Comparative Analysis of Financial Distress Prediction Models: Evidence from African Industries

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ABSTRACT

Comparative Analysis of Financial Distress Prediction Models: Evidence from African Industries

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Accurately forecasting financial distress in companies is crucial in the turbulent economic conditions of our time. This study highlights the potential benefits of incorporating qualitative data into financial distress prediction models. The study assessed the relative effectiveness of traditional distress prediction models against integrated models, determined which variables significantly impacted the predictive performance and ascertained the consistency of the models across Africa.

The study employed three distinct classification techniques to evaluate the performance of both models: logistic regression, decision trees, and random forests, to ensure that the best-performing technique was identified. The study found that incorporating governance factors into the model did not positively impact the model's performance, affirming that traditional distress prediction models are relatively effective. The study also found that Current Ratio, ROA, ROE, DCE, and Asset Turnover significantly impacted the predictive performance of the models. Finally, it identified regional discrepancies in the performance of the analyzed models.

Keywords: Financial Distress, Traditional Models, Integrated Models, Logistic Regression, Random Forest, Decision Tree, Current Ratio, Return on Asset (ROA), Return on Equity (ROE), Debt to Common Equity (DCE), Net Profit Margin (NPM), Asset Turnover, Account Receivable (A/R) Turnover, Market Capitalization (Market Cap).

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CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

1.1.1 Global Economic Landscape

Today, the world of business and economics is filled with challenges and trends that require the proper knowledge of financial mechanisms. Trends such as the growth of technology, geopolitical tensions, changes in consumer behaviour, and the environment are among the factors affecting volatility and uncertainty in the business landscape (Wittmann & Aktiengesellschaft, 2013; Atik et al., 2023). In the presence of a diverse set of problems faced by the international economy, such as financial crises and trade deficits, sound financial management practices are of utmost importance.

The global economic outlook suggests a deceleration, with growth expected to decrease from 3.6% in 2023 to 2.7% in 2024 and then 3.0% and 4.3% in 2025 and 2026 (Macchiarelli et al., 2022). These forecasts reflect the complex and dynamic global economic setting, which stresses the significance of financial management and predictive models as a critical aspect of making decisions in the advent of uncertainties. Organizations need to be financially resilient, which is aimed at helping them adapt to unfolding events, minimize risks, and find emerging opportunities. This requires the use of various economic modelling techniques like the Autoregressive Integrated Moving Average (ARIMA), which incorporates the complexities of appropriate cash flow management, budgeting, and prudent resource allocation (Li et al., 2020; Mohamed & Galal-Edeen, 2018).

Unprecedented financial risks caused by this uncertain landscape call for predictive modelling, a critical risk assessment and mitigation tool. Using sophisticated tools like machine learning, statistics, and prediction models yields valuable information regarding the possible future (Cariceo et al., 2021). This leads to informed, data-driven decisions, specifically forecasting market trends, probable disruptions, and correct resource assignment. Consequently, dealing with the unknowns of the international economic environment greatly influences organizational survival. Financial management practices integrating scenario planning, stress testing, and contingency measures allow organizations to address crises more confidently. Furthermore, using predictive models facilitates identifying dangers in advance, seizing the present opportunities, and keeping the finances in balance in an environment where the economy is constantly changing (Breuker et al., 2016). Businesses can use developed predictive models and incorporate active financial management practices to influence their finances in an uncertain global economic landscape.

1.1.2 Financial Landscape in Ghana

Africa's financial landscape is marked by a mix of dynamic growth and structural challenges, influenced by global macroeconomic pressures, local governance issues, and the effects of worldwide events. Real GDP growth across the continent slowed to an average of 3.8% in 2022, compared to 4.6% in 2021, with countries like Nigeria, Ghana, South Africa, and Egypt facing some of the most challenging economic conditions (African Development Bank, 2023). This slowdown was exacerbated by the lingering effects of the COVID-19 pandemic, volatile commodity prices, and the impact of the Russia-Ukraine war on food and energy prices, which have increased fiscal vulnerabilities across the region.

Countries like Ghana and Nigeria have seen inflation skyrocket in response to these global and domestic challenges. Ghana's inflation surged to 54.1% in December 2022 due to rising energy costs and currency depreciation (Bank of Ghana, 2023). Similarly, Nigeria's inflation rose to 21.8% in early 2023, driven by currency volatility and supply chain disruptions (National Bureau of Statistics, Nigeria, 2023). The Central Bank of Nigeria (CBN) and the Bank of Ghana have responded by tightening monetary policy and raising interest rates to combat inflation, yet these efforts have also constrained private sector credit access, dampening growth prospects (Ogwu, 2021; Bank of Ghana, 2023).

Morocco has maintained relative financial stability in North Africa, benefiting from strong regulatory oversight and a diversified economy. Morocco's financial system, which is deeply connected to European markets, has shown resilience despite external economic shocks (IMF, 2023). Conversely, Egypt has grappled with inflation soaring beyond 40% in 2023, driven by currency devaluation and external debt pressures (Central Bank of Egypt, 2023). However, Egypt has attracted significant foreign direct investment (FDI), particularly in tech and manufacturing, helping to offset some of these macroeconomic challenges.

East Africa, particularly Kenya, has emerged as a leader in digital financial services, with mobile banking platforms like M-Pesa driving financial inclusion across the region. Kenya's fintech sector is a regional hub for innovation, enabling millions to access financial services that were previously inaccessible (World Bank, 2023). However, Kenya continues to face fiscal challenges, including rising public debt and inflationary pressures, which threaten long-term stability.

South Africa, the continent's most industrialized economy, continues confronting deep-rooted structural challenges. While the country's financial sector remains well-developed, with the Johannesburg Stock Exchange (JSE) as one of Africa's leading capital markets, the economy has been hampered by slow growth, energy crises, and persistent unemployment. South Africa's GDP grew by 0.4% in 2023, reflecting these long-standing constraints (South African Reserve Bank, 2023). Investor confidence has been weakened by domestic and global uncertainty, though the country's diversified economy has helped mitigate some risks.

Across Africa, businesses have adapted to these economic challenges by adopting modern financial management practices. In many countries, including Ghana, Nigeria, and South Africa, companies increasingly rely on financial analytics, predictive models, and scenario planning to forecast financial risks and adjust strategies accordingly (Gyimah et al., 2020). Predictive analytics, for instance, helps businesses in Ghana anticipate changes in consumer behaviour and market demand, enabling them to mitigate risks associated with macroeconomic instability (Owusu & Ismail, 2018).

Export-oriented economies like Ghana, Nigeria, and Morocco remain highly dependent on oil, gold, cocoa, and phosphates, leaving them vulnerable to global price fluctuations. Ghana's reliance on gold and cocoa exports and Nigeria's dependence on oil have exposed both countries to significant risks during low commodity prices (OECD, 2023). However, Morocco has diversified its economy with growth in renewable energy and the automotive industry, reducing its reliance on traditional sectors (World Economic Forum, 2023).

In Egypt and South Africa, businesses increasingly use financial technologies to enhance efficiency and capital management. Egypt's adoption of fintech solutions has streamlined operations in various industries, helping firms improve cash flow and boost resilience in economic uncertainty (World Bank, 2023). Similarly, South African firms have adopted cost-saving measures, supply chain diversification, and new revenue streams to mitigate financial risks (PwC Africa, 2023).

Moreover, digital financial services are transforming the financial inclusion landscape across Africa. In addition to Kenya's fintech success, Nigeria has witnessed a surge in mobile banking and fintech solutions, expanding access to financial services for underserved populations (Ozili, 2018). This trend is mirrored across Africa, where digital platforms are increasingly helping to bridge the gap between the formal banking sector and the unbanked population, fostering greater economic participation (Demirgüç-Kunt et al., 2018).

Despite these advancements, challenges persist. High levels of non-performing loans (NPLs), currency instability, and insufficient regulatory frameworks hinder financial sector growth in many African markets. Countries like Ghana and Nigeria, in particular, struggle with weak regulatory enforcement, which exacerbates economic volatility and slows financial sector development (Owusu & Ismail, 2018; Nabena, 2019). Strengthening regulatory oversight, improving governance, and implementing targeted financial sector reforms are essential to ensuring long-term financial stability across the continent.

1.1.4 Financial Distress in African Industries

Both internal and external factors often shape financial distress across African industries. The root causes of distress can be broadly grouped into systemic failures, individual actions, regulatory shortcomings, and wider economic conditions. A historical analysis of financial crises within key industries across the continent reveals the underlying vulnerabilities and evolving nature of economic challenges.

Banking crises are often at the centre of financial distress, as has been the case in several African countries. These crises have been exacerbated by high levels of debt, poor financial management, and regulatory failures. For example, the Global Financial Crisis (GFC) 2008 highlighted how interconnected financial markets are, as failures in the U.S. housing market spread worldwide, affecting African economies reliant on foreign markets and investment (Johnstone et al., 2019). The ripple effect was felt in countries like South Africa and Egypt, where financial institutions faced significant losses. The crisis also revealed gaps in regulatory frameworks that failed to mitigate the impact of global financial shocks on African markets.

In Ghana, financial stress has contributed significantly to the country's debt challenges. Aboagye (2018) notes that Ghana's heavy reliance on foreign loans, inadequate export earnings, and low domestic savings rates have fueled its debt problems. The banking crisis in Ghana between 2017 and 2020 resulted in the government taking over several banks, including UT Bank Ltd. and Capital Bank Ltd., due to their inability to repay loans. This banking crisis was primarily triggered by poor credit management, economic distress, and regulatory inefficiencies (Birches Group, 2023). By the end of 2022, Ghana's debt-to-GDP ratio had reached 98.7%, severely impairing economic growth and stability. Inflationary pressures, reduced purchasing power, and unsustainable debt levels have undermined business performance and financial stability across various industries (Birches Group, 2023).

Nigeria, Africa's largest economy, has also faced significant industrial distress due to external and internal factors. The country's heavy reliance on oil exports and fluctuating global oil prices have left its economy vulnerable to external shocks (Oladunni, 2019). Currency devaluation, inflation, and inadequate infrastructure—such as unreliable power supply and poor transport networks—have further strained businesses, leading to increased operational costs and diminished productivity (Akekere et al., 2017; Onwuka, 2014). Small and medium-sized enterprises (SMEs) in Nigeria are particularly hard-hit, facing stringent borrowing conditions and high interest rates due to their perceived risk by financial institutions (Ihua & Siyanbola, 2012). This lack of affordable credit has stifled business growth, leaving many companies vulnerable to financial distress (Ugoani, 2013).

In addition, the regulatory environment in Nigeria presents significant challenges for industries. Inconsistent policies and regulatory inconsistencies have increased compliance costs, creating uncertainty and making long-term business planning difficult (Chude, 2014). These regulatory hurdles have compounded the financial strain on businesses, particularly in the manufacturing, services, and retail sectors (Imhonopi et al., 2018). Elsewhere in Africa, similar patterns of distress can be observed. South Africa, for example, faces ongoing economic pressures related to high unemployment, power shortages, and stagnant growth. The country's industrial sector, particularly in mining and manufacturing, has been affected by energy shortages, labour unrest, and rising operational costs.

These challenges, combined with global market volatility, have pushed several industries into financial distress, exacerbating the country's already high levels of inequality and poverty (South African Reserve Bank, 2023).

North African economies such as Morocco and Egypt have also experienced significant industrial distress. Morocco's banking sector has remained relatively stable, yet its heavy dependence on European markets makes it vulnerable to external shocks, including those from the eurozone (IMF, 2023). Conversely, Egypt has faced financial strain due to high inflation, currency devaluation, and increasing debt levels. These macroeconomic challenges have hampered the government's attempts to attract foreign direct investment (FDI), resulting in financial stress in crucial sectors such as tourism, manufacturing, and real estate (Central Bank of Egypt, 2023).

In East Africa, Kenya has emerged as a leading player in fintech and mobile banking, with innovations like M-Pesa transforming the financial services landscape. However, the country's manufacturing and agricultural sectors have faced financial difficulties due to rising input costs, poor infrastructure, and regulatory bottlenecks. While the fintech sector has enabled greater financial inclusion, many industries still struggle with affordable financing, particularly SMEs seen as high-risk by traditional banks (World Bank, 2023). Across the continent, industries are also grappling with the aftershocks of the COVID-19 pandemic. The Global Financial Stability Report (2023) noted that the pandemic led to revenue losses and liquidity challenges for many firms, particularly in the retail, tourism, and manufacturing sectors.

Vulnerable companies, especially those with low solvency and liquidity, have faced heightened financial distress, leading to corporate bankruptcies in multiple countries. This distress was compounded by global economic instability, which affected businesses across Africa.

The failures of major global financial institutions, such as Silicon Valley Bank and Credit Suisse, and the collapse of cryptocurrency-related firms like FTX have indirectly affected African markets, given the continent's growing integration into the global financial system (Thompson, 2023). Although African economies were less exposed than their Western counterparts, these failures have highlighted the importance of strong regulatory oversight and prudent financial management to prevent contagion in African industries.

1.2 The Problem Statement

Accurately forecasting financial distress in companies is a crucial task in the turbulent economic conditions of our time. Therefore, investors, financial institutions, and corporate decision-makers know so well that early detection of signs of financial distress is of critical importance. Conventional financial distress predictive models primarily rely on quantitative metrics, such as financial ratios and market-based indices (Zhu et al., 2021; Utami et al., 2021). Nevertheless, the models still do not entirely understand the internal workings of current financial markets. These constraints, and more, include the inability to consider qualitative factors and the influence of exogenous events on a company's financial situation. To overcome these limitations, researchers have more recently used a comprehensive approach involving financial and non-financial variables in their forecasting models (Indriaty et al., 2019; Tao, 2005; Tie-sheng, 2002).

Most financial distress prediction models were designed considering the data and factors of the Western or developed economies (Šarlija & Jeger, 2011; Künzli, 2005; Charitou et al., 2004). The direct incorporation of African countries' specific economic, financial, and regulatory contexts in financial distress prediction models remains insufficiently explored. Like many developing economies, Ghana, Nigeria, South Africa, Egypt, Morocco, and

Kenya exhibit unique market dynamics, business operations, and accounting practices that differ from the Western and developed environments where traditional financial models have primarily been formulated. As a result, there is a pressing need to ascertain how well these traditional financial distress prediction models, predominantly developed in Western economies, apply within African contexts, which are marked by distinctive macroeconomic and regulatory environments.

While some researchers have advocated for the inclusion of qualitative data in financial distress models (Hsiao et al., 2017; Hu & Sathye, 2015; Gudmundsson, 1999), the relevance and practical implementation of these qualitative factors in African countries, including Ghana and Nigeria, remain largely untested. This gap underscores the need for more empirical research that explores the contribution of qualitative factors, such as corporate governance structures, management competencies, and political influences, to the accuracy of financial distress prediction models. In economies with significant informal sectors and political volatility, such as those in many African countries, these qualitative factors could be critical in enhancing the robustness of financial predictions.

Moreover, there is a need to understand better the varying dynamics of different African industry sectors. While some industries may be well-suited to traditional financial distress models, others may face unique challenges that necessitate more nuanced approaches (Oz & Yelkenci, 2015; Meressa, 2018). For example, the oil sector in Nigeria, the mining industry in South Africa, and the agricultural sectors in Kenya and Egypt present different risk profiles and operational dynamics that require industry-specific considerations. These sectors are often deeply tied to global commodity prices, political stability, and regulatory changes, which generic financial models may not fully capture.

A financial crisis, marked by a company's inability to meet its financial commitments, can result in significant financial losses for investors, heightened risk for lending institutions, and disruptions in market stability (Handayani et al., 2021). This is particularly concerning for African countries, where systemic financial vulnerabilities often exacerbate the impacts of corporate financial distress. For instance, Ghana's banking sector faced significant restructuring following the banking crisis of 2017-2020, which led to the collapse of several indigenous banks (Birches Group, 2023). Similarly, Nigeria's reliance on oil exports has made its economy highly vulnerable to fluctuations in global oil prices, leading to periodic financial strain across industries (Oladunni, 2019).

Given these risks, there is an urgent need to develop more comprehensive and robust financial distress prediction models tailored to the African context. Such models should be capable of quickly identifying the symptoms of financial distress while accounting for both quantitative and qualitative factors. The traditional financial distress prediction model, which focuses primarily on quantitative data such as liquidity, solvency, and profitability ratios, may overlook critical contextual elements such as regulatory compliance, macroeconomic conditions, corporate governance, and managerial expertise (Alkaraan, 2020; Schmidt, 2010). These qualitative factors are often crucial in African markets, where political uncertainty, economic instability, and regulatory changes can significantly impact business operations.

In contrast, the integrated approach better incorporates financial, market, and qualitative data to assess a company's likelihood of financial distress. By including factors such as corporate governance, management skills, and operating environment, the integrated model captures the contextual factors particularly relevant in African economies, where informal markets, governance issues, and economic instability play a larger role in determining business outcomes. This approach offers a more comprehensive framework for predicting financial distress by recognizing that the numbers alone may not tell the whole story of a company's financial health.

In light of these factors, this study analyses two distinct approaches to financial distress prediction: the conventional model, which primarily relies on quantitative financial and market data, and an integrated model that combines quantitative data with qualitative factors. The study aims to assess the effectiveness of these two approaches in predicting financial distress within the African context, focusing specifically on Ghana, Nigeria, South Africa, Morocco, Egypt, and Kenya. By comparing the predictive accuracy of both models, this research seeks to identify the most influential factors that drive financial distress predictions and assess the operational consistency of these models across diverse African economies.

Ultimately, the study aims to highlight the potential benefits of incorporating qualitative data into financial distress prediction models, emphasizing that a more comprehensive approach can significantly improve the accuracy and adaptability of such models in Africa's unique economic landscape. This research seeks to identify the most effective method for predicting financial distress and explore the advantages of integrating qualitative data in financial models, particularly in economies as complex and dynamic as those across Africa.

1.3 Research Objectives

The specific objectives of this study are summarized below:

i. To assess the relative effectiveness of traditional financial distress prediction models against integrated models.
ii. To determine which variables significantly impact the predictive performance of both the traditional and integrated models.
iii. To ascertain the consistency of traditional and integrated models across Africa.

1.4 Research Questions

The following research questions will be examined:

i. Does the integrated financial distress prediction model exhibit a significantly higher predictive accuracy than traditional models?
ii. Which specific variables significantly influence the predictive accuracy of both the traditional and integrated models?
iii. What is the consistency of traditional and integrated models across Africa?

1.5 Significance of the Study

The study demonstrates new arguments in discussing the modernity of financial distress prediction by proving that hybrid models are far more practical than traditional ones. This is critical not only for research but also for practice. Additionally, it aids in understanding the factors that affect the credibility of such models, making the process of future research much easier. This study will yield valid instruments and instructions for investors, financial institutions, management personnel, and regulators, enabling them, in turn, to influence investment decisions, risk management, corporate finance, and regulatory compliance while discerning the role of qualitative data in forecasting financial distress. Furthermore, the study's finding of country (or region) differences aids in constructing region-specific predictive models, increasing the precision of predictions.

The study attempts to advance the financial distress prediction field by comparing traditional and integrated models. The research aims to increase our comprehension of financial stress prediction and the practical applications of the models regarding their ability to predict financially stressed organizations, key variables, and how they perform by country.

CHAPTER TWO
LITERATURE REVIEW

2.0 Introduction

This chapter presents a literature review of the study derived from the research objectives. It is structured in three sections: theoretical, conceptual, and empirical review. The theoretical review section assesses information theory, contingency theory, and the resource-based view as the theoretical frameworks that guide the study. The conceptual review section considers prominent concepts relevant to the current research, focusing on the literature regarding financial distress, key financial indicators, financial distress in Ghanaian industries, traditional distress prediction models, integrated distress prediction models, and a comparison of conventional and integrated models. In the empirical review, this paper discusses the findings from studies similar to the present one. Lastly, the conclusion addresses the research gap in the reviewed empirical studies that this study aims to cover.

