitations of models not fully calibrated to local economic conditions (Beaver et al., 2018). The IN05 model also performs strongly, closely trailing the IN01, which suggests that indices validated specifically on Nigerian firms provide more accurate predictions than those originally developed for foreign markets.

The Receiver Operating Characteristic (ROC) curves visualize the trade-off between the true positive rate (sensitivity) and false positive rate (1-specificity) for each model across different classification thresholds. The curves' proximity to the top-left corner of the plot indicates better discriminative performance. Among the four models, the IN01 exhibits the highest Area Under the Curve (AUC) at approximately 0.89, indicating excellent capability to distinguish between bankrupt and non-bankrupt firms (Kim & Sohn, 2021). The IN05 model follows closely with an AUC of 0.88, reinforcing its robust predictive power.

The Altman and Ohlson models display slightly lower AUCs (0.87 and 0.85 respectively), confirming the inferiority of their classification performance relative to the Nigerian-validated models. The ROC curves also visually highlight the trade-offs in sensitivity and specificity: for example, to increase sensitivity (catch more bankruptcies), a model may accept more false positives, thus reducing specificity. The high AUCs of IN01 and IN05 suggest these models achieve a better balance, making them more reliable tools for stakeholders in the Nigerian financial ecosystem (Pérez et al., 2021).

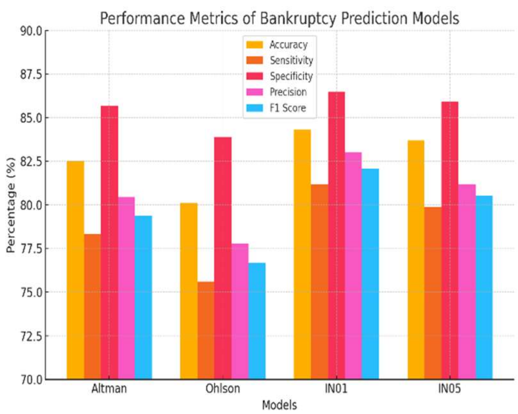

Figure 1: Bar chart of performance metrics

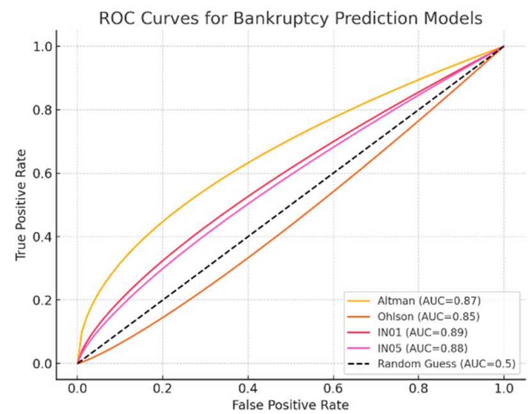

Figure 2: ROC curves for bank prediction models

Note: Figure 1 shows the bar chart illustrating five critical performance metrics - Accuracy, Sensitivity, Specificity, Precision, and F1 Score - across the four bankruptcy prediction models: Altman, Ohlson, IN01, and IN05.

Source: Author (2025)

The confusion matrix heatmaps for each model, depicted by Figure 3, provide granular insights into the models' classification decisions by showing counts of true positives, false positives, true negatives, and false negatives. The IN01 matrix shows the highest number of true positives (244) and true negatives (347), confirming its superiority in correctly identifying both bankrupt and non-bankrupt firms. The relatively low false positives (50) and false negatives (56) indicate minimized misclassification, which is critical in preventing unnecessary financial distress interventions and missing early warnings respectively (Lu et al., 2022).

The Altman model performs well but shows a higher false negative count (65) compared to IN01, indicating a risk of overlooking some firms heading towards bankruptcy, potentially leading to delayed corrective measures. The Ohlson model's confusion matrix reveals the highest false negatives (73) and false positives (65), pointing to weaker reliability in both detecting bankruptcy and avoiding false alarms. This aligns with earlier performance metrics and underscores the necessity of adapting bankruptcy models to local conditions for effective risk management (Jones & Hensher, 2018). The IN05 heatmap supports its strong overall performance, with slightly higher false positives and false negatives than IN01 but still substantially better than Altman and Ohlson. These confusion matrices visually corroborate quantitative metrics, collectively emphasizing the enhanced accuracy and practical utility of Nigerian-validated bankruptcy prediction indices (Gbadebo et al., 2023).