2.1 Theoretical Review

These two theoretical frameworks underpin the study: contingency theory and resource-based view (RBV).

2.1.1 Contingency Theory

The contingency theory, developed by Emery (1958), Burns and Stalker (1994), and Lawrence and Lorsch (1967), asserts that the individual system's effectiveness or decision-making efficiency depends on how well it accommodates changes that occur in its organizational systems or environmental conditions. This theory contradicts the universal "one-size-fits-all" approach. It stresses the necessity of the organization of operation models and strategy matching, especially the conditions of its relationship with its external environment.

The contingency theory asserts that the accuracy of these models can be limited or affected by the industry or sector in which a firm operates (Platt & Platt, 1990). Different industries vary concerning unique characteristics, risk factors, and financial patterns, which may significantly influence the popularity of the various variables used in distress prediction models (Sehgal et al., 2021).

For instance, industries with a high capital intensity, such as manufacturing or construction, often borrow for fixed assets and, thus, heavily depend on debt financing. Financial distress in these industries could largely depend on the debt-equity ratio and liabilities-to-assets ratio. On the contrary, capital-intensive service industries may focus on liquidity and cash flow, among others. Still, capital-intensive service industries may focus on the variables related to the return on capital employed, among other things (Chava & Jarrow, 2004).

Therefore, the contingency theory states that the significance of the presence or absence of such variables may vary at different phases of an enterprise and is dependent on the country's economic conditions (Pindado et al., 2008). In that regard, growth factors such as business opportunities or market conditions might be more significant during intense economic activity, and cost factors such as financial flexibility or cost efficiency might dominate during recessions or industry downturns.

As a result, it turns out that contingency theory helps to determine whether the building of region or sector-specific models can result in corresponding accurate predictions.

According to this theory, management approaches must be adapted to individual circumstances for organizational practices to succeed (Alsaid & Ambilichu, 2023). Because industry-specific models represent the only possibility for accurate predictions, contingency theory indicates that multifield models are the only option for adequately implementing state programs (Søgaard et al., 2019).

Nevertheless, it is necessary to mention that although some models are based precisely on sector-specific assumptions, they may be more accurate only in some situations while introducing extra complexity and restrictions associated with data availability and model generalization (Shumway, 2001). A model that builds from industry-specific variables and combines them with more general financial and non-financial variables can be a method to account for uncertainty and also have a degree of robustness and applicability across different circumstances.

In predicting financial distress, contingency theory states that the accuracy of the prediction models may depend on the industry or sector that the firm is part of. Different industries may have different characteristics, risk factors and financial patterns that require region or sector-specific models for precise predictions. This theory underpins determining if accurate predictions require sector-specific models (objective 3).

2.1.2 Resource-Based View (RBV)

The resource-based view (RBV) developed by Penrose (1959) and then expanded by Wernerfelt (1984) and Barney (1991) puts forth the conception that organizations' profit-making performances and competitive advantages are derived from their unique assemblies of capabilities and resources. This theory emphasizes that a company's position of success depends on the special and unique resources the organization must possess to gain a competitive advantage because they are valuable, rare, non-substitutable and inimitable (Chin et al., 2018). RBV assumes that through the practical usage of resources, corporations can increase their strategic capabilities and performance of organizations (Lubis, 2022).

According to this theory, firms with valuable and rare resources such as sound financial management practices, efficient management processes and skilled human capital are better positioned to overcome financial difficulties and avoid distress (Arend, 2004). RBV's approach, therefore, argues that the commonly used ratios, which are a good predictor of financial distress in traditional models, are not always or entirely representative of the firm's particular resource base and capabilities. Although financial ratios enable a look into how a firm is performing financially, they are not directly related to the actual resources of the company or what would be the main driving force behind the performance (Kraaijenbrink et al., 2010).

This model will generally introduce some non-financial factors that can effectively represent the firm's capabilities and resources and thus improve the model's accuracy. For instance, the quality of management, the number of years the company has actively participated in the industry, the intensity of research and development (R&D) as well as the capability of the firm in terms of technological development could be some of the variables that enable economists to point out the intangible resources and capabilities through which the firm's performance is enhanced, and its resilience maintained (Mselmi et al., 2017).

In addition, Crook et al. (2008) point out that the essentiality of different resources and capabilities can vary across industries. Regarding knowledge-intensive industries, human capital and intellectual property play an important role, while in capital-intensive sectors, physical assets and effective manufacturing techniques are deemed the most critical. This becomes consistent with the study of whether accurate predictions require region or sector-specific models because they can provide the region or industry-specific resources and capabilities that are the main drivers for predicting financial distress.

Notwithstanding this, the RBV shows that the main impediment described in Newbert (2007) is sometimes difficult to distinguish and measure the intangible resource from the intangible capability. While ratios are highly quantifiable and simple, qualitative items may be more challenging to identify and estimate due to their complexity. The growth of this approach might give rise to additional problems in designing and validating comprehensive models of financial distress assessment.

In the financial distress forecasting situation, the RBV can identify the primary resources and core capabilities (both financial and non-financial) that either cause or indicate a company's financial health or distress. With this theory, experts can pinpoint the factors that significantly impact the predictive abilities of traditional and integrated models and perform effective diagnoses (objective 1). Furthermore, the RBV can illuminate the dynamics between regions or sectors to predict whether region or sector-specific models (research area 3) are essential.

2.2 Conceptual Review

2.2.1 Concept of Financial Distress

The notion of financial distress is presented differently in various studies, with some centring on specific financial indicators, whereas others focus on a broader set of factors. Several authors rely on multiple signs of financial distress to determine the states of distress. Foster (1978), for instance, puts the four levels of financial distress into the following: debt payment, product power, dividend payment, and bond default. Lau (1987) classified five stages of financial distress: security, dividend cut or decrease in dividend, loan defaults, seeking protection under the law, and bankruptcy. On the other hand, Cheng and Li (2003) modified the financial administration stages of the Lau (1987) model and, in general, defined them depending on financial distress and financial stability with the four states of financial distress used in Foster's (1978) original model.

Kliештik et al. (2020) highlighted that there is no standard definition of financial distress and provided the different operational determinants of financial distress in companies. They emphasize integrating divergent views to get a comprehensive picture of financial hardship. Sehgal et al. (2021) propose an accounting-based model of financial distress centred on the firm's ability to service current and long-term debts and its promise of managing other financial obligations. This definition refers to the company's financial health and solvency as the significant parameters in determining financial distress.

Balasubramanian et al. (2019) describe financial distress as a situation where a company's total assets are liquidated for less than the total value of creditor claims. In this definition, the critical point is the asymmetry between the assets and liabilities as a main indicator of financial strain. Ceylan (2021) defines financial distress as a closure when cash flow cannot cover the company's long-term liabilities. This stresses cash flow as the critical factor in forecasting financial distress.

In Chung and Kim's (2022) study, financially distressed companies were identified as those with negative net income or operating cash flow. This research investigates various definitions of financial distress and their impacts on corporate performance. Yousaf et al.

(2021) point out that basing the evaluation of financial distress on a single criterion might be misleading and recommend a wide range of factors to establish the risk of financial distress in companies.

According to Ashraf et al. (2019), financial distress is now a more comprehensive term used after analyzing the early signs of financial failure but not overlooking the firms already amid financial distress. This definition extension provides more ways to take preventive actions to deal with financial issues. Zhu et al. (2022) point out that terms including `financial toxicity,` `financial burden,` and `financial distress` tend to be used interchangeably within research, suggesting some overlap in their definitions and implications. Alhady et al. (2021) argue that bankruptcy is potentially the next step of financial distress, which certifies the criticality of evaluating a company’s financial health.

2.2.2 Key Financial Indicators Associated with Distress

2.2.2.1 Profitability Ratios

Profitability ratios are vital financial indicators to test whether a company can generate income for a given period (Delen et al., 2013). These ratios delve into different elements of the firm, such as performance, efficiency, effectiveness, and profitability. A recent study by Arsyad et al. (2021) revealed that profitability ratios are essential for capital market investors to identify a company’s dividend policy. This dependency on these ratios is a clear sign that the profitability ratios make a hell of a difference in the investor’s decision and the way they perceive a company’s financial health. Suardana et al. (2018) underlined that ratios like Return on Assets (ROA) should attest to the ability of the company to create profits. The study emphasized that higher ROA indicates good profitability levels. This represents the company’s ability to use its assets to produce high profits.

In addition, Suwandi et al. (2023) pointed out the importance of profitability ratios, including ROA and ROE, for evaluating a company's performance. The ratios are helpful as they can be applied to determine how efficiently a company operates its assets and equity to create profits, which is a performance measure. One of the most popular measures of profitability wedged into probit models is the Net Income to Total Assets, which is discussed in the Zmijewski model (Zmijewski, 1984; Chava & Jarrow, 2004).

2.2.2.2 Liquidity Ratios

Liquidity ratios are financial metrics that evaluate a company's ability to settle its short-term liabilities properly. A firm deploys these ratios as a liquidity gauge by measuring the ratio of current assets to current liabilities. The liquidity ratio mainly comprises the current ratio and quick ratio. The current ratio analysis estimates the company's exact capacity to settle its short-term liabilities from its current assets. In contrast, the quick ratio is a more refined version of the current ratio as it excludes the inventories from the current assets for a more stringent evaluation (Ohlson, 1980; Tinoco & Wilson, 2013).

According to research by Ardekani (2023), setting minimum liquidity ratios and capital ratios aligns with the Basel Committee's recommendation, which stresses the necessity of liquidity management within the banking sector to foster financial stability. Moreover, Ali and colleagues (2019) and Loo and Lau (2019) point out that liquidity ratios ensure profitability and investment outcomes, evidenced by a window of opportunity. In other words, the liquidity ratios influence profitability and investment output.

Similarly, Bala-Keffi et al. (2022) focus on the efficiency of monetary policy tools in regulating liquidity conditions, thus determining the relationship between monetary policy and liquidity risk. A clear vision of how monetary policy affects liquidity management is indispensable for maintaining financial stability in banking.

Concerning financial distress prediction, Waqas and Md-Rus (2018) highlight the influence of liquidity ratios as a critical parameter in evaluating firms' financial positions. Liquidity ratios are influential tools that determine a firm's distressed state and signify upcoming financial problems.

2.2.2.3 Leverage or Solvency Ratios

Leverage ratios are essential for assessing companies' financial performance and standing. This ratio, usually scientifically determined by metrics such as debt to equity ratio or debt-to-asset ratio, provides valuable information on the company's degree of debt usage for operational financing (Susdaryo et al., 2021; Susanti & Takarini, 2022). High leverage ratios can expose companies' financial risk due to the burden of significant debt, as these entities may not have core values to meet their financial commitments (Sengottaiyan & Vijayalakshmi, 2021). Research has found that highly leveraged firms are more vulnerable to financial risks than those with lower leverage (Sengottaiyan & Vijayalakshmi, 2021).

In the same vein, the role of leverage ratios in financial stability has got people talking and has been put in the spotlight, particularly after financial banking crises. Further, countries experienced a decline in leverage ratios after the crisis, highlighting asset management and risk reduction by different nations to avoid crises (Zhang & Kai, 2021). The leverage ratio is predominant in the banking sector, as the studies highlight its role in risk management and examining a bank's performance (Sari, 2021).

One of the crucial areas of research is the correlation between leverage ratio and profitability. While some studies find a negative link between financial leverage and profitability, indicating that leverage level might decrease profitability (AL-Habashneh, 2022), other studies explore how different levels of leverage might affect the Weighted Average Cost of Capital (WACC) and then profitability (Okeya et al., 2020). Moreover, high leverage ratios have usually indicated higher probabilities of debt troubles and bankruptcies in financial areas (Susilowati et al., 2021; Gunawan & Putra, 2021).

2.2.2.4 Operational Efficiency Ratios

Operational efficiency ratios are performance financial indicators used to evaluate and assess the operations' efficiency and effectiveness, especially in the finance and banking sectors. These ratios illustrate how effectively a firm utilizes assets that produce income and cut costs. The ratio of Operational Cost to Operating Income (BOPO) is the most commonly used ratio, which is an indicator of the level of operating expenses concerning operating income (Asiyah et al., 2022).

Research has noted several factors influencing banks' operational efficiency: the CAR, credit risk, money supply, inflation, exchange rates, and national GDP (Msomi & Olarewaju, 2022). Moreover, considerations like green supply chain management affect operational efficiency, including cost- and time-based efficiency (Nguyen et al., 2023). Another strand of research has turned to the connection between efficient operations and financial performance, concentrating on capital structure, with earnings management moderating (Abd-Elmageed et al., 2020).

Apart from showing the financial performance of banks, the efficiency ratios also apply to other sectors. For instance, the higher operating efficiency ratios of the real estate investment trusts sector imply higher operational efficiency (Feng & Liu, 2021). In addition, operational efficiency is a pivotal factor in the business sector, which is instrumental in keeping companies competitive in the market landscape (Vivekananda & Shrawankar, 2022).

Operational efficiency is the underlying factor of profitability and risk management focused on banks. Research has found a solid and positive relationship between credit risk, operational risk and operational efficiency ratios, showing that risk management is vital for supporting efficiency (Khan et al., 2023). Furthermore, research on the influence of working capital management efficiency of listed real estate companies on their operating result shows the importance of managing working capital effectively (Research on the Influence of Working Capital Management Efficiency of Listed Real Estate Companies on Business Performance, 2022).

2.2.2.5 Market-Based Indicators

Many research works have brought attention to the role of debt and equity in financial analysis and different aspects of corporate finance. The market value of equity equals the number of shares outstanding multiplied by the share price. On the other hand, the book value of equity is calculated as the assets minus the liability minus the preferred stock plus the deferred tax (Abdeljawad, 2023). Ernaani (2020) claimed that the market value to equity ratio to debt ratio, or the solvency ratio, measures a company’s ability to fulfil its long-term obligations in contrast to the book value of equity.

Distance to default (DtD) is the fundamental metric for evaluating default risk in different financial situations. It measures the difference between the company’s asset value and default rate, offering a perspective on default probability. Different studies emphasized the role of DtD in predicting defaulter probabilities and evaluating credit risk (Miao et al., 2018; Nagel & Purnanandam, 2019; Bloechlinger & Leippold, 2018; Vu et al., 2019; Haque & Varghese, 2021). Models, including the KMV-Merton model, have been applied to predict DtD, a quantitative evaluation technique for default risk (Ayomi et al., 2021; Hunjra et al., 2020).

Moreover, the estimation of DtD has also experienced different economic determinants, including the influence of monetary policy, bank competition and corporate leverage (Haque & Varghese, 2021; Ayomi et al., 2021; Feng et al., 2021). Research has also explored the role of distance to default in bank stability, firm credit risk, and leverage, illustrating its significance in evaluating financial stability (Feng et al., 2021; Saha et al., 2019; Lei et al., 2022). Additionally, DtD models have been utilized in various industries and across regions. This process has generated multiple proofs of its versatility in estimating default risks (Delapedra-Silva, 2021; Duong & Bertrand, 2021; Zhou et al., 2019).

2.2.3 Traditional Distress Prediction Models

Traditional models for predicting financial distress often depend on financial ratios computed from a firm's financial statements to explain the possibility of financial distress or bankruptcy. These models have been accepted and developed ever since they were established. Here are some of the most prominent traditional distress prediction models:

1. **Altman Z-Score Model:** The Altman Z-Score model, developed by Edward Altman in 1968, is recognized as one of the most widely used bankruptcy prediction models (Altman, 1968). The model utilizes a set of grouped financial ratios to form a single score. The score can range from distressed to non-distressed level. The ratio used in the

model includes working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to book value of total liabilities, and sales to total assets (Altman et al., 2017). Altman Z-Score model evaluating companies' financial distress level has been highlighted in studies by Younas et al. (2021) and Dewi and Dewi (2022). As revealed in Khawaja (2023), the ability of the Z-Score model to forecast financial distress for companies in sophisticated countries has been compared, confirming the model's effectiveness in a broad economic environment. The well-known Altman Z-Score model has shown up in different industries, from the nursing home sector, as Lord et al. (2020), to the general insurance business in Bangladesh, as Rahman et al. (2022) described. Furthermore, Bogamuwa & Perera (2022) and Pratiwi et al. (2022) studies have stressed the importance of modelling the Altman Z-Score adjustment to befit the peculiar traits of developing nations such as Sri Lanka and Indonesia, respectively. Additionally, Ud-Din et al. (2020) and Septyanto et al. (2022) have shown that the Altman Z-Score is a threshold that is helpful in the prediction of financial health and distress levels for firms. Elia et al. (2021) confirmed the suitability of the Altman Z-Score model for credit risk forecasting in the banking system. Normiati and Amalia (2021) and Toly et al. (2020) also used the Altman Z-Score model to analyze financial distress among manufacturing companies listed on the stock market. Furthermore, the Altman Z-Score model has been compared with other bankruptcy prediction models in studies such as (Pratapam & Kmanuel, 2021), which measured the performances of Altman, Springate, Ohlson, and Zmijewski models in the automotive components industry. The model has been implemented in various nations, and studies have included firms and individuals in

India, Vietnam, and Ethiopia (Sharma & Patra, 2021; Thinh et al., 2020; Meressa, 2018).

2. **Ohlson O-Score Model:** The O-score model was first proposed by James A. Ohlson in 1980. It is a logistic regression model that estimates the probability of firm bankruptcy occurring within a specific time frame (Ohlson, 1980). The model has nine independent variables: size, financial leverage, liquidity, profitability, and solvency ratios of firms (Tinoco & Wilson, 2013). Like the Z-score, the O-score has revealed high predictive power in detecting financial distress and bankruptcy risk (Ahmad et al., 2018). The researchers developed the Ohlson O-Score to analyze the company's likelihood of defaulting in the next two years, building on existing models for predicting default risk (Lisin et al., 2022). The predictability of the Altman Z-Score and Ohlson O-Score is also under examination, emphasizing small and medium enterprises in Indonesia (Pramudita, 2021). The O-Score is used to assess the systematic risk related to the bankruptcy of a firm, which was explained by Chhapra et al. in 2020. In the research on Islamic social reporting and financial distress, models such as the Ohlson O-Score were used together with other scoring systems as proxies of financial distress (Cahyani et al., 2020). The O-score has been incorporated into financial frameworks with liquidity and systematic risk as an additional variable to assist with share price prediction and firm valuation (Soon & Basiruddin, 2018). Research has been done to compare different bankruptcy prediction models, such as the Z-Score of Altman and the O-Score of Ohlson, to find out how well they perform versus each other (Najib & Cahyaningdyah, 2020).

Moreover, the O-Score has been used to evaluate the effect of corporate governance on the cost of equity for businesses by increasing the determination coefficient if corporate governance variables are incorporated into the Ohlson model (Khassanov, 2021). The Ohlson model with the O-Score has been utilized in various regions to evaluate the value relevance of accounting information and foresee financial distress (Krismiaji, 2020). Additionally, O-Score has proven to be a helpful instrument in predicting the financial crisis in Indonesia's large and small-sized automotive component sectors (Pratama & Mulyana, 2020; Nikmah, 2021).

3. **Zmijewski Probit Model:** Developed by Mark E. Zmijewski in 1984, this model uses a probit analysis of a company's probability of bankruptcy. The model includes three financial ratios: the net income to total assets, total debt to total assets, and current assets to current liabilities (Chava & Jarrow, 2004). The Zmijewski Probit Model effectively aids companies' financial distress prediction and bankruptcy forecasting. This model has an advantage in considering various financial ratios such as net income to total assets, total debt to total assets, and other significant indicators to assess the company's financial health (Avi & Giulia, 2022). Research has shown that employing probit analysis in the Zmijewski model ensures greater prediction accuracy when compared with other traditional financial distress prediction models (Ashraf et al., 2019). Zmijewski's Probit Model is founded on the fact that a company is financially distressed doesn't mean it must go bankrupt (Ďuranova et al., 2021). The employment of the probit analysis technique not only provides the model of Zmijewski with a statistical method but also a methodology which gives insight into the relationship between financial woes and bankruptcy risk (Ďurana et al., 2021). This strategy allows

for a more precise estimate of the chance of occurrence of the insolvency condition by the company in a short-term period (Cheng et al., 2023).

Furthermore, this model is popular among researchers for conducting bankruptcy prediction and financial distress analysis (Kim et al., 2020). Scholars have confirmed that the probit model is the best-fit model to explain the complex nature of corporate default risk (Kim et al., 2020). The model considers numerous financial variables and uses probit regression, which multiplies its ability to detect firms at risk of financial distress (Kim et al., 2020).

4. **Merton Structural Model:** Robert C. Merton proposed this model in 1974, and it is based on the option pricing theory, considering the firm's equity as a call option on its assets (Merton, 1974). The presumption is that the firm fails to pay its liabilities when its value exceeds its book value (Bharath & Shumway, 2008). The Merton model is an option-based structural model that links the firm's equity value to debt value, facilitating the estimation of default probabilities and credit spreads (Bodie, 2019). Modifications to the Merton model include embracing the idea of Leland's structural model of credit risk, which in turn leads to a comprehensive approach to assessing the corporation's financial soundness (Choudhury et al., 2021). Furthermore, the Merton-KMV approach, based on the Merton model, considers market-based information to calibrate models for predicting corporate defaults (Andrikopoulos & Khorasgani, 2018).

   Notwithstanding its importance, the Merton model has suffered the credit risk premium puzzle, which has affected classical structural models like Merton's and the short-term credit spread of corporate bonds (Ogunsolu et al., 2023). The Merton model is being tested and compared with other models using empirical data to examine its efficacy in pricing risky corporate bonds (Baaquie & Karim, 2022). The Merton model has also been applied in different settings, such as analyzing the behaviour of debt and equity markets in particular companies (Sanderson, 2019), estimating default probabilities of non-financial companies (Malasari et al., 2020), and modelling bond spreads and credit default risk in financial markets (Nagel & Purnanandam, 2019).

These traditional models have been widely used in different manufacturing sectors to serve as performance assessment parameters to enhance the accuracy of predictive performance (Bauer & Agarwal, 2014). On the other hand, established models face some limits because they depend on financial ratios only, and they cannot explain industry-specific factors or non-financial things that may influence the economic condition of the firm either positively or negatively in general (Platt & Platt, 1990; Chava & Jarrow, 2004).

To overcome these limitations, researchers have proposed integrated models that combine financial ratios and non-financial measures such as management quality, industry features, and macroeconomic indicators (Bemš et al., 2015; Bauer & Agarwal, 2014). Furthermore, more advanced techniques have been developed to use artificial intelligence and machine learning for capturing non-linear relationships and handling high-dimensional data (Barboza et al., 2017; Zieba et al., 2016).

2.2.4 Integrated Distress Prediction Models

Integrated financial distress prediction models are designed to overcome the shortcomings of traditional models by also considering non-financial variables coupled with financial ratios. These models acknowledge that financial ratios might not fully capture a company's financial condition and risk of distress. Here are some examples of integrated distress prediction models:

1. Hazard Models: Some researchers have used hazard models like Cox proportional hazards and accelerated failure time models in bankruptcy prediction (Shumway, 2001; Chava et al., 2004). These models compute the likelihood of a firm getting into bankruptcy or financial distress at a particular time by considering time-varying and time-invariant covariates (Bauer & Agarwal, 2014). Also, proportional hazard models like the Cox proportional hazards model are widely spread in the survival analysis for modelling cause-specific hazards (Acuña & Dossa, 2019). These models help explain the factors behind a specific event and the means of deferring or enhancing outcomes.
2. Market-Based Models: Market-based models, like the Merton distance to default (DD) model and the method of contingent claims analysis (CCA) models, use market data and option pricing theory to carry out the analysis of credit risk (Bharath & Shumway, 2008; Hillegeist et al., 2004). These models are based on the firm's equity value, asset value, and volatility estimates used to estimate the distance to default, a sign of financial distress. Market-based models could be used with accounting-based ratios and non-financial parameters to increase their predictive ability (Hull et al., 2005). Incorporating market data into those models for predictive purposes helps improve their accuracy. Studies show that combining market transaction data with financial and governance traits will enhance the precision of distress prediction models (Zeng et al., 2020). The most comprehensive approach to predicting financial distress can be achieved by combining market-based and financial indicators. Macroeconomic signals and market determinants must be considered to properly design a consistent distress

prediction model (Sehgal et al., 2021). Using a wide range of indicators, these models can offer a holistic view of the health and resiliency of a firm, especially during times of pronounced market volatility.

3. Artificial Intelligence and Machine Learning Models: In recent years, researchers have delved into the use of artificial intelligence (AI) and machine learning (ML) mechanisms such as neural networks, decision trees and support vector machines to predict financial distress (Barboza et al., 2017; Zieba et al., 2016). These models can depict intricate non-linear relationships and handle multi-dimensional data that may lead to more accurate predictions. Financial markets' decision-making procedures are improved consistently by using AI and ML in financial distress predictions (Buchanan & Wright, 2021). With the help of AI technologies, financial institutions can enhance the accuracy and efficiency of the decision-making process, which may eventually result in more informed decisions and timely actions (Buchanan & Wright, 2021). Therefore, applying AI and ML techniques in bankruptcy prediction is becoming increasingly attractive because the prediction of financial difficulties using these methods has shown good accuracy and, in some cases, better than traditional ones (Abuzov, 2023).

4. Hybrid Models: Hybrid models may combine different modelling methods and data sources to exploit their distinct advantages (Cheng et al., 2016; Tsai et al., 2014). For instance, a hybrid model could combine conventional statistical models, such as logistic regression, with a machine learning tool, such as neural networks. In this context, such models may also combine financial ratios (such as profitability, liquidity and leverage indicators) and non-financial variables (like quality of management, corporate governance indicators and macroeconomic parameters). In addition, Shen & Chen (2022) emphasized creating an exact financial distress tracking and prediction model using hybrid machine learning technology. Through a blend of different methods, they worked to increase the accuracy of corporate financial distress prediction. In addition, Kim et al. (2018) presented a combination of SVM and GA, GOSVM, to improve SVM algorithms in financial distress prediction. Their new strategy was designed to eliminate problems such as overfitting that led to precision loss.

The inclusion of non-financial variables in these models is based on different theoretical perspectives, including, for instance, the Resource-Based View (RBV), which asserts that a firm's exclusive resources and capabilities enable it to achieve financial success and resistance (Barney, 1991; Wernerfelt, 1984). Through integrating variables linked to a firm's resources and competencies like management quality, industry experience, and technological capabilities, integrated models can, therefore, seize industry-specific factors and give more accurate predictions (Mselmi et al., 2017; Crook et al., 2011).

Though integrated models have the advantage over financial models regarding improved predictive performance, their effectiveness depends on selecting relevant non-financial variables, the modelling techniques used, and the specific industry and economic context (Platt & Platt, 1990; Chava & Jarrow, 2004). Moreover, the availability and the quality of non-financial data are the other obstacles to implementing such models.

2.2.5 Traditional vs Integrated Distress Prediction Models

Traditional and integrated distress prediction models are compared in multiple studies. The precision of these models in predicting financial distress is a matter of discussion. Some researchers contend that the traditional statistical methods, such as the Logit model, perform better than the integrated ones, such as Artificial Neural Networks (ANN) (Martini et al., 2023). On the contrary, other studies explain that integrated models, profound learning models using attention mechanisms, show perfect results in financial distress predictions (Muparuri & Gumbo, 2022). Furthermore, machine learning classifiers and ensemble techniques, like Neural Network (NN), Decision Tree (DT), Support Vector Machine (SVM), Majority Voting (MV), Random Forest, and AdaBoost, have been used to build more precise prediction models (Li & Wang, 2023).

Altman, Zmijewski, Springate, and Fulmer models have long been the fundamental models that are pivotal in determining the financial health of companies in the market (Kristanti et al., 2023). On the other hand, new research shows that those traditional models may have different levels of reliability regarding the stage of distress a firm is experiencing. To exemplify, a study done in Pakistan discovered that loss forecasting models may not be able to spot early signs of distress (Ashraf et al., 2019).

On the other hand, other methods like hybrid neural networks and machine learning models have demonstrated the potential to enhance the accuracy level of financial distress predictions. A hybrid neural network technology applied in a study comparing it with the traditional statistical methods and artificial neural network models showed that the hybrid neural networks performed the best in predicting financial distress (Ruan & Liu, 2021). Moreover, machine learning-based distress prediction models have demonstrated higher accuracy against the time series models commonly used, particularly in countries experiencing high corporate financial distress like India (Sehgal et al., 2021).

Furthermore, incorporating dynamic distress threshold values in prediction models has enhanced prediction accuracy compared to models using traditional threshold values (Chen et al., 2020). This suggests that adjusting models to consider dynamic thresholds could strengthen their predictive capabilities. Additionally, deep learning models, such as convolutional neural networks, have been proposed as a robust approach to financial distress prediction, indicating the potential for advanced technologies to transform distress forecasting (El-Bannany et al., 2020).

As traditional models like discriminant analysis and logit models have provided the basis for the development of distress prediction, the growing complexity of the financial world may prompt the continuous development and testing of the prediction models (Shahwan & Maysara, 2020). Combining non-financial aspects that have to do with governance may also help to increase prediction accuracy, primarily when the design and implementation of distress prediction models are aimed at small and medium-sized enterprises (SMEs) (Ragab & Saleh, 2021).

Contingency theory postulates that financial distress prediction models may only work well for firms in a particular industry or sector (Chava & Jarrow, 2004; Platt & Platt, 1990). Different industries feature specific attributes, risks, and financial patterns, which can, in one way or another, affect the forecasting ability of the included variables in the models. Traditional models, which deal with the financial ratios only, may not cover the specific features of an industry entirely. At the same time, integrated models can evaluate particular sectors accurately, including the non-financial variables related to the industry characteristics.

Besides, integrated distress prediction models have given strongly enhanced results in most empirical studies compared to traditional models (Mačėnaitė et al., 2023). For instance, as Mačėnaitė et al. (2023) predicted financial distress, a random forest model that considered financial and non-financial factors outperformed the traditional models such as Altman Z-score.

Finally, this comparison between traditional and integrated distress prediction models shows a shift towards developing newer techniques like machine learning and hybrid neural networks. Although ancient models had their advantages, the fluctuating nature of financial markets demands the continual improvement of distress prediction models to deliver highly exact and up-to-date evaluations of financial health.

2.3 Empirical Studies

Many empirical studies were conducted to compare and measure the performance of different models for forecasting financial distress. Bellovary et al. (2007) offered a comprehensive review of bankruptcy prediction studies from 1930 to 2007, comprising various methods, including univariate analysis, multivariate discriminant analysis, logit analysis, recursive partitioning, and neural networks. Authors compare the performance of these models by their predictive accuracy, using data from different industries and periods. It turned out that later works were more concerned with applying mixed models and including market-dependent variables to improve prediction accuracy.

Zięba et al. (2016) evaluated the application of ensemble methods, particularly boosted trees and random forests, as tools for bankruptcy prediction. The authors suggest a new approach that uses these approaches along with synthetic feature generation to heighten model accuracy. Using Polish companies' data, they compare their model's performance with other models, such as logistic regression and support vector machines. The results indicated that the boosted trees with an ensemble's synthetic features outperformed others in predictive accuracy.

Tinoco and Wilson (2013) studied the performance of different financial distress prediction models in the context of conglomerates, which are companies with multiple business segments and are spread over various industries. The researchers compare the predictive accuracy of the Altman Z-score, Ohlson O-score, and Zmijewski probit models that use the list of conglomerate companies on the NYSE and NASDAQ as data. The results indicated that the Altman Z-score model outperformed other models when predicting financial distress for conglomerate firms.

Jackson & Wood's (2013) research sought to test the efficacy of distinct insolvency prediction and credit risk models for UK companies. The authors aim to ascertain the precision of models like the Altman Z-score, Ohlson O-score, Zmijewski probit model, and the credit scoring models developed by leading credit rating agencies. The findings show that credit scoring models better detect insolvency for UK companies than conventional financial distress prediction models.

Pindado et al. (2008) use data from Spanish firms to assess the predictive ability of diverse financial distress prediction models such as the Altman Z-score, Ohlson O-score, and hazards models. In addition, the authors present a new model that is a mixture of accounting and market-based variables. Results demonstrate that the new model performs better than the traditional models in predicting financial distress, implying that including market-based factors can help increase prediction accuracy.

Altman et al.'s (2017) study evaluated Altman's Z-score model in the context of cross-country and industry-level financial distress prediction. The authors based their conclusions on data collected from industries in the United States, Canada, Mexico, France, Germany, Italy, Netherlands, Belgium, and the United Kingdom. The findings prove that

Altman's Z-score model is a useful predictive tool in international settings, but the model's performance is not the same across countries and industries.

Tsai & Chen (2010) suggested a hybrid machine learning approach for credit scoring and financial distress prediction. The authors use the combination of SVMs and SOMs clustering techniques to increase the prediction accuracy. They apply their hybrid approach to financial data from publicly traded companies in Taiwan and compare it with first-generation techniques such as discriminant analysis and logistic regression. Results showed that the hybrid SVM-SOM model surpassed the traditional methods regarding financial distress prediction.

2.4 Research Gap

Most firms examined by empirical studies on financial distress prediction models are from developed countries or emerging economies such as China and Poland (Wu et al., 2010; Altman et al., 2017). However, a significant research gap exists regarding financial distress prediction models tailored to African countries. Few studies have focused on African economies like Ghana, Nigeria, South Africa, and Kenya, where unique economic, financial, and regulatory environments prevail (Asongu & Odhiambo, 2019). This gap highlights the need to investigate the effectiveness of current models or develop new models tailored to the African business environment, which often presents challenges such as political instability, volatile commodity prices, and less developed financial markets (IMF, 2023; African Development Bank, 2023).

Despite several attempts, applying hybrid models and using market indicators in financial distress forecasting for locally owned companies in countries like Ghana, Nigeria, and other parts of Africa have been largely overlooked (Aboagye, 2018). Investigating the feasibility of hybrid models and incorporating relevant market-based indicators specific to African economies could significantly enhance the accuracy of financial distress prediction models. The failure of Indigenous banks in Ghana from 2017 to 2020, including UT Bank and Capital Bank, due to credit issues and regulatory gaps underscores the need for more comprehensive models considering local market dynamics (Birches Group, 2023).

In light of the above, this study undertakes a comparative analysis of two distinct approaches to financial distress prediction: a traditional approach, which focuses exclusively on financial and market data, and an integrated approach that incorporates financial, market, and qualitative data to improve the reliability and accuracy of forecasts in the African context. The integrated model will include factors such as corporate governance, regulatory changes, and management competency, which have been shown to influence financial performance but are often neglected in traditional models (Alkaraan, 2020; Schmidt, 2010).

CHAPTER THREE

METHODOLOGY

3.0 Introduction

This chapter presents the methodological approach taken to fulfil the study. It comprises the research design, sampling technique and sample size, data collection procedure, definition and measurement of variables, model development and data analysis.

3.1 Research Design

The study adopted a quantitative research design, focusing on the development and performance evaluation of both traditional and integrated financial distress prediction models. This design was chosen due to its ability to systematically analyze large datasets and generate statistically significant insights, which is crucial for predicting financial distress across Africa's diverse economic environments. Quantitative research designs are widely recognized for their capacity to produce objective, measurable data that can be analyzed to draw reliable conclusions about the relationships between variables (Saunders, Lewis, & Thornhill, 2019). Given the study's focus on financial ratios, market data, and governance metrics, all of which can be quantified and modelled, a quantitative approach was the most suitable.

The traditional models relied solely on financial ratios, including liquidity, profitability, solvency, and efficiency ratios, established as crucial indicators in financial distress prediction (Altman, 1968). In contrast, the integrated models combined financial and non-financial variables, such as governance metrics, market performance indicators (e.g., stock prices, market capitalization), and firm-specific characteristics, to provide a more comprehensive financial distress prediction. Recent research suggests that integrated models improve predictive accuracy, particularly in emerging markets like Africa, where economic conditions are highly variable and influenced by external factors (Altman et al., 2017; Zhang, 2022). Using integrated models allowed the study to capture internal financial health indicators and external environmental factors, offering a holistic view of companies' risk profiles.

The study employed three distinct classification techniques to evaluate the performance of both the traditional and integrated models: logistic regression, decision trees, and random forests. These methods were chosen to ensure that the best-performing technique for each model type (traditional and integrated) was identified, allowing for the selection of the most accurate method for predicting financial distress.

Logistic regression was used due to its robustness in modelling binary outcomes, such as whether a firm will experience financial distress. Logistic regression has long been a popular method in financial distress prediction because of its ability to model the probability of financial distress as a function of predictor variables (Hosmer, Lemeshow, & Sturdivant, 2013). This method provided insights into the relationship between financial variables and the likelihood of distress, making it suitable for traditional models focused on financial ratios.

Decision trees offered a more interpretable, non-linear approach to prediction. By recursively partitioning the dataset into subsets based on decision rules, decision trees can identify key decision points and interactions among variables. This method is particularly useful for datasets where relationships between variables are not linear, making it well-suited for traditional and integrated models. This study used decision trees to highlight the most significant financial ratios, market indicators, and governance metrics contributing to financial distress (Breiman, 1984). The intuitive structure of decision trees provided practical, actionable insights for understanding the factors driving financial distress.

Lastly, the study applied random forests, an ensemble learning method that builds multiple decision trees and averages their predictions to enhance accuracy and reduce overfitting. Random forests have gained prominence in financial distress prediction because of their ability to handle high-dimensional data and complex interactions between variables (Breiman, 2001). Given the complexity and variability of financial data in Africa, random forests were particularly well-suited for this study, ensuring that predictions were robust across different sectors and regions. The aggregation of multiple trees helped mitigate the risk of overfitting and increased the reliability of the predictions made by both the traditional and integrated models.

The design of this study was also influenced by the need to account for the economic diversity across African countries. Previous research has shown that financial distress prediction models must adapt to different industries and regions, especially in emerging markets where volatile economic conditions and data quality can vary (Mselmi, Lahiani, & Hamza, 2017). By incorporating a diverse set of predictors and applying multiple methods for evaluation, the study ensured a comprehensive assessment of the model's ability to predict financial distress across various African contexts.

Moreover, this quantitative research design allowed the study to produce generalizable findings by analyzing a large dataset of companies from across Africa. This approach is consistent with best practices in financial modelling research, where quantitative methods are preferred for their ability to test hypotheses and model relationships between variables precisely and objectively (Creswell, 2014). Using three classification methods across both traditional and integrated models ensured that the most accurate technique was identified for each model type, providing concrete, data-driven recommendations for improving financial distress prediction models in Africa.

3.2 Sampling Technique and Sample

This research employed a census sampling technique to select the sample companies from multiple African stock exchanges. Census sampling involves including the entire population of interest and ensuring that all relevant companies from the stock-chosen exchanges are studied. In this case, the sample included companies listed on stock exchanges across various African countries, providing a comprehensive basis for predicting financial distress across the continent (Taherdoost, 2016).

The sample covered many countries, including South Africa, Nigeria, Ghana, Kenya, Botswana, Egypt, Eswatini (formerly Swaziland), Tanzania, Morocco, and Gambia. By encompassing companies from diverse economic regions, this study captured the broad spectrum of challenges that firms across Africa face. This wide geographic scope ensured that the integrated financial distress prediction model was tested in various economic environments, from the resource-driven economies of Nigeria and Botswana to the more diversified markets of South Africa and Kenya (African Development Bank, 2023). The census sampling technique was particularly appropriate in Africa, where the number of publicly listed companies varies significantly across countries. For example, countries like South Africa and Nigeria have relatively large stock exchanges, while smaller economies like Eswatini and Gambia have fewer listed firms. The study avoided selection bias by including all listed companies from these countries. It ensured that both large and small firms were included, offering a more representative analysis of financial distress risks in Africa (Hair et al., 2019).