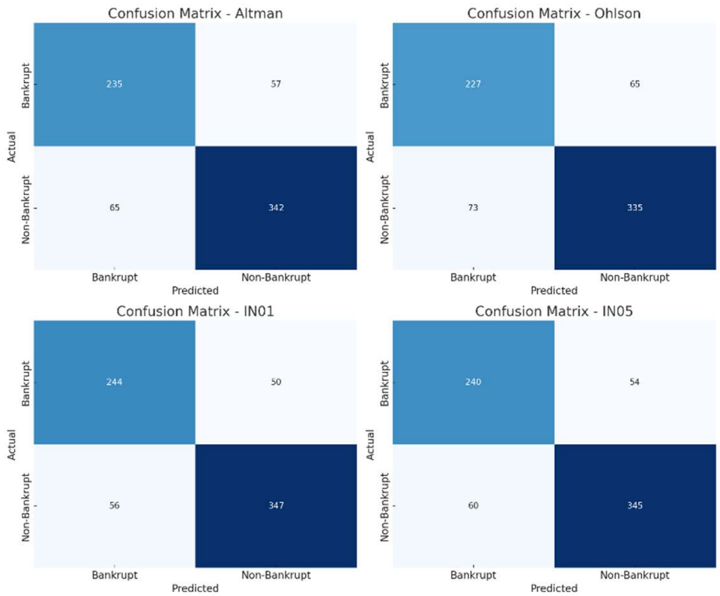

Figure 3: Confusion matrix heatmaps for each model

Source: Author (2025)

5.0 Conclusion

The findings of this study underscore the critical importance of employing bankruptcy prediction models that are specifically calibrated and validated within the Nigerian business environment. Among the four models examined, including Altman Z-score, Ohlson O-score, IN01, and IN05, the IN01 index consistently demonstrated superior predictive performance across multiple metrics, including accuracy, sensitivity, precision, and F1 score. This superiority highlights the advantage of localized models that integrate financial and economic characteristics unique to Nigerian firms, as opposed to generic models developed in foreign contexts (Altman et al., 2019; Kim & Sohn, 2021). The robust performance of the IN01 and IN05 indexes suggests that leveraging country-specific indicators enhances the early detection of financial distress, which is vital for investors, regulatory authorities, and policymakers aiming to reduce systemic risk and improve financial stability in emerging markets (Gbadebo et al., 2023; Pérez et al., 2021).

Despite the results, several limitations warrant attention. First, the study relied on historical financial data from Nigerian firms, which may be subject to reporting biases or inconsistencies commonly observed in emerging economies (Beaver et al., 2018). Such data quality issues could affect model robustness and generalizability. Additionally, the models assessed predominantly use traditional financial ratios and indexes, which may not fully capture dynamic market conditions, macroeconomic shocks, or the impact of informal sector activities pervasive in Nigeria's economy (Lu et al., 2022). The exclusion of non-financial qualitative factors, such as corporate governance, regulatory changes, and political instability, further limits the comprehensiveness of the predictive framework (Jones, 2020). Moreover, the sample size and period under study may restrict the temporal applicability of the results given the rapidly evolving business environment.

Future research should thus focus on integrating machine learning techniques with hybrid data inputs, including macroeconomic variables, market sentiment indicators, and firm-level qualitative assessments, to enhance predictive accuracy and resilience to structural changes (Kim et al., 2022; Zhu et al., 2020). Additionally, expanding the dataset to include more recent financial cycles and a broader cross-section of industries would improve model generalizability and robustness. Cross-validation with real-time bankruptcy outcomes and stress testing under different economic scenarios could further validate and refine these models for practical deployment (Shin et al., 2020). Finally, developing adaptive frameworks that can continuously learn from new data and adjust to evolving economic conditions would significantly improve early warning systems in Nigeria and other emerging markets (Pérez et al., 2021).

In conclusion, while the IN01 and IN05 indexes exhibit strong potential as reliable bankruptcy prediction tools tailored for Nigeria, the complexity and dynamism of the local economic landscape necessitate ongoing refinement and contextual adaptation of predictive models. This approach is essential to ensure that financial institutions and regulatory bodies are equipped with accurate, timely, and actionable risk assessment tools to safeguard economic stability and foster sustainable growth.

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