This study covered three years, from 2021 to 2023, enabling a longitudinal analysis of the firm's financial performance. The longitudinal design allowed the researcher to assess the consistency and accuracy of the integrated financial distress prediction model and observe trends in financial distress over time. The three-year span was sufficient to capture fluctuations in firm performance and external factors, such as commodity price changes, currency fluctuations, and shifts in economic policy that might affect companies across different regions (Zikmund et al., 2013).

Including multiple countries and industries allowed for cross-country comparisons and identifying region-specific factors that contribute to financial distress. For instance, firms in commodity-dependent countries like Nigeria and Tanzania might be more sensitive to global price changes. In contrast, companies in countries like Kenya and Egypt, which have more diversified economies, may face different risks, such as governance or regulatory issues. This comprehensive approach provided insights into how the integrated financial distress prediction model performed in various economic environments and under varying levels of market development (Mugume et al., 2020).

This study provided a comprehensive analysis of financial distress across Africa using a census sampling technique that spanned a broad range of countries and industries. This approach allowed for a detailed evaluation of the integrated model's performance, ensuring the results are generalizable across the continent's diverse economic and industrial landscapes.

3.3 Data Collection Procedure

The financial data used in this study were obtained from the Bloomberg terminal, a reliable and widely recognized source of secondary financial and market data used by financial analysts and researchers to access real-time, historical, and predictive financial information (Refinitiv, 2020). The dataset comprised companies listed on major African stock exchanges, including the Johannesburg Stock Exchange (South Africa), Nairobi Securities Exchange (Kenya), Egyptian Exchange (Egypt), Nigerian Stock Exchange (Nigeria), and Ghana Stock Exchange (Ghana).

The financial ratios collected for this study spanned the last three years. They covered critical aspects of corporate financial health, including liquidity ratios (current ratio and quick ratio), profitability ratios (return on assets, return on equity, gross profit margin, and net profit margin), solvency ratios (debt-to-equity ratio and interest coverage ratio), and efficiency ratios (accounts receivable turnover, accounts payable turnover, and asset turnover) (Altman, 1968; Zhang, 2022). These ratios provided a holistic view of companies' operational efficiency, profitability, and overall financial risk.

Additionally, market data, such as market capitalization, was collected for the companies in our sample. These market variables were particularly useful for understanding investor sentiment and market performance. Market capitalization helped identify firm size, and insights into market reactions to company-specific or macroeconomic developments (Brealey, Myers, & Allen, 2020).

In contrast to quantitative financial and market data, qualitative data was also acquired from the Bloomberg terminal through specific metrics indicative of governance and management issues and potential bankruptcy risks. One key qualitative metric was the governance score, which comprehensively assessed each company's governance practices and management performance. This metric encompassed various aspects of corporate governance, such as board structure, audit quality, and risk management practices. It was a proxy for management and governance issues affecting the company's financial stability (Saunders et al., 2019).

In addition, the Altman Z-Score, a widely accepted measure used to predict bankruptcy risk, was obtained from Bloomberg. This score, based on a combination of five financial ratios, is designed to identify firms at risk of filing for bankruptcy. By incorporating the Altman Z-Score, the study was able to account for potential bankruptcy filings and financial distress risks within the African companies analyzed (Altman, 1968; Mselmi et al., 2017). A rigorous data collection protocol was established to ensure financial and qualitative data accuracy, completeness, and reliability. The protocol included systematic procedures for data extraction, verification, and validation and handling missing or inconsistent data points (Li et al., 2015). In cases where key financial variables were missing, extrapolation techniques were applied to estimate the missing values based on historical trends and existing data. This approach ensured that the dataset remained complete and robust without compromising the integrity of the analysis (Swapna et al., 2016).

Once collected, the data were stored in a secure environment and subjected to data cleaning and preprocessing procedures to ensure accuracy and consistency. The financial and qualitative data were then reorganized and coded to facilitate the use of predictive models, such as logistic regression, decision trees, and random forests, for financial distress prediction. These procedures were essential to preparing the data for model development and subsequent performance comparisons.

3.4 Predictive Modelling Techniques

The study is designed to model all three classification techniques of logistic regression, random forest, and decision trees for each of the traditional and integrated models. The method that produces the best results for each model type is used for the prediction.

3.4.1 Logistic Regression

Logistic regression is a widely used statistical modelling technique for predicting binary outcomes based on one or more predictor variables (Hosmer et al., 2013). The logistic regression model estimates the probability of the occurrence of an event by fitting data to a logistic curve (Sperandei, 2014). It is instrumental when the dependent variable is categorical, such as the company's presence or absence of financial distress (Agyemang et al., 2022). The model equation takes the form:

$$\log(p/(1-p)) = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta kXk$$

Where p is the probability of the event occurring, β0 is the intercept, β1 to βk are the regression coefficients, and X1 to Xk are the predictor variables (Menard, 2010).

3.4.2 Random Forest

Random Forest is a machine learning technique that has become popular as a financial stress prediction model because it can deal with high-dimensional data and capture non-linear relationships between variables (Breiman, 2001). This method integrates multiple decision trees, making a more precise prediction and avoiding overfitting (Biau & Scornet, 2016).

In modelling financial distress companies, a Random Forest model is trained with a dataset composed of financial ratios, market data, and other individual company features, as well as their corresponding outcomes (distressed or non-distressed) (Zięba et al., 2016). The model randomly selects a subset of features and training samples to construct each decision tree (Breiman, 2001). This randomization process is responsible for the de-correlation of trees, which helps capture various data components (Biau & Scornet, 2016).

3.4.3 Decision Tree

Decision tree modelling is a standard machine learning method applied to financial distress prediction (Sun et al., 2014). This tree-like model consists of internal nodes representing a particular feature-based decision, branches representing an outcome, and leaf nodes representing a class label (distressed or non-distressed) (Breiman et al., 1984).

During financial distress forecasting, decision trees are created from a dataset with financial ratios, market information, and other relevant features for companies and their distress status (Gepp et al., 2010). The tree is built up by progressively breaking down the data into smaller chunks based on the feature that improves the information gain or provides the most significant impurity reduction (Quinlan, 1986).

3.5 Model Development

The study aimed to develop and compare traditional and integrated financial distress prediction models using three predictive modelling techniques - logistic regression, random forest, and decision trees. The dataset included 1003 observations from companies across major African stock exchanges. The dataset spanned three years (2021–2023), and the data was averaged over the three years. The averaged data was then used for model development. Traditional and integrated models were built using financial, market, and governance data, with the conventional model focusing primarily on financial ratios. In contrast, the integrated model included additional governance and market metrics. The process below outlines the model development stages, from data collection to model evaluation and deployment.

3.5.1. Data Collection and Preprocessing

The financial and market data used in this study were obtained directly from the Bloomberg terminal, which provided the required ratios and metrics for each company in the dataset. The financial ratios collected included liquidity ratios (current ratio, quick ratio), profitability ratios (return on assets, return on equity, gross profit margin, net profit margin), solvency ratios (debt-to-equity ratio), and efficiency ratios (accounts receivable turnover, accounts payable turnover, asset turnover). The only market data collected was market capitalization, which provided insights into the size of each firm and how it may relate to financial distress. The financial ratios and market capitalization were then averaged over three years to produce a more stable dataset of each company's financial health. In addition to financial and market data, governance metrics, including governance scores and Altman Z-scores, were also sourced from Bloomberg. Governance scores measured the quality of corporate governance, while the Altman Z-score was used to evaluate bankruptcy risk and/or filings. These metrics, converted into numerical variables, were compatible with the predictive models. The qualitative metrics were then merged with the financial and market data to create a comprehensive dataset for each firm. This integrated dataset ensured the models captured internal financial indicators and external governance factors influencing financial distress.

3.5.2 Missing Data

In addressing the issue of missing data within the dataset, an initial step was taken to remove variables that contained significant amounts of missing values. This was necessary to preserve the integrity of the analysis while maximizing the number of observations that could be used. Specifically, columns related to Accounts Payable, Gross Profit Margin, and Quick Ratio were removed. These variables exhibited high levels of missingness, and their exclusion reduced the dataset's total observations from 1003 to 979, affecting the overall robustness of the model.

Following removing these variables, the remaining dataset was subjected to various imputation methods to handle the missing values. Variables such as Debt-equity ratio, Net Profit Margin, Return on Assets (ROA), Return on Equity (ROE), and others were retained and filled using the K-Nearest Neighbors (KNN) imputation technique. This method was chosen due to its effectiveness in estimating missing values based on the similarity of the observations, preserving the relationships between the remaining variables.

Our approach aligns with contemporary best practices in missing data treatment. According to Zhang et al. (2020), imputation methods like KNN offer a practical balance between simplicity and accuracy, mainly when the dataset contains continuous variables like financial ratios. Moreover, studies such as those by Molenberghs and Kenward (2017) advocate for a pragmatic approach to handling missing data, stressing the importance of evaluating the impact of missingness on the overall results before making decisions on deletion or imputation. By removing certain variables and applying imputation to the remaining data, the researcher ensured that the dataset maintained its predictive power and validity for model development. This careful handling of missing values is critical in ensuring that the final models provide reliable results across the different regions in Africa.

3.5.3 Feature Selection

Feature selection was conducted to reduce the dimensionality of the dataset and retain only the most relevant predictors for financial distress. A correlation analysis was performed on the financial ratios and market data to determine the strength of their relationships with the binary dependent variable - financial distress. Only the financial ratios and market metrics that exhibited strong predictive power were included in the traditional model.

A correlation analysis was also performed on the governance scores and Altman Z-scores alongside the integrated model's financial ratios and market capitalization. This step ensured that only the most significant predictors were retained, allowing the integrated model to account for the full range of factors that contribute to financial distress, both internal and external to the firm.

3.5.4 Data Splitting

The dataset, comprising 979 observations, was split into training and test subsets, with 70% of the data allocated to the training set and 30% to the test set. This split ensured that the models could be trained on a large portion of the data while maintaining an independent test set for performance validation. The training set was used to develop the models, while the test set was reserved for evaluating the final models' predictive capabilities.

3.5.5 Model Development

The models were trained using the selected financial, market, and qualitative features as the independent variables and the binary financial distress indicator as the dependent variable.

3.5.6 Model Evaluation

Each model (logistic regression, decision trees, and random forests) was evaluated using standard performance metrics, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). These metrics provided a comprehensive assessment of each model's predictive performance. The comparison of the models allowed the study to identify the most effective technique for predicting financial distress within both the traditional and integrated models.

3.5.7 Model Interpretation

The interpretation of the models was essential for understanding how each predictor contributed to financial distress. For logistic regression, the model coefficients were analyzed to determine the relationship between each feature and the odds of financial distress. For decision trees and random forests, feature importance scores were examined to identify the most influential variables driving financial distress predictions. This analysis provided insights into the relative importance of financial ratios, market capitalization, and governance metrics in predicting financial distress.

3.5.8 Model Deployment

After evaluating the models, the best-performing model was selected for both the traditional and integrated frameworks. The chosen models were then deployed to forecast financial distress for companies using their financial and market data. The integrated model allowed for more comprehensive predictions by incorporating governance data alongside financial ratios and market capitalization. The final model provided a robust tool for predicting financial distress, offering valuable insights for stakeholders such as investors, managers, and policymakers in identifying firms at risk and taking preemptive action to mitigate financial instability.

3.6 Data Analysis

The effectiveness of traditional and integrated financial distress prediction models was compared to achieve the first research objective using evaluation metrics such as accuracy, sensitivity, specificity, and AUC-ROC. These metrics provided a comprehensive assessment of the model's predictive capabilities. A paired t-test was conducted to determine whether there were significant differences in the performance of the two models when applied to the same dataset. The test allowed for a comparison of the mean performance metrics for each model to assess whether the integrated model outperformed the traditional model in predicting financial distress.

Feature importance techniques were employed to identify the most significant variables in the traditional and integrated models to achieve the second research objective. For the logistic regression model, the coefficients of each variable were analyzed to determine their impact on the model’s predictive power. The feature importance scores were calculated for the random forest and decision tree models to identify which financial, market, and governance variables played the most significant role in predicting financial distress. These methods provided insights into each variable's relative contribution to the models' overall predictive performance. The significance of the selected variables was further evaluated by analyzing p-values (for logistic regression) and importance rankings (for decision trees and random forests).

To achieve the third research objective, the predictive performance of the models was compared across different countries. The same evaluation metrics as in Objective 1 (accuracy, sensitivity, specificity, and AUC-ROC) were used to assess the models' consistency and predictive power across the regions of Africa. A McNemar’s test was conducted to determine whether the predictive performance of the models varied significantly across regions. This test allowed the researcher to examine whether the distribution of the model's predictions (distress or no-distress classifications) was consistent across countries, providing insights into the generalizability of the models across Africa.

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.0 Introduction

This chapter provides a comprehensive analysis of the dataset used in this study, focusing on descriptive statistics, model development, and evaluation to address the research objectives. The analysis aims to assess the effectiveness of traditional and integrated financial distress prediction models, identify significant predictors, and examine the consistency of model performance across various regions in Africa. The chapter begins with a descriptive analysis of key financial metrics, followed by a detailed discussion of the model development process, including variable selection, standardization, and checking for multicollinearity. The performance of logistic regression, random forest, and decision tree models is then evaluated and compared.

4.1 Descriptive Analysis

4.1.1 Descriptive Statistics for Financial Ratios

The analysis began with generating descriptive statistics for key financial ratios, including Current Ratio, ROA (Return on Assets), ROE (Return on Equity), Debt to Common Equity, Net Profit Margin, Asset Turnover, and Accounts Receivable Turnover. Significant variability was observed across these ratios, as shown in Table 4.1 below:

Table 4.1: Financial Ratios Overview

Metrics	Current Ratio	Return on Equity	Return on Asset	Debt to Com Equity	Net Profit Margin	Asset Turnover	A/R Turnover
Min	0.01	(121.08)	(103.87)	-	(124,881.49)	(0.10)	0.02
1st Qu.	1.07	4.06	0.89	18.82	1.94	0.16	5.66
Median	1.48	11.21	3.30	54.17	8.11	0.51	10.21
Mean	2.40	13.11	4.40	113.85	43.64	0.71	72.02
3rd Qu.	2.07	20.61	7.61	113.17	20.16	0.98	20.82
Max	265.79	240.65	133.10	6,900.09	170,402.41	6.53	18,283.97

The current ratio in this dataset varies to a large extent, with the minimum value being 0.01 and the maximum value being 265.79, while the average and median values are 2.40 and 1.48, respectively. This is further evidence of liquidity differences across firms. Current ratio of less than one means that a company may be unable to meet its short-term obligations, which is a sign of increased probability of financial woes (Altman et al., 2019). Firms with meagre current ratios, especially those close to the minimum acceptable level, are susceptible to having problems in meeting their obligations and, therefore, default. On the other hand, firms with very high current ratios, almost near the upper limit, can also be taken to mean that the firm is not using its liquidity effectively or is not being put back into the business for better returns. This large variation is especially important for the integrated financial distress model because firms with very low or very high liquidity may affect the model's accuracy differently in the different African regions. The ROE indicates significant dispersion, with the minimum value being -121.08%, the maximum value being 240.65%, an average of 13.11% and a median of 11.21%. Negative ROE values mean the firms have incurred considerable losses; thus, they may be on the brink of financial crisis or already in it.

On the other hand, high ROE values for the firms may represent good performance, although there is evidence of extreme values at both ends of the scale. These considerable changes in profitability may be attributed to volatile markets, especially those based on commodities. The integrated model should consider these fluctuations to eliminate biases when predicting distress conditions (Bhimani et al., 2013).

The net profit margin shows high fluctuations in proportion, with values oscillating between -124,881.49% and 170,402.41%. It measures 43.64% as a mean and 8.11% as the median, showing many outliers in the distribution. The tremendous range of net profit margins presented for the group of banks requires the exclusion of companies with outstanding financial statements, which, for instance, may reflect the influence of the

African macroeconomic environment, namely fluctuations in exchange rates and policy risks acquainted with some African markets (OECD, 2023). The predictive model needs to deal with extreme variations, and similar approaches, such as decision trees and random forests, for instance, might be superior to the ordinary logistic regression when the primary distribution is skewed (Bhimani et al., 2013). Debt to standard equity ratio corresponds between 0.00 and 6,900.09, with an average of 113.85 and a median of 54.17. This variation is quite broad because underlying firms can have varied levels of financial leverage. Companies with high leverage, especially those in the upper tail, are more vulnerable to financial imbalances, especially in areas with high interest rates and instability (IMF, 2022). Leveraged businesses are future cash flow risks, meaning they can be at risk of being unable to pay off their debts. As can be seen, debt access across African countries varies considerably by region, and local financial structures determine the degree of leverage tolerance (Beck, 2022). These regional financial practices have to feature in the predictive model to predict distress across the continent accurately.

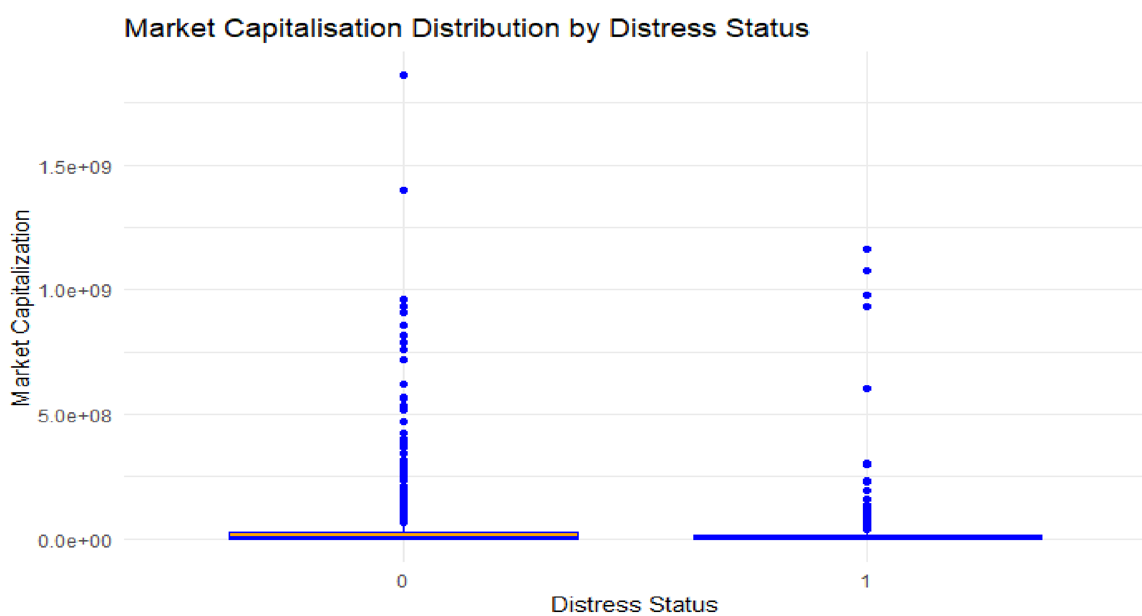
The asset turnover ratio reflecting the varied figure from -0.10 to 6.53 shows how efficiently a company has used its assets to generate sales. The negative minimum value refers to the idea that some firms are not only non-efficient but may present losses. Companies with low figures of asset turnover have a higher probability of facing financial risks because they have poor efficiency in converting their assets into sales (Altman et al., 2019). High variability of the asset turnover ratio implies that it is necessary to consider regional differences in the operational environment that can affect efficiency, decreasing the turnover rate for companies located in areas with infrastructural problems or supply chain deficiencies. The A/R turnover ratio varies from 0.02 to 18,283.97, implying significant differences between specific firms' efficiency in collecting A/R. A high A/R turnover rate means that the collection processes are effective, while low turnover rates mean there could be problems with cash flows. Some studies reveal variations in working capital management across the regions, mainly for firms in African countries with comparatively underdeveloped financial systems that may fail to ensure credit terms (Bhimani et al., 2013). These regional challenges were captured within the predictive models to evaluate distress risks associated with working capital management properly.

4.1.2 Market Data Overview

Market capitalization ranged from $1,204 to $1.86 billion. The distribution was positively skewed, indicating the existence of both 'mom-and-pop' and large firms, as depicted in Figure 4.1.

Figure 4.1: Market Capitalization

```
##       Min.   1st Qu.   Median     Mean    3rd Qu.       properly ev
aluate distress risks associated with working capital management
##     1.204e+03 8.026e+05 4.621e+06 4.581e+07   2.303e+07    1.8
61e+09
```



The study results show that firms with close to the first quartile of $802,600 and a median of $4.62 million market capitalization are more vulnerable to financial distress because of their small capital base and availability of funds. Research shows that information asymmetries are acute in small firms with little access to external funds and propensities towards illiquidity (Beaver et al., 2005). Moreover, plotting the distribution of market capitalizations by the distress status shows that firms in the distressed market are significantly dominated by the smaller ones, thus establishing their weakness. The mean market capitalization of $45.81 million is above the median due to a high coefficient of variation attributed to the presence of huge organizations. These large outliers are in both the distressed and non-distressed groups, suggesting that firm size cannot, on its own, determine financial distress. This observation also aligns with Bhimani et al. (2013), who opine that whilst market capitalization offers background information, it cannot be used to explain distress on its own. For example, even the biggest firm in the given dataset, with a market capitalisation of $5.135 trillion, can encounter financial pitfalls in certain circumstances; hence, the requirement for greater scrutiny.

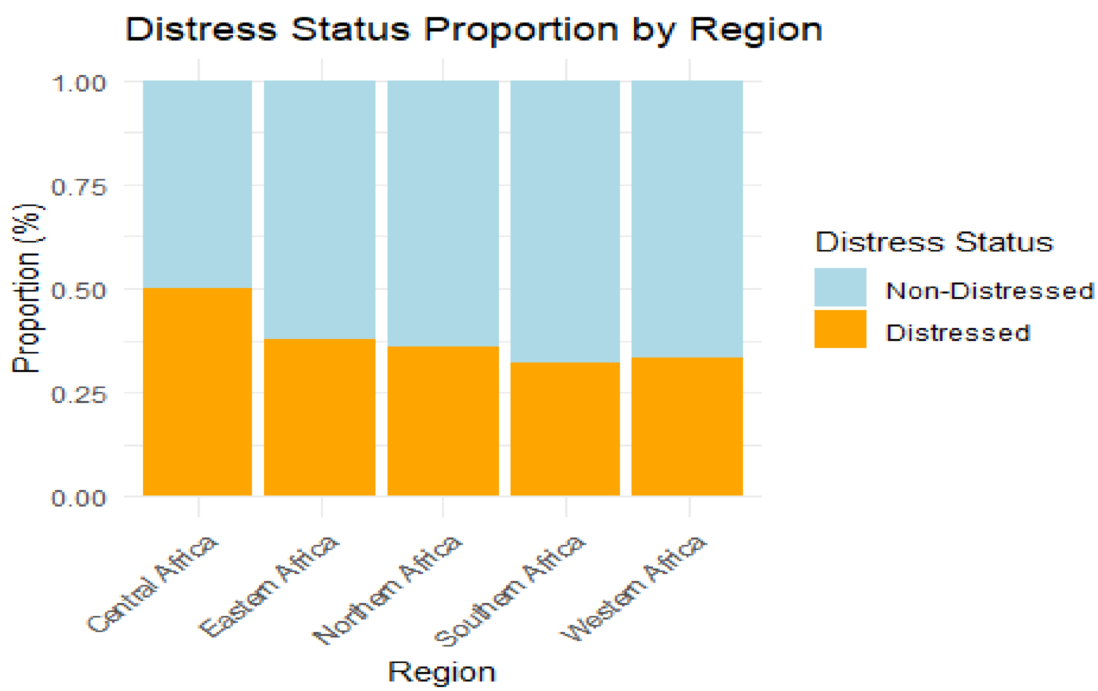
Based on the scatter plot that measures market capitalization against the variable financial distress, it failed to differentiate the size of the distressed and non-distressed firms, which means that using market capitalization to test and predict the financial distress of firms is not advisable. Existing models, like Altman's Z-Score (1968), incorporate size using ratios (e.g., total sales/total assets) and other firm-specific variables like profitability and leverage to perform better. Similarly, newer models capture that market capitalization should be complemented with financial ratios for more accurate predictions (Laitinen & Laitinen, 2018). While a credit crunch might affect a more prominent firm with higher resources differently from a small firm, more prominent firms might reach for distress for reasons different to the small firms. Ohlson (1980) established that companies may encounter adverse stock returns due to over-extension, unsound management decisions, or environmental factors. This is why large, distressed firms are outliers in this data set.

On the other hand, liquidity constraints tend to be more severe in small firms, increasing the chances they will experience cash flow and insolvency issues (Altman, 1968). The high prevalence of technology employers in the lower quartiles distressed category supports other studies pointing to the fact that small firms are the most vulnerable to financial distress. This issue is especially so in developing economies where access to capital markets is somewhat limited, and smaller firms might find it harder to manage their cash flows and maintain their financial stability, especially during turbulent times (Bhimani et al., 2013). This is especially the case in African markets, where financial infrastructure is still relatively limited, thereby presenting SMEs with a challenge in securing the necessary financing to survive the initial years of business (Mensah, 2003).

4.1.3 Distress Status by Regional Breakdown

Regional analysis further revealed different distress proportions in Fig.4.2 below.

Figure 4.2: Distress Status by Regional Breakdown



The stacked bar chart shows the proportion of distressed and non-distressed firms in the African regions, which gives valuable information regarding the geographical spread of the distress status of the firms. These insights are crucial for relating the economic conditions, financial markets, and business circumstances across Africa in developing models predicting financial distress. This analysis explores distress status in Central, Eastern, Northern, Southern, and Western African regions. These insights offer a better view of the reasons behind the likelihood of financial distress depending on the area.

Central Africa has the highest percentage of distressed firms at 50 percent out of all reviewed firms. This concurs with previous literature indicating that the region is economically unstable with political upheavals, poor infrastructure, and over- depending on marginal professions like oil and mining (World Bank, 2022). Some nations, like the Central African Republic and Chads, are over-dependent on poor financial structures and are not fully integrated into international capital markets (OECD, 2023). All these considerations explain why firms become more susceptible to economic shocks and thus experience distress. Studies by the African Development Bank (AfDB, 2023) suggest that macroeconomic fluctuations and debt sustainability in Central Africa negatively impact firms' performance and increase the intensity of financial stress. According to the above chart, this region's high level of distressed firms is attributed to these economic and institutional problems. Applying region-specific factors such as political risk, volatile commodity prices, and restricted access to financing could have increased the predictive power of the financial distress prediction models for Central African firms.

On the other hand, distressed firms are lower in Eastern Africa, having less than fifty percent of the total firms. This lower proportion might be owed to the relatively slower economic growth that the region has been experiencing in the last couple of years, especially compared to the growth rates experienced in such countries as Kenya, Tanzania and Rwanda. The World Bank report for 2023 shows that the region has witnessed significant structural transformation and enhanced FDI in the telecommunication, tourism, and manufacturing sectors. These developments have helped strengthen the business environment, thus reducing the incidences of financial distress, as seen in the chart. Moreover, concerning the development of monetary policies and enhancing access to financial services worldwide, new developments like Kenya's M-Pesa mobile banking have boosted credit and financial services (International Monetary Fund, 2022). This access to funds assists firms in maintaining good working capital and overcoming the odds of Economic distress. While developing predictive models, it has been noted that financial inclusion and credit access are essential for Eastern Africa since they enhance business resilience.

The Northern, Southern, and Western African regions are relatively close to equal numbers of distressed and non-distressed firms, ranging from 25% to 40% in distress. The Egyptian and Moroccan economies within the North African region have moved on to a diversified and robust financial structure. However, they are sensitive to macroeconomic shocks and political risks (AfDB, 2023). For instance, sectors with nature-based products, such as tourism, are usually prone to conditions beyond their control, and often, firms from such sectors end up experiencing severe financial strain. South Africa is one of the sub-regions in southern Africa that enjoys a relatively more developed financial market; this supports the stability of some firms. However, there are still constraints such as high unemployment rates and political instability in some countries like Zimbabwe that are still felt in the region, hence the presence of many distressed firms. The same applies to Western Africa, which is dominated by economies such as Nigeria and Ghana; the vulnerability of this region to international trends, as reflected by the fluctuations in the prices of its dominant export products such as oil, is well evident. This economic instability usually challenges the companies' finances, especially those dealing with commodities within the region (IMF, 2022). This is evidenced by the chart, which shows that a large number of firms were found to be in distress in Western Africa.

4.2 Model Development and Evaluation

The subsequent stage in the analysis was model development, which included the proper selection of the variables and managing the data. Three types of models were considered: scenarios include logistic regression, random forest, and decision tree types of models.

4.2.1 Variable Selection

Following the descriptive analysis, definitive financial ratios were selected for models such as Current Ratio, Return on Asset (ROA), Return on Equity (ROE), Debt to Common Equity, Net Profit Margin, Account Receivable Turnover, Market Capitalization, and Asset Turnover. These variables were chosen in that they give a broad picture of the financial health of a firm in terms of liquidity, profitability, and leverage. An integrated model was also built by adding governance scores (Governance Score and Altman Z-Score (AZS)) to test whether non-financial measures could improve prediction accuracy.

4.2.2 Standardization of Predictors

Since the scales used in the different types of financial ratios differed, standardization is essential if all predictors are to be treated with similarity. Normalization of the predictors is necessary in creating an effective financial distress prediction model, especially where firms are from different and distinct countries, as in the case of Africa. The dataset used in this study comprises the current ratio, the debt-to-equity ratio, and the net profit margin, all of which scale differently. If not standardized, large numbers such as those representing the debt-equity ratio (which might range from thousands) swamp the model, obscuring the effect of other predictors such as liquidity ratios. Standardization is essential in ensuring that all the predictors are treated equally by standardizing them to have a zero mean and unit standard deviation, which makes the model more reliable and accurate across different financial metrics (James et al., 2013). Similarly, it is when working with skewed distributions and outliers, which are usually present in financial ratios, that the use of standardization is vital. For instance, the net profit margin can have extreme values, and the accounts receivable turnover rate can be significantly influenced by atypical observations that impact the model's efficaciousness. This means that by standardizing the predictors, the effect of such extreme values is reduced, thus enhancing the stability of the model. As mentioned, non-normal data might undergo log transformations and pass through standard scaling (Géron, 2019). This is particularly beneficial for the integrated financial distress model since providing inconsistent or extreme data from either end of the spectrum distorts the model's results.

4.2.3 Checking Multicollinearity Using VIF

The issue of multicollinearity arises when two or more predictor variables are closely related, negatively affecting the estimates of the model and its conclusions. Therefore, multicollinearity was measured using the Variance Inflation Factor (VIF). The statistical analysis in the following table indicated no multicollinearity problem, with all the VIF values below 1.6, as presented in Table 4.2 below.

Table 4.2: VIF for each Predictor

Predictors	VIF Value
Current Ratio	1.012284
Return on Assets	1.510956
Return on Equity	1.550312
Net Profit Margin	1.010555
Debt to Common Equity	1.014884
Account Receivable Turnover	1.020991
Asset Turnover	1.12766

Market Capitalization	1.049901
Governance Score	1.034754
Alman Z-Score (AZS)	1.059475

This means that the predictors used did not correlate strongly with each other, so their coefficients would not shift significantly in the models. Dealing with multicollinearity was important, particularly in logistic regression models, whereby the variables involved yielded boosted standard errors and, therefore, reduced predictive capability. To do this, it is imperative to prevent multicollinearity when developing and applying models containing these indicators, given that regional differences in African countries regarding financial activities and market conditions may influence the relationships between predictors. For example, differences in leverage ratios' dynamics may exist across Western and Southern African countries due to differences in credit status and financial market maturity (Beck, 2022). Multicollinearity may cause variation in the model and can be solved by either deleting such variables or combining the variations. This will help the model predict the variations of different regions more accurately.

4.2.4 Fitting Financial Distress Prediction Models

4.2.4.1 Relative Effectiveness of Traditional against Integrated Financial Distress Prediction Models

I) Fitting Logistic Regression Model

A) Traditional Logistic Regression Model

```
##                                                          Call:
## glm(formula = Distress_Status ~ . - Country - Region - Gov.Sco
re                                                              -
##     AZS, family = binomial, data = training_data, control = gl
m.control(maxit                      =                       100))
##
##                                                  Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.04696    0.11863  -8.825  < 2e-16 ***
## Curr.Ratio           -2.53045    0.72910  -3.471 0.000519 ***
## ROA                  -0.88039    0.17602  -5.002 5.69e-07 ***
## ROE                   -0.45691    0.15987  -2.858 0.004262 **
##  Net.Profit.Margin   -0.05274     0.33241   -0.159  0.873929
##  Debt.to.Com.Equity   0.22486     0.11046    2.036  0.041775  *
##  A.R.Turnover          -0.07200     0.19585   -0.368  0.713132
##  Asset.Turnover      -0.70960    0.12984  -5.465 4.62e-08 ***
##  Market.Cap             -0.01390     0.10712   -0.130  0.896732
##                                                            ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  (Dispersion  parameter  for  binomial  family  taken  to  be  1)
##
##        Null  deviance:  884.40   on  685   degrees  of  freedom
##  Residual  deviance:  714.16   on  677   degrees  of  freedom
##                             AIC:                        732.16
##
## Number of Fisher Scoring iterations: 7
```

The output above produced the model below:

$$\log\left(\frac{P(\text{Distress\_Status}=1)}{P(\text{Distress\_Status}=0)}\right) = -1.04696 - 2.53045\cdot\text{Curr.Ratio} - 0.88039\cdot\text{ROA} - 0.45691\cdot\text{ROE} - 0.05274\cdot\text{Net.Profit.Margin} + 0.22486\cdot\text{Debt.to.Com.Equity} - 0.07200\cdot\text{A.R.Turnover} - 0.70960\cdot\text{Asset.Turnover} - 0.01390\cdot\text{Market.Cap}$$

Based on the fitted model, net profit margin, account receivable turnover, and market capitalization cannot capture financial distress in the analytically tested model. The researcher discarded all of them from the variables and re-fitted them to check the new model's performance.

```
##                                                           Call:
## glm(formula = Distress_Status ~ Curr.Ratio + ROA + ROE + Debt.
to.Com.Equity                                                    +
##      Asset.Turnover, family = binomial, data = training_data,
##                 control   =   glm.control(maxit   =   100))
##
##                                                   Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.0436     0.1180  -8.847  < 2e-16 ***
## Curr.Ratio           -2.5201     0.7262  -3.470  0.00052 ***
## ROA                  -0.8812     0.1757  -5.015 5.30e-07 ***
## ROE                  -0.4674     0.1586  -2.946  0.00322 **
## Debt.to.Com.Equity    0.2253     0.1106   2.037  0.04163 *
## Asset.Turnover       -0.7089     0.1299  -5.458 4.82e-08 ***
##                                                             ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##  (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 884.40  on 685  degrees of freedom
##  Residual deviance: 714.42  on 680  degrees of freedom
##                        AIC:                          726.42
##
## Number of Fisher Scoring iterations: 7
```

The output above produced the model below:

$$\log\left(\frac{P(\text{Distress\_Status}=1)}{P(\text{Distress\_Status}=0)}\right) = -1.0436 - 2.5201\cdot\text{Curr.Ratio} - 0.8812\cdot\text{ROA} - 0.4674\cdot\text{ROE} + 0.2253\cdot\text{Debt.to.Com.Equity} - 0.7089\cdot\text{Asset.Turnover}$$

The logistic regression model fitted above provides rich information on the determinants of the financial distress of the firms. Among the suggested parameters, one of the most significant discoveries is the role of liquidity, as seen from the Current Ratio. In the model, this variable is given a coefficient of -2.52 with a p-value of 0.000520. This result signifies that for every increment in the current ratio, there is likely to be a corresponding decrement in financial distress. In real terms, firms that enjoy better solvency positions are relatively less vulnerable to angels of financial endangerment as they are more capable of fulfilling their current obligations.

Similarly, many profitability measures determine the firm's financial position. The Return on Assets (ROA) proved to have a coefficient of -0.88 and a p-value lesser than 0.0001; this confirmed the hypothesis that firms with high returns concerning their total assets (ROA) have a lower probability of distress. This means increased effectiveness in deploying assets to generate revenues and improves a firm’s financial health. Further, the Return on Equity (ROE) is also significant, with a coefficient of -0.47 and a p-value of 0.003. This further supported the idea that a higher level of profitability for shareholders reduces the level of financial distress. Combined, these indicators highlight profitability as they sum up the overall condition of a firm in terms of staking operation and finance. Companies that make operational profits and high asset productivity are usually less vulnerable to financial troubles.

On the same note, the model shows that leverage, captured through the Debt to Common Equity ratio, exerts a differential effect. When a firm’s leverage is used to predict the likelihood of financial distress, the results have a positive coefficient of 0.23 and a p-value of 0.0416. This result is consistent with the theoretical framework of financial theory, which suggests that financial risk increases with the level of debt, especially during an economic downturn. However, the result also shows that leverage magnifies the risk of distress. Still, its impact on this model is relatively less significant than that of the liquidity and profitability variables. Thus, the current findings indicate that leverage might not be the dominant factor influencing distress.

Furthermore, Asset Turnover is another significant variable with a coefficient of -0.71 and p-value < 0.0001. This implies that firms with higher efficiency in converting their assets into operational revenues are at lower risk for financial difficulties. Asset turnover is thus another important aspect of operational efficiency since it measures the capacity of the firm to turn its assets into revenues efficiently.

The model chi-square and the goodness-of-fit chi-square of the logistic regression model are also helpful in assessing the model's overall fit. The given model indicates that the value of deviance has decreased from 884.40 to 714.42 (residual deviance), which suggests that the selected predictors enhance the model's ability to capture variability in distress status. In addition, the value of 726.42 of the Akaike Information Criterion (AIC) is not very high, which could mean that the model possesses a lower ability than other models. In summary, the model also finds that liquidity, profitability, leverage, and operational efficiency are key factors necessary for financial analysis of potential financial distress and can be helpful for firms and their stakeholders.

B) Fitting the Integrated Logistic Regression Model

```
##                                                              Call:
## glm(formula = Distress_Status ~ Curr.Ratio + ROA + ROE + Debt.
to.Com.Equity                                                       +
##     Asset.Turnover + Gov.Score + AZS, family = binomial, data =
training_data,
##                  control    =    glm.control(maxit    =    100))
##
##                                                      Coefficients:
##                          Estimate  Std. Error  z value  Pr(>|z|)
## (Intercept)          -4.892e+03   2.397e+05   -0.020     0.984
## Curr.Ratio           -2.779e+01   1.306e+05    0.000     1.000
## ROA                   4.115e+00   4.351e+04    0.000     1.000
## ROE                  -2.075e+01   6.322e+04    0.000     1.000
## Debt.to.Com.Equity  -5.518e+00   6.080e+04    0.000     1.000
```

```
## Asset.Turnover        8.273e+00  4.009e+04   0.000     1.000
## Gov.Score            -1.005e+01  1.498e+04  -0.001     0.999
## AZS                  -5.168e+04  2.526e+06  -0.020     0.984
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 8.8440e+02  on 685  degrees of freedom
## Residual deviance: 4.6319e-08  on 678  degrees of freedom
##                          AIC:                           16
##
## Number of Fisher Scoring iterations: 80
```

The output above produced the model below:

$$\log\left(\frac{P(\text{Distress\_Status}=1)}{P(\text{Distress\_Status}=0)}\right) = -4892.0 - 27.79 \cdot \text{Curr.Ratio} + 4.115 \cdot \text{ROA} - 20.75 \cdot \text{ROE} - 5.518 \cdot \text{Debt.to.Com.Equity} + 8.273 \cdot \text{Asset.Turnover} - 10.05 \cdot \text{Gov.Score} - 51680.0 \cdot \text{AZS}$$

The logistic regression model shows that none of the predictors: Quick Ratio, ROA (Return on Assets), Gross Profit Margin, Debt to Common Equity, Asset Turnover, Market Capitalization, Governance Score, and AZS are statistically significant since the p-values for all these variables are greater than 0.05. However, the residual deviance is almost zero (5.015e-08), which may indicate specific problems in the model, such as separation or perfect prediction, and the AIC value of 18. This implies that the presence of such signs points to a conclusion that the model is likely to be unreliable in its current format. Therefore, more analysis is necessary to eradicate such problems. The researcher then fitted the integrated model without the ‘AZS’ variable and saw the model's performance.

```
##                                                          Call:
## glm(formula = Distress_Status ~ Curr.Ratio + ROA + ROE + Debt.
to.Com.Equity                                                   +
##     Asset.Turnover + Gov.Score, family = binomial, data = trai
ning_data,
##                 control   =   glm.control(maxit   =   100))
##
```

```
##                                                       Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.04671    0.11829  -8.849  < 2e-16 ***
## Curr.Ratio           -2.51254    0.72732  -3.455 0.000551 ***
## ROA                  -0.89490    0.17647  -5.071 3.96e-07 ***
## ROE                  -0.45748    0.15928  -2.872 0.004077 **
## Debt.to.Com.Equity   0.22448     0.11060    2.030  0.042401  *
## Asset.Turnover       -0.71022    0.13005  -5.461 4.74e-08 ***
## Gov.Score               0.07737     0.09257    0.836  0.403246
##                                                              ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##       Null deviance: 884.40  on 685  degrees of freedom
## Residual deviance: 713.72  on 679  degrees of freedom
##                       AIC:                              727.72
##
## Number of Fisher Scoring iterations: 7
```

The output above produced the model below:

$$\log\left(\frac{P(\text{Distress\_Status}=1)}{P(\text{Distress\_Status}=0)}\right) = -1.04671 - 2.51254 \cdot \text{Curr.Ratio} - 0.89490 \cdot \text{ROA} - 0.45748 \cdot \text{ROE} + 0.22448 \cdot \text{Debt.to.Com.Equity} - 0.71022 \cdot \text{Asset.Turnover} + 0.07737 \cdot \text{Gov.Score}$$

The integrated logistic regression model displays that Current Ratio, ROA, ROE, Debt to Common Equity, and Asset Turnover are the factors that affect the prediction of financial distress. The coefficient for the current ratio variable is -2.51 for the p-recent model at a p-value of 0.00055, which shows that a higher current ratio will significantly lower the chances of an organization experiencing financial distress. Likewise, ROA is significantly negative with a regression coefficient of -0.89 ($t < 3.75$, $p < 0.0001$), meaning that firms with high Returns on Asset are less likely to experience Distress. ROE also shows a negative coefficient of -0.46 with a significant value of 0.0041, indicating that increased profitability decreases the probability of distress. On the other hand, Debt to Common

Equity was found to have a positive coefficient of 0.22, p-value =.0424, supporting the hypothesis that leverage increases the likelihood of financial risk and, ultimately, distress. Asset Turnover has a negative coefficient of -0.71 (p-value < 0.0001), meaning higher efficiency in using assets decreases the probability of distress. The Governance Score, nevertheless, has a coefficient of 0.077 (P-value =0.403), which means it does not affect the likelihood of the firms under analysis experiencing a possibility of financial distress in this research study.

Model fit improves as the deviance decreases to 713, 72 from the null deviance of 884.40, showing that these predictors help explain financial distress. The overall AIC value obtained for this model is equal to 727.72, which indicates a reasonably good fit because this value is slightly more augmented than the previous model, thanks to the introduction of the 'Gov Score', a non-significant predictor. The key financial ratios: The Current Ratio, ROA, ROE, Debt to Common Equity and Asset Turnover are informative in measuring financial distress and the different factors that mitigate and exacerbate the risk of distress, with liquidity, profitability and operational efficiency decreasing distress risks but higher leverage increasing the risk of distress. Interestingly, it has been established that the 'Gov Score' does not seem to play a role in this instance.

C) Evaluation of the Models on the Test Data – Logistic Regression

Table 4.3 below compares the performance of two traditional (Trad) and the integrated (Integ) models, employing different measures such as accuracy, sensitivity, specificity and AUC. These metrics help evaluate how well each model classifies observations into financial and non-financial stress.

Table 4.3: Traditional and Integrated Model Evaluation

Metric	Traditional Model	Integrated Model
Accuracy	0.6928328	0.6894198
Sensitivity	0.6770833	0.671875
Specificity	0.7227723	0.7227723
AUC	0.755131	0.7548989

When measured in terms of overall correct predictions, which include both true positives and true negatives, the traditional model performs minutely better with an accuracy of 69.28 percent than the integrated model, which stands at 68.94 percent. This shows that both models can be equally efficient in making correct predictions and classifying cases with 69% accuracy. The difference between the two models is very small; thus, the traditional model is slightly more accurate.

In terms of sensitivity or recall or true positive rate, the proposed traditional model performs slightly better than the integrated model, with 67.71 percent compared to 67.19 percent. Sensitivity shows how good the model is in correctly identifying positive cases, such as predicting financial distress. A higher sensitivity means that the number of actual distress cases not reported is also lower. Despite the small differences in accuracy, the traditional model is slightly better at identifying as many positive cases as possible, thus slightly diminishing the likelihood of false negatives or missed firms in distress. The true negative rate (demonstrating the model's capability to correctly classify negatives or lack of distress) is 72.28 % for both models. This indicates that both models are equally appropriate for identifying non-distressed firms. Hence, the similar specificity of the two models reveals that they had an equal ability to avoid false positives or wrongly identify firms expecting distress when they were not.

Similarly, the area under the Receiver Operating Characteristic curve (AUC), which reflects the model's performance in differentiating between positive and negative cases, is approximately equal for both models. The method applying the traditional model has an AUC equal to 0.7551, and when using the integrated model, the AUC is slightly lower and equals 0.7549. The higher the AUC nearest to one, the better the discrimination, while 0.5 is the worst performance represented by the chance level. The two models have an AUC of approximately 0.75, illustrating that they can have good discriminatory capability to differentiate between distressed and non-distressed firms.

Therefore, the implication is that the traditional and the integrated models provide comparable or similar results. The conventional model exhibits slightly improved accuracy, sensitivity, and area under the ROC curve compared to the evaluations of the integrated model; however, the model's specificity is the same. These slight variations indicate that either model can be used to predict financial distress and that the traditional model, which is slightly superior in predicting distressed firms, does not compromise the performance of the firms.

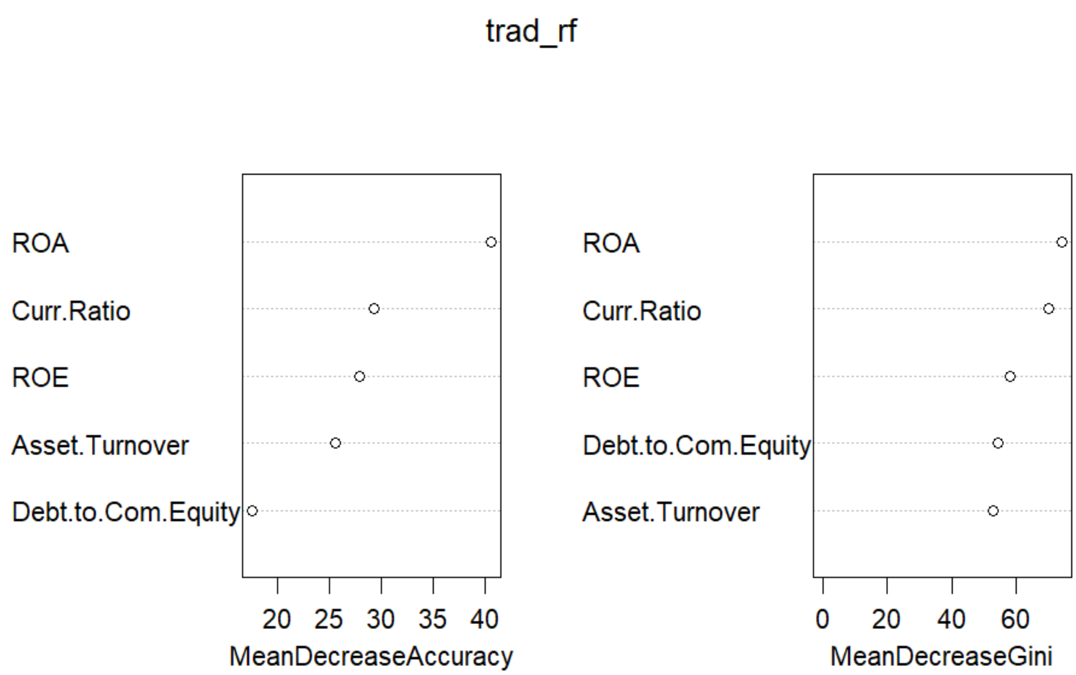
II) Fitting Random Forest Model

A) Traditional Random Forest Model

```
##                                                          Call:
##  randomForest(formula = Distress_Status ~ Curr.Ratio + ROA + R
OE +      Debt.to.Com.Equity + Asset.Turnover, data = training_da
ta,                                   importance      =      TRUE)
##                      Type  of  random  forest:  classification
##                                          Number  of  trees:  500
##    No.    of    variables    tried    at    each    split:    2
##
##                   OOB   estimate   of     error   rate:   23.62%
##                      Confusion                          matrix:
##                          0                 1      class.error
##       0       387               62                   0.1380846
## 1 100 137   0.4219409
```

The random forest model was also applied to forecast financial distress employing the Current Ratio, ROA, ROE, Debt to Com Equity, and Asset Turnover, as indicated in the model above and figure 4.3 below.

Figure 4.3: Traditional Random Forest



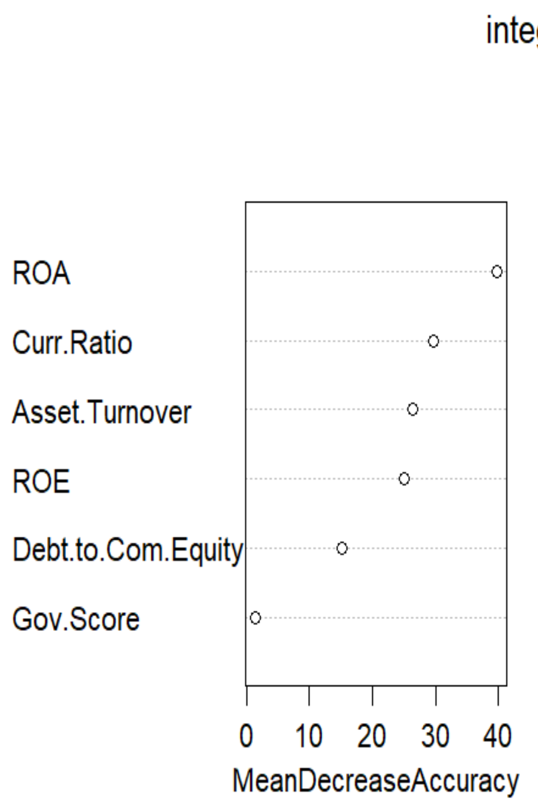
A model that used 500 trees and sought to fit 2 variables per split found the OOB error rate at 25.51%. This means that the model properly allocated the status of roughly 74.49% of the observations with an error rate of 25.51 % out of all observations. The confusion matrix shows that non-distress cases (class 0) have a class error rate of 14.69%, which is still lower than distress cases, which have an error rate of 45.92%. Variable importance was equally evaluated using two metrics: Mean Decrease in Accuracy and Mean Decrease in Gini are the two measures we have to select from the available list. This also instructs the same regarding the order of importance of the aspects involved in the model, and it reveals that ROA is the most critical factor to consider with the Current Ratio and ROE following it. These variables are very important in ensuring the model's accuracy is retained, and node purity is kept to a minimum. Debt to Com Equity and Asset Turnover are less significant when sorting securities. The model’s performance is generally satisfactory, though non-distress outcomes are predicted significantly more accurately than distress ones.

B) Integrated Random Forest Model

```
##                                                          Call:
##  randomForest(formula = Distress_Status ~ Curr.Ratio + ROA + R
OE + Debt.to.Com.Equity + Asset.Turnover + Gov.Score, data = trai
ning_data,                                  importance     =     TRUE)
##                          Type  of  random  forest:  classification
##                                            Number  of  trees:  500
##    No.    of    variables    tried    at    each    split:    2
##
##                     OOB   estimate   of     error   rate:   25.07%
##                          Confusion                         matrix:
##                              0                 1      class.error
##       0       381              68                      0.1514477
## 1 104 133   0.4388186
```

The random forest model, which includes both financial ratios and governance score, has an OOB accuracy of 24.78% and has slightly better predictive accuracy than the traditional model, as seen in the model output above and Figure 4.4 below.

Figure 4.4: Integrated Random Forest



Overall, it has an accuracy of 75.22% regarding case classification. Non-distress cases are classified with a much higher level of accuracy, with a class error rate of 14.92%, but distress classification is a significant issue, with an error rate of 43.46%. The variable importance plots reveal that out of all predictors, ROA, Current Ratio, and ROE are the most important predictors of financial distress. In contrast, the Gov Score was less important, suggesting that the ratios primarily drive the model's performance. Though increasing the sample by including the governance variable slightly enhances the accuracy of the prediction model, financial data is still the most significant factor in predicting distress.

C) Evaluation of the Models on the Test Data – Random Forest

Table 4.4 below compares the performance of the traditional and the integrated model, using the same metrics as with the logistic regression, like accuracy, sensitivity, specificity, and AUC.

Table 4.4: Traditional and Integrated Model Evaluation – Random Forest

Metric	Traditional Model	Integrated Model
Accuracy	0.7133106	0.6894198
Sensitivity	0.984375	0.984375
Specificity	0.1980198	0.1287129
AUC	0.7100608	0.7202197

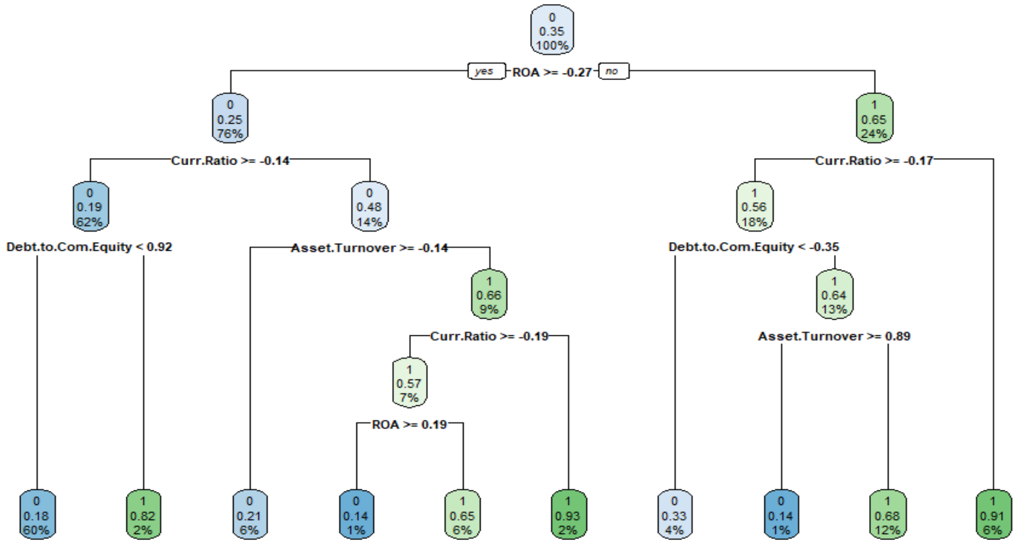
The evaluation process is based on four performance metrics: accuracy, sensitivity, specificity, and AUC (Area Under the Curve), which are applied to assess the differences between the traditional and integrated Random Forest. Therefore, the conventional model categorises a slightly higher percentage of cases correctly overall, with an accuracy figure of 71.33% against the integrated model of 68.94%. The sensitivity of both models is very high, with an average sensitivity of 98.44%; hence, both traditional and integrated models do not miss many distressed cases. However, both models suffer from a lack of discrimination, which evaluates the capacity of the models to classify the non-distressed instances appropriately. The specificity of the traditional model is 19.80%, and that of the integrated model is 12.87%, which means that many non-distressed firms are classified incorrectly as distressed firms in both models. As we can see, even with a lower level of specificity, the integrated model provides the highest AUC of 0.7202 compared to 0.7101 for the traditional model. The clarity of AUC reveals that the integrated model performs marginally better regarding overall classification accuracy in identifying distressed and non-distressed firms. However, both models have relatively low specificity, meaning that while they are very effective at pinpointing distressed firms (as established by high sensitivity values), they have difficulty distinguishing between distressed and non-distressed firms. Although the AUC of the integrated model is slightly higher than that of the traditional model, the latter has slightly higher accuracy and specificity for both classes.

III) Fitting Decision Tree Model

A) Traditional Decision Tree Model

The traditional decision tree model uses the financial ratios, ROA, Current Ratio, Debt to Common Equity, and Asset Turnover to predict financial distress, as shown in Figure 4.5 below:

Figure 4.5: Decision Tree



The tree starts with the root node that tests the model based on the ROA below -0.27. This split creates two main branches: The first equation is estimated for firms with ROA ≥ -0.27, whereas the second one is estimated for firms with ROA < -0.27. The first split is made by breaking the left branch for ROA less than -0.27, based on the Current Ratio of -0.14. From this, we observe two key branches. One branch goes to a split using the Debt to Com Equity at 0.92, thus indicating that firms with low current ratios and low DE ratios are likely to be categorized as non-distressed. The other path is asset turnover negative at -0.14, this fine-tunes the classification; the result of which posits the firm as distressed or non-distress. The first split in the right branch of the tree is by Current Ratio at -0.17 for firms with ROA values greater than or equal to -0.27. These branches lead to other splits, such as Debt to Common Equity at -0.35 and Asset Turnover at 0.89, before arriving at the last step of classifying the firms as distressed or non-distress. The previous classification occurs in terminal nodes, values of t = P(Distress) and t = P (non-Distress).

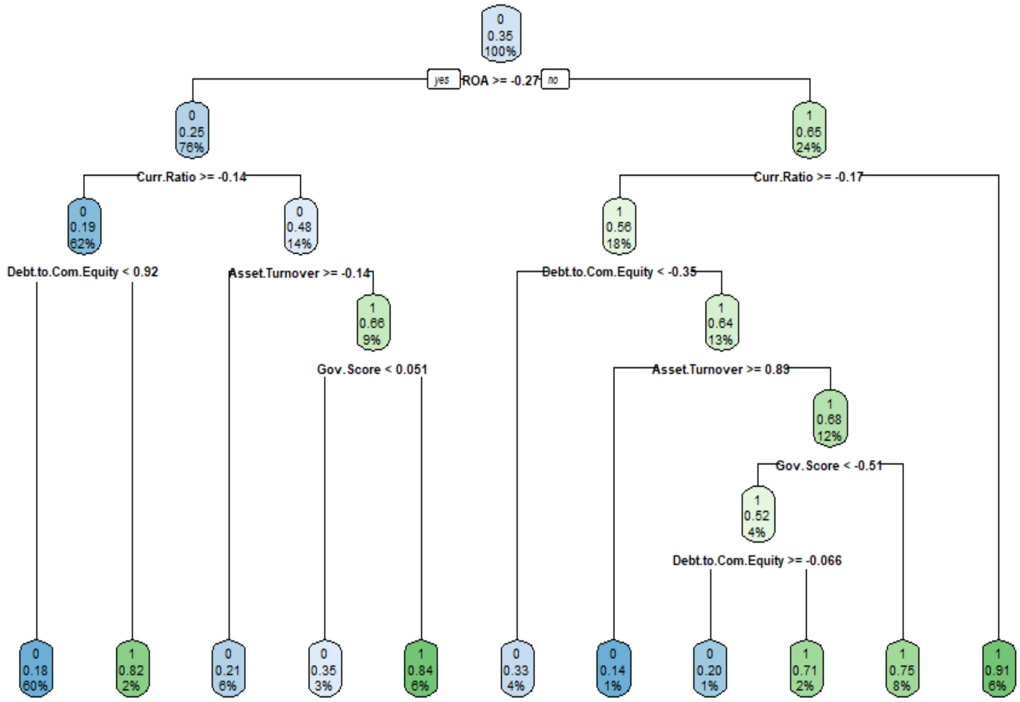
The structure of the decision tree means that among the tested variables, ROA is the one that best separates the firms in distress from those not in distress. However, other variables, including Current Ratio, Debt to Common Equity, and Asset Turnover, are also involved in more detailed discrimination of the classifications along the tree branches. The application of splits on these variables shows that distressed firms are likely to have poor financial ratios such as low ROA and low Current ratio.

Altogether, the decision tree for identifying distressed firms is logical and systematic as it systematically moves from one variable to another while applying different tests on the scaled-down set of operations chosen on significant financial ratios. When evaluating the financial state, they underlined key values such as liquidity, profitability, and leverage. Another advantage of the decision tree model is that the probability values at the left nodes reveal how certain the model is in the classifications it makes, thus being beneficial to users, as in the case of financial distress analysis in firms.

B) Integrated Decision Tree Model

As shown in Figure 4.6 below, the Integrated Decision Tree model incorporates financial ratios and a governance score to predict financial distress.

Figure 4.6: Decision Tree



The tree begins with the ROA variable as the root node, and the values are split at this initial split using -0.27 as the cut-off. There is the notion that ROA remains the most sensitive predictor of distressed firms against non-distressed firms. Firms with lower ROA values, those with a score of less than 0.27, are further subdivided depending on the Current Ratio and Debt to Common Equity, suggesting that profitability and liquidity ratios are the most crucial measure of distress. On the left side, major splits from the best-split point of ROA < -0.27 are the Current Ratio at -0.14, splitting firms with worse liquidity, Debt to Common Equity at 0.92, splitting firms with higher debt levels, and Asset Turnover at -0.14 establishing that firms experiencing lower asset productivity are more likely to be distressed. Surprisingly, the governance score is used again as a splitting criterion slightly lower in the tree; however, it is less important than the financial ratios. For instance, the split at Gov Score = 0.051 enables the definition of firms with greater precision, particularly when supplemented by other financial characteristics. On the right side of the tree, where ROA is greater than or equal to -0.27, the decision process continues by the rule of Current Ratio at -0.17 and Debt to Common Equity at -0.35. These splits also provide support in favour of liquidity and leverage ratios as the criteria for distinguishing companies. Asset Turnover and the Gov Score are introduced at subsequent stages of the tree to split the firms into distressed and non-distressed categories. The Gov Score is located further down the tree, dividing it at -0.51, meaning that although governance is present in this model, it is less influential than financial ratios.

The last branches of the model allow for the distinction between distress or no distress, with the numbers under each branch denoting the probability of the respective classification. For instance, while class 1 nodes are expected to exhibit high probabilities of distress, these observations include low ROA, low Current Ratio, low Asset Turnover, and weakened governance. The integrated decision tree model accentuates the value of ROA, Current Ratio, and Debt to Common Equity as part of the financial distress classification. At the same time, the Gov Score included in the model has a supportive role compared to the financial ratios.

C) Evaluation of the Models on the Test Data – Random Forest

Table 4.5 below compares the performance of the traditional and the integrated model, using the same metrics as with the logistic regression and random forest: accuracy, sensitivity, specificity, and AUC.

Table 4.5: Traditional and Integrated Model Evaluation – Decision Tree

Metric	Traditional Model	Integrated Model
Accuracy	0.3686007	0.3686007
Sensitivity	0.07291667	0.07291667
Specificity	0.9306931	0.9306931
AUC	0.4194771	0.4194771

Subsequently, the evaluation of the traditional and integrated decision tree models shows poor accuracy in identifying the cases of financial distress, and the metrics of the two models are almost similar throughout the evaluation criteria. The precision of both models is also generally low and stands at 36,86%, which means they provide correct classification only in 37% of cases. This suggests a considerable problem regarding the general accuracy of classifications because most of them are wrong. For the measure of sensitivity, which is defined as the capability of identifying the right number of distress cases among the total number of retrieved cases, both models again show negligible performance, scoring a sensitivity of 0.0729. This implies that the models only predicted approximately 7% of the actual distress. At the same time, the rest were wrong, as reflected by the high status of false negatives, where distressed firms are classified as non-distressed firms.

However, according to the same architectures, models yield a high specificity value of 0.9307; models accurately exclude almost 93 percent of non-distress samples. This means that although the models can recognize many undistressed firms, they perform poorly in recognizing distressed firms. The models are thus oriented towards maximizing the total correct classification of non-distressed firms at the cost of missing out on a significant number of distressed firms. Also, for the statistical performance of the accuracy, the AUC (Area Under the Curve) of both models is 0.4195 below the standard 0.5, which shows that the models are performing below chance. This low AUC value shows that the models fail to accurately classify real distressed firms from the other non-distressed firms, meaning the models have poor discriminating capability. As for the last impact, the decision tree models' assessment results indicate that these models do not help predict financial distress. Truthfully, both the traditional and integrated models have low accuracy, very poor sensitivity, and low AUC for correctly identifying distressed firms. Though both models have a very high specificity level, this is inadequate for us because both models failed to identify distress cases; hence, they should not be used practically to predict firms' financial health.

D) Evaluation of the Models on the Test Data Using Paired T-test

```
# Paired t-test for Logistic Regression
## Paired t-test
##
## data: logistic_trad and logistic_integ
## t = 1.7483, df = 3, p-value = 0.1787
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
## -0.001815636 0.006242336
## sample estimates:
## mean difference
## 0.00221335

# Paired t-test for Random Forest
## Paired t-test
##
## data: rf_trad and rf_integ
## t = 1.1738, df = 3, p-value = 0.3252
```

```
## alternative hypothesis: true mean difference is not equal to 0
##         95         percent        confidence        interval:
##                     -0.03552523                     0.07704463
##                        sample                        estimates:
##                         mean                         difference
##       0.0207597

#        Paired        t-test        for        Decision        Tree
##                                      Paired                t-test
##
##         data:                dt_trad        and        dt_integ
##     t     =     NaN,     df     =     3,     p-value     =     NA
## alternative hypothesis: true mean difference is not equal to 0
##         95         percent        confidence        interval:
##                                          NaN                 NaN
##                        sample                        estimates:
##                         mean                         difference
##               0
```

The paired t-test results for the logistic regression models reveal no significant difference in the performance of both traditional and integrated models. The t-statistics value of 1.7483 and the p-value of 0.1787 clearly state that the observed values between the models under consideration (accuracy, sensitivity, specificity, and AUC) are not significantly different and, therefore, can be referred to as random chance. The mean difference between the models is 0.0022. This is small and practically insignificant value. Also, the 95% confidence interval = -0.0018 to 0.0062 shows no significant difference between the two models since the value of zero is between the interval.

Likewise, there is no significant difference in accuracy between the traditional and integrated random forest models. The t-statistic value is 1.1738, and the calculated p-value equals 0.3252; hence, it is significantly higher than 0.05, so we cannot reject the null hypothesis that states no difference in means. The mean difference between the two models is 0.0208, slightly more significant than the difference between the logistic regression models but still insignificant. The 95% confidence interval ranges from -0.0355 to 0.0770, which also contains zero, indicating that the performance metrics between the traditional and integrated random forest models are statistically identical.

Furthermore, the paired t-test did not apply to the decision tree models since the traditional and integrated models' performances are, in theory, equal. This is evident from the output where the t-statistic, confidence interval and p-value are shown to be NaN or NA. Indeed, because x and y are equivalent across all observations on these models, the t-test cannot yield meaningful results. The mean difference is 0, so comparing them does not make sense since they both have the same results regarding accuracy, sensitivity, specificity, and AUC.

Therefore, by conducting the paired t-tests, it can be inferred that there is no significant difference between the traditional and integrated logistic regression and random forest models at a 5% level of statistical significance. Since both decision tree models' performances were similar, there is no discernible difference to compare. Consequently, the performance analysis concludes that the performance of the traditional and the integrated models is comparable based on each evaluated criterion.

4.2.4.2 Variables Significantly Influencing Predictive Accuracy

I) Fitting Random Forest Models: Feature Importance Scores

A) Traditional Random Forest Feature Importance Scores Model

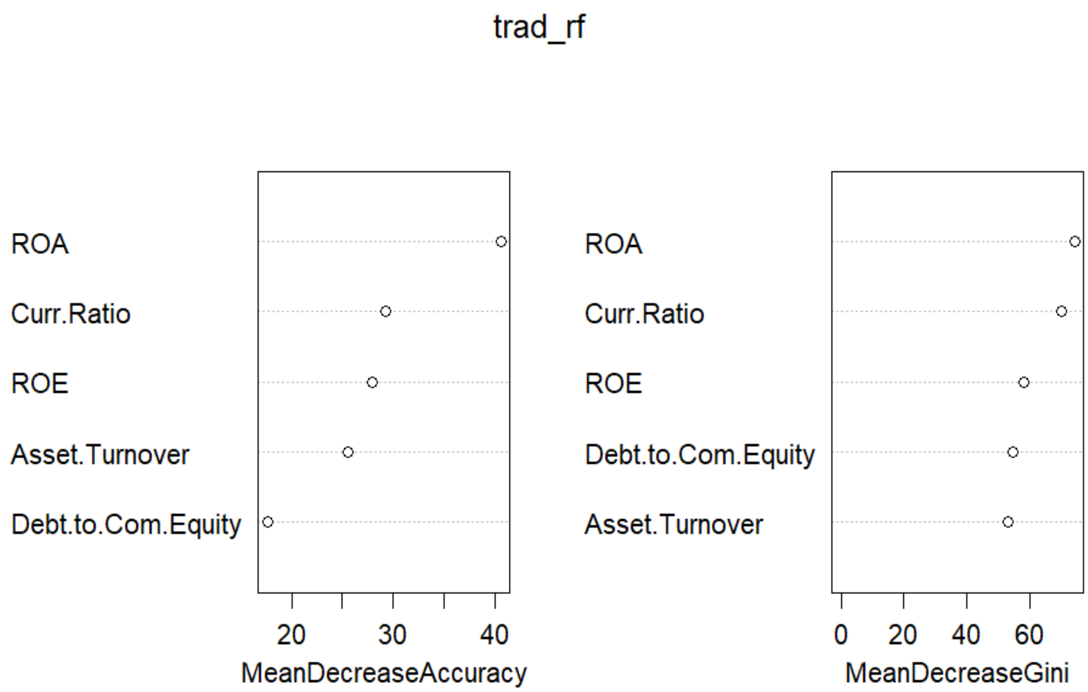
```
importance(trad_rf) # Shows importance of each feature

##                              0          1 MeanDecreaseAccuracy Me
anDecreaseGini
## Curr.Ratio          23.13505 16.7803216             27.02005
68.33953
## ROA                 35.21932  8.0717394             37.63372
74.88340
## ROE                 29.64750  0.9769543             30.00030
58.66478
```

```
## Debt.to.Com.Equity 16.51144   7.0669997                16.76896
54.06980
## Asset.Turnover      20.09007 12.4176412                24.05469
53.06318
```

From the traditional random forest model above and Figure 4.7 below, which shows the feature importance analysis of the traditional random forest model, we can infer that ROA is the most important variable for predicting financial distress.

Figure 4.7: Traditional Random Forest Feature Importance Scores Model



This indicates that the ROA is the most important variable based on the Mean Decrease in Accuracy with 40.60 and the Mean Decrease in Gini at 74.17. This suggests that by eliminating ROA, the overall predictive accuracy of the model and precision in decision trees in terms of splits would be adversely affected, further supporting its value as an indicator of financial distress. The most crucial index identified by the algorithm is the Current Ratio with an AUC of .2881, a Gini of .1454, an MDI of 29.31, and an MGI of

69.95. These high values underscore the importance of liquidity to the model; firms that exhibit relatively better liquidity will not fall under the distressed firms category. ROE also has strategic significance; however, it is less important than ROA and the Current Ratio, with an accuracy contribution of 27.93 and a Gini contribution of 58.14. This again emphasizes that profitability for shareholders is paramount in assessing the sound state of a firm. The Asset Turnover and Debt to Common Equity are moderately important, with the lowest values of influence on accuracy and node purity among the top features. Debt to Common Equity has 17.61 with a Mean Decrease in Accuracy and 54.58 with a Mean Decrease in Gini, indicating that it impacts the decisions made by the model. Still, it does not have a significant impact on accuracy as compared to profitability and liquidity. Likewise, Asset Turnover has an average reduction of accuracy of 25.62 and a mean reduction in the Gini coefficient of 53.02, making it another efficiency component. In general, ROA is the most significant characteristic, which claims that profitability should be used as the most important variable that predicts financial distress; however, other variables, such as liquidity, measured by the Current Ratio, also play an important role in the accuracy of the models. This pattern also supports the assertion that profitability and liquidity measures are necessary when classifying firms as distressed.

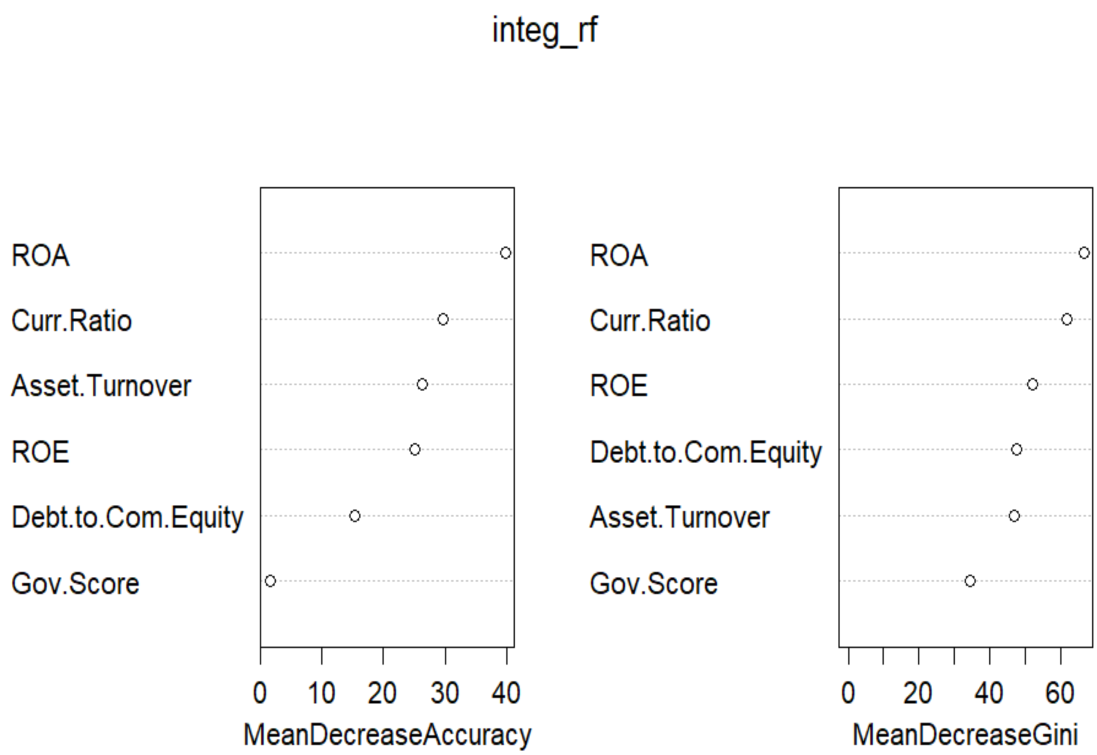
B) Integrated Random Forest Feature Importance Scores Model

```
importance(integ_rf)  # Shows the importance of each feature
```

```
##                                0         1 MeanDecreaseAccuracy Me
anDecreaseGini
## Curr.Ratio             24.128425 15.302149           28.9052617
61.20243
## ROA                    33.828968 11.070281           38.5702994
67.58959
## ROE                    23.764998  2.533698           24.3636020
```

```
52.32882
## Debt.to.Com.Equity 13.090810   7.418726            15.0566378
47.45677
## Asset.Turnover      19.298235 11.773004            22.6409158
46.77784
## Gov.Score           -3.770725   5.270865            0.4254476
35.05206
```

Figure 4.8: Integrated Random Forest Feature Importance Scores Model



In the integrated random forest model, as mentioned in the model And Figure 4.8 above, ROA remains the most important feature for the reason that it consists of the highest value of both Mean Decrease in Accuracy at 39.79 and Mean Decrease in Gini at 66.54. This suggests that profitability is the most important variable closest to the level of predicting financial distress, as evidenced by the result from the tarted model. The second most important feature is the Current Ratio, which has a Mean Decrease in Accuracy of 29.60= and a Mean Decrease in Gini of 61.72=, highlighting the significance of liquidity in classifying firms that faced financial distress. ROE is just as important but considerably less important than ROA and the Current Ratio. Its Mean Decrease in Accuracy is 25.05, and the Mean Decrease in Gini is 52.02, suggesting that, although it also plays some role in the model's ability to predict distress, its impact is slightly lesser than the first two—other variables of moderate importance in the model including Asset Turnover and Debt to Common Equity. The findings for Asset Turnover were a Mean Decrease in Accuracy of 26.38 and a decrease in the Gini of 46.98, which underlines the variable's application in terms of operational efficiency. The findings for Debt to Common Equity were a Mean Decrease in Accuracy of 15.25 and a decrease in the Gini of 47.56, which shows its impact on the going concern aspect. These variables help build the model to improve the node's purity and are less effective than profitability measures and liquidity ratios. The new integrated model includes the Gov Score variable with the least contribution, with a Mean Decrease in Accuracy of 1.48 and a Mean Decrease in Gini of 34.58. This would indicate that, to a certain extent, governance delivers some incremental value but that the different financial ratios in the prediction of financial distress significantly overshadow this.

II) Fitting Decision Tree Models: Feature Importance Scores

A) Traditional Decision Tree Feature Importance Scores Model

Table 4.6: Traditional Decision Tree Feature Importance Scores

Feature	Overall Importance

ROA	75.61724
Current Ratio	69.00696
ROE	63.18602
Asset Turnover	55.85578
Debt to Common Equity	49.20285

The modification of the traditional decision tree model, called feature-important analysis, reveals the significance of various financial ratios for the general decision-making of the model. The most important feature is ROA, which has an overall importance score of 75.62, as highlighted in Table 4.6 above. This suggests that the profitability defined by return on assets bears the most significant influence on determining financial distress in this model. The second factor after ROA is the Current Ratio, ranked 2nd with an importance score of 69.01, proving that Liquidity is another criterion used by the model. ROE (Return on Equity) is also a significant factor affecting the cosmetics industry, with an importance score of 63.19, making it the third most important factor. This indicates that profitability and returns on equity help significantly define the model for distinguishing between distressed and non-distressed firms.

Features such as Asset Turnover besides Debt to Common Equity have lower importance values of 55.86 and 49.20, respectively. Although they still contribute to the model's performance, their contribution is much less than the key features. These scores indicate that while asset efficiency and leverage have some bearing, the model appears to emphasise its prognoses' profitability and liquidity factors. The analysis in the conventional decision tree structure assigns the highest priority to ROA, Current Ratio, and ROE; in this way, we observe that the model utilizes profitability and liquidity as the primary maneuvers in the prediction of distress, while the roles of asset turnover and leverage (Debt to Common Equity) are less important.

B) Integrated Decision Tree Feature Importance Scores Model

A more detailed understanding of the factors that feed into the integrated decision tree model, alongside the financial ratios and the governance score, is given by the feature importance analysis in Table 4.7 below.

Table 4.7: Integrated Decision Tree Feature Importance Scores

Feature	Overall Importance
Current Ratio	72.3679
ROA	71.73078
ROE	62.39669
Asset Turnover	57.88909
Debt to Common Equity	46.94398
Gov Score	20.79801

The current ratio is the most important attribute in this model with an overall importance score of 72.37. This means that the balance sheet's current ratio component, a liquidity measure, is important in assessing the level of financial distress in the integrated model. ROA occupies the second place with 71.73 points, indicating that profitability remains a decisive factor even when supplemented with data on corporate governance.

The third on the list, with a score of 62.40, is ROE (Return on Equity), which implies that profitability and returns influence firms' distress. Asset turnover is still moderately important, with a score of 57.89; asset efficiency is considered in the model's decision-making process. Debt to Common Equity, with 46.94%, is also moderate, which is an important factor, though not as important as the rest of the financial ratios. Notably, the 'Gov Score' variable, which measures governance, has the lowest importance score of 20.80 out of 100. This implies that although governance is incorporated in the model, it is not as significant as the financial ratios in detecting financial distress.

Consequently, the two most significant variables are the current ratio and return on assets, confirming the observation about the role of liquidity and profitability in determining firms likely to experience financial distress. Although it is included in the analysis, it has low significance compared to financial ratios, indicating that governance has a much lesser influence on the predictive model. Liquidity and profitability are the two main drivers of the model, while asset efficiency and leverage can be considered more secondary.

4.2.4.3 Consistency of Traditional and Integrated Models across Africa

I) Model Evaluation by Region

A) Logistic Regression Model Evaluation by Region

Table 4.8: Logistic Regression Model Evaluation by Region

Region	Accuracy	Sensitivity	Specificity	AUC
Central Africa	0	NA	0	NA
Eastern Africa	0.6382979	0.5714286	0.7368421	0.682331
Northern Africa	0.6893204	0.6567164	0.75	0.778192
Southern Africa	0.7553191	0.765625	0.7333333	0.801823
Western Africa	0.6458333	0.6363636	0.6666667	0.707071

B) Random Forest Model Evaluation by Region

Table 4.9: Random Forest Model Evaluation by Region

Region	Accuracy	Sensitivity	Specificity	AUC
Central Africa	0	NA	0	NA
Eastern Africa	0.6382979	0.9285714	0.2105263	0.669173
Northern Africa	0.7281553	1	0.2222222	0.714138
Southern Africa	0.7234043	1	0.1333333	0.659896
Western Africa	0.75	0.969697	0.2666667	0.807071

C) Decision Tree Model Evaluation by Region

Table 4.10: Decision Tree Model Evaluation by Region

Region	Accuracy	Sensitivity	Specificity	AUC
Central Africa	1	NA	1	NA
Eastern Africa	0.3617021	0	0.8947368	0.379699
Northern Africa	0.3786408	0.05970149	0.9722222	0.394901
Southern Africa	0.3404255	0.09375	0.8666667	0.445833
Western Africa	0.3958333	0.1212121	1	0.458586

Comparing the results of logistic regression, random forest, and decision tree in the Central, Eastern, Northern, Southern, and Western African regions described in tables 4.8, 4.9, and 4.10, it is clear that these methods have different levels of accuracy when it comes to financial distress prediction. The logistic regression model, in general, is good enough, with the best accuracy recorded at 75.53% in South Africa and a strong AUC of 0.8018. This reveals good accuracy in identifying distressed and non-distressed firms. In this region, specifically Northern Africa, logistic regression has 68.93% accuracy, acceptable sensitivity at 65.67%, specificity of 75%, and the best AUC of 0.7782. However, applying this model to Central Africa does not yield valuable results because class imbalance occurs when only the non-distressed class is available, rendering the distressed class undeterminable. In Eastern Africa, logistic regression establishes a fairly reasonable precision of 63.83% with an AUC of 0.71, while in Western Africa, the outcomes depict an AUC of 0.70 and a precision of 64.58 percent. Therefore, logistic regression generally has reasonable sensitivity and specificity rates, with the highest performance in Southern and Northern African nations.

Finally, focusing on the random forest model, we see that it has a different trend; the region that yielded the best result is Western Africa. It gets an accuracy of 0.75, implying that the model got 75% of the predictions correct, and the AUC is 0.80, suggesting good predictive performance. In other regions, random forests are sensitive, especially in Eastern, Northern, and Southern Africa, where they almost have a perfect level of sensitivity (92.86%, 100%, and 100%, respectively), indicating their ability to identify firms in distress correctly. However, the intention with broad sweeping categories carries substantial inaccuracies, and the specificity loss is again uniform across all regions, for instance, 21.05 % in Eastern Africa and 13.33% in Southern Africa, contributing to high false favourable rates. Nevertheless, due to the specific problem of detecting distressed firms, it still provides valuable information when the failure to detect a distressed firm is worse than having a false alarm. Indeed, the random forest model's moderate to strong discriminatory ability is observed across the regions with AUC ranging between 0.66 and 0.80, with the highest value depicted in Western Africa.

Like the previous experiments, the decision tree model performs poorly compared to the other two. This study established that the decision tree model exhibits low sensitivity in all regions, indicating the inability to identify many distressed firms. For example, in Eastern Africa, the sensitivity stands at 0%, while in Northern Africa, it is slightly above 5.97%. Although the model has high specificity levels in most regions, for instance, 97.22 % in Northern Africa and 100% in Western Africa, this is realized at the expense of high levels of misclassifying the distressed firms as non-distressed. The accuracy of the decision tree is also notably low; values such as 36.17% in Eastern Africa and 34.04% in Southern Africa further augment the inefficiency of the decision tree. The AUC values, between 0.37 and 0.45, show that this model has the poorest discrimination capability. This makes the decision tree model the least accurate model in predicting financial distress for all the regions.

Thus, the logistic regression is considered to be the most balanced and accurate model across Africa. However, such regions as Southern and Northern Africa have the best balance of sensitivity and specificity and the increased AUC. The random forest model is highly sensitive and most accurate in Western Africa, thus helpful in identifying distressed firms, but low specificity may hinder its usage. Last but not least, the decision tree model yields the worst scores for sensitivity and poor AUC across all the regions, hence outranking the other models as the worst model for financial distress prediction in this study.

II) McNemar's Test by Region

A) Logistic Regression Vs Random Forest

```
## Region: Central Africa
## Not Applicable (Non-2x2 Contingency Table)
##
## Region: Eastern Africa
## McNemar's Chi-squared: 18.05
## p-value: 2.151786e-05
##
## Region: Northern Africa
## McNemar's Chi-squared: 35.02703
## p-value: 3.251606e-09
##
## Region: Southern Africa
## McNemar's Chi-squared: 31.0303
## p-value: 2.540312e-08
```

```
##
##                  Region:                  Western                  Africa
##              McNemar's              Chi-squared:              15.05882
## p-value: 0.0001042119
```

B) Logistic Regression Vs Decision Tree

```
##                  Region:                  Central                  Africa
##      Not      Applicable      (Non-2x2      Contingency      Table)
##
##                  Region:                  Eastern                  Africa
##              McNemar's              Chi-squared:              15.42857
##                          p-value:                          8.568298e-05
##
##                  Region:                  Northern                  Africa
##              McNemar's              Chi-squared:              42.48077
##                          p-value:                          7.138061e-11
##
##                  Region:                  Southern                  Africa
##              McNemar's              Chi-squared:              37.12281
##                          p-value:                          1.109188e-09
##
##                  Region:                  Western                  Africa
##               McNemar's               Chi-squared:               18.375
## p-value: 1.814228e-05
```

C) Random Forest Vs Decision Tree

```
##                  Region:                  Central                  Africa
##                 McNemar's                 Chi-squared:                 0
##                                p-value:                                1
##
##                  Region:                  Eastern                  Africa
##              McNemar's              Chi-squared:              37.02564
##                           p-value:                           1.16586e-09
##
##                  Region:                  Northern                  Africa
##              McNemar's              Chi-squared:              83.01176
##                          p-value:                          8.156649e-20
##
```

```
## Region: Southern Africa
## McNemar's Chi-squared: 76.10976
## p-value: 2.683283e-18
##
## Region: Western Africa
## McNemar's Chi-squared: 37.02564
## p-value: 1.16586e-09
```

Therefore, McNemar’s test by region offers valuable information in comparing the accuracy of various classification models in detecting financial distress. Like most non-parametric tests, McNemar’s test compares the results of two classifiers or, in this case, examines the results where the two classifiers differ. A small p-value means that the models are highly likely to behave differently; therefore, it can be inferred that the models vary in their classification abilities.

First, the differences between the logistic regression and random forest models appear to have specific trends. In Central Africa, both proportions were significantly different ($p < 0.05$), but McNemar’s test could not be valid since it lacks the 2x2 contingency table. Nevertheless, when we focus on Eastern Africa, we find a different story: clear evidence of an association according to McNemar’s chi-squared test with a statistic of 18.05 and a significance level of 0.00 when $p < 0.05$. This highly statistically significant finding suggests a significant difference in prediction between the two models. Therefore, one model may be more accurate in this region. The results for Northern Africa are even more striking: the chi-squared value equals 35.03, and the p-value is larger than 0.0 but less than 0.000000325. These outcomes unequivocally indicate that the two models yield noticeably different classification results. In addition, Southern Africa and Western Africa can be compared as they have higher chi-squared values of 31.03 and 15.06, respectively, and the p-values are less than 0.05. This consistent pattern for all the regions, excluding Central Africa, suggests that logistic regression and random forest models exhibit differing predictive behaviours, mainly due to how each approach handles the data features.

Regarding the contrast between logistic regression and decision tree models, we still see this disparity. As expected, central Africa again does not yield a meaningful result because of the shortcomings of the contingency table, and no applicable interpretation can be derived for this region. On the other hand, McNemar's test of significance was conducted on the results obtained for the two models on the samples from Eastern African countries, and it yielded a significant chi-square of 15.43 and a significance level of $8.57e^{-05}$, thus showing that the two models do not classify the financial distress in the same way. Most notably, Northern Africa has the highest chi-squared value, which is 42.48, meaning that the classifications made by both models are significantly dissimilar, and the p-value ($7.14e^{-11}$) is very close to zero. Southern Africa also exhibits the same nature: it has a chi-square of 37.12 and a p-value of $1.11e^{-09}$. The gap in western Africa also reveals a gap in the chi-squared value, estimated to be 18.38, with a p-value of $1.81e^{-05}$. These results suggest that logistic regression and the decision tree are not always in sync with the classification assignments. This could be a strong selling point because, in certain areas, one of these models is superior based on the data set characteristics or the feature distribution.

Central Africa gives a unique result when comparing the random forest and the decision tree models. The McNemar test indicates a 0 chi-squared, with a $p = 1$, confirming that the models make equivalent classifications. This strongly implies no performance disparity between the two, contrary to the situation in other parts. On the other hand, Eastern Africa has a chi-square value of 37.03 with a p-value of 1.17×10^{-9}, which shows a significant difference between random forest and decision tree models. Equally, Northern Africa has a high chi-squared value of 83.01 with a very small $p = 8.16e^{-20}$, which indicates that the two models perform differently. Similarly, Southern Africa and Western Africa yielded high results with a chi-square value of Southern Africa 76.11 and $p < 0.001$ and Western Africa's chi-square value of 37.03 and $p < 0.001$. These results imply that random forest models are stronger because of the ensemble method, are superior in analyzing the features' interactions compared to decision trees and exhibit different classification methods.

In essence, McNemar's test results for the different regions answered several pertinent questions while highlighting the below findings, except for the central African region where some of the compare could not be made: From the comparison between logistic regression and random forest, as well as logistic regression and decision tree, it was found that logistic regression yields different classification on the same features from these other models. Thus, it points to the possibility that logistic regression might consider various aspects of the data other than the two models. On the other hand, the outcomes of random forest vs. decision trees analysis reveal that compared to decision trees, the random forest models are substantially different, possibly due to their more complex way of decision-making. This indicates that the random forest algorithm has the potential to find higher polynomial complexity and interactions between the features that might make it better suited for specific regional datasets than a pruned decision tree. In sum, existing research implies that while the type of model for use in predicting financial distress might be sufficient for the data in certain geographical locations, in others, it may be necessary to adapt the model itself to address regional aspects adequately. Random forests are generally known to provide a more complex classification model; thus, it may be more effective when overly complex feature interactions are expected to be present. However, the statistics presented by the McNemar test show that it is essential not to disregard the peculiarities of each model and possible opportunities to apply them in certain conditions.

4.3 Discussion

The study's objectives were to examine the performance of traditional and integrated financial distress prediction models, determine key financial ratios that significantly predict financial distress and compare the predictive accuracy of the models in different regions of Africa. Hence, the results are informative, especially regarding the efficiency and adaptability of the logistic regression, random forest and decision tree models.

4.3.1 Effectiveness of Traditional vs Integrated Financial Distress Prediction Models

This analysis aims to determine whether integrated models perform better than traditional financial distress prediction models such as logistic regression, random forest and decision tree models. These measures include accuracy, sensitivity, specificity and the AUC, while paired t-tests sought to compare the statistically significant differences in the accuracy between traditional and integrated models. Logistic regression is also popularly used in predicting financial distress because of its simplicity and straightforward interpretation (McLernon & Bullock, 2017). The common conventional logistic regression model used in the present study gives an overall recognition rate of 69.28%, sensitivity of 67.71%, specificity of 72.28%, and AUC of 0.7551. An almost similar performance is achieved by the integrated model with an accuracy of 68.94%, a sensitivity of 67.19%, and a nearly similar AUC of 0.7549. Although there are minor discrepancies in accuracy and sensitivity, the statistical differences between the results deduced from the traditional and integrated models are insignificant with the help of paired t-test ($t = 1.7483$, $p = 0.1787$). Also, it is important to note that the confidence interval is [-0.0018, 0.0062], which means that the observed results could be due to random chances rather than any systematic improvement from using integrated features. The results obtained in this study are similar to the research of Zhang et al. (2020), indicating that the use of logistic regression models for financial distress prediction may have reduced sensitivity to added integrated features. In this regard, the efficiency of the traditional model remains on par with the integrated model, meaning that further complications of the feature integration do not translate to enhanced performance.

Among these, random forest models considered nonlinear primarily provide high accuracy, sometimes even outperforming other techniques, for financial distress prediction (Tobback et al., 2017). This study's original random forest method establishes an accuracy of 71.33%, sensitivity of 98.44%, and specificity of 19.80% with an AUC of 0.7101. The integrated random forest model has slightly less accuracy of 68.94%, similar sensitivity of 98.44%, and less specificity of 12.87%, but slightly more AUC of 0.7202. Therefore, although the integrated model not only has a slightly higher average AUC value, suggesting that the model has a higher discrimination ability between distressed and non-distressed firms, but also the paired t-test results ($t = 1.1738$, $p = 0.3252$) prove that there is no significant difference between the two models. The 95% confidence interval [0.0355, 0.0770] contains zero; any performance differences may be due to random variability and not integration of any additional features. This finding is also in line with Wang and Ma’s (2021) study, showing that although random forest models might compare well for financial distress prediction, it is not complicated features or integrated data that enhance the model’s performance. This is especially the case when the models already contain most of the nonlinear effects in the data. Therefore, the standard random forest model offers comparable accuracy to the integrated model, indicating that the latter provides no additional benefit.

While the decision tree models are relatively simple and easy to interpret, which makes them very popular, they are proven to provide relatively low accuracy with complex data patterns (Laitinen & Laitinen, 2018). The results of the traditional decision tree model are an accuracy of 36.86%, a sensitivity of 7.29%, a specificity of 93.07%, and an AUC of 0.4195. The resulting integrated decision tree model yields the same accuracy, AUC, gini, and BCI values as the traditional model. The paired t-test results are unavailable (NaN), as the values for the traditional and integrated models are equal. Due to the lack of variation, it becomes statistically impossible to calculate meaningful statistical tests, and the mean difference of 0 reminds us that the integrated model does not perform better than the conventional decision tree model. Research by Hamid and Mutasini (2022) has indicated that the decision tree model can be regarded as relatively weaker when predicting financial distress compared to methods like random forest or gradient boosting algorithms. This is more so where the units of the variables have interdependencies, something that decision trees may not easily capture. As a result, the integrated decision tree model does not significantly enhance performance over the standalone models, thus supporting the idea that decision trees could be less suitable for this type of analysis.

Based on the analysis of the three models, logistic regression, random forest, and decision tree, the study concludes that integrated models are not superior to traditional models in financial distress prediction. Paired t-test results indicate no significant difference in the performance of traditional and integrated logistic regression and random forest models.

Hence, we can say that integrating feature selection and modelling does not seem to enhance the performance of the models much when tested on the test dataset. Regarding the decision trees, the performance of the integrated and the traditional models is unaffected, which means there is no added advantage in integrating features.

4.3.2 Significant Predictors of Financial Distress

The hierarchy of the variables necessary for assessing financial distress becomes apparent while studying the coefficients of the logistic regression models and the importance of features from the random forest and decision tree models. The critical variables across the board are invariably oriented in profitability, liquidity, and asset management, and this is consistent with the basic antecedents outlined in the earliest literature on financial distress prediction models (Altman & Hotchkiss, 2020). Nevertheless, the value of these factors may differ for a particular model, which can be explained by the higher sensitivity of some types of algorithms and the characteristics of the financial environment in which the corresponding model should operate. Among all the established variables, return on assets (ROA) is one of the most significant predictors of financial distress across all analysis models. Among all the ratios, ROA remains one of the most attractive and highlights the importance of this factor in evaluating companies' efficiency in making profits from assets. This aligns with Beaver et al. (2021), who continued and supported the idea that profitability ratios such as ROA are fundamental to financial distress. Companies that cannot generate adequate returns from their assets are in a weak position, as other shortcomings typically accompany poor asset utilization. The fact that ROA was ranked as the most important variable in all three methods: logistic regression, random forest, and decision tree indicates that profitability outweighs all other measures of a company's success. The same observation was made by Sun et al. (2022), who pointed out that based on the literature, ROA is often employed in machine learning models because it measures the firm's Operating and Financial performances. These models support this view since high-importance scores are awarded to ROA in all forms, including traditional and integrated models.

The Current Ratio, one of the liquidity variables, is also ranked highly throughout all the models, especially with the help of the random forest and decision tree models. In the integrated decision tree model, this is in the first place of feature importance, suggesting it is crucial. Liquidity is a key driver of distress since it refers to a given firm’s capacity to honour short-term commitments (Beaver et al., 2021). Businesses with an entry in the liability side of balance sheets and poor liquidity can easily nose-dive and be considered distressed. The significance of the Current Ratio echoes current studies revealing liquidity as being a key determinant of financial sustainability, especially during economic fluctuations (Wang & Ma, 2021). The results also showed a high significance of the Current Ratio in this analysis, which supports the notion that liquidity problems were present before the more severe forms of FDH and thus is a valuable element of an early warning system for financial distress. Another essential variable identified in all the models is the Return on Equity (ROE), which ranks between two and three. ROE thus measures the companies’ ability to generate returns to shareholders, and the figure's relevance in forecasting financial distress underlines the relevance of shareholder value in evaluating firms’ financial position. Low ROE signifies poor capital management, which creates problems in the organization’s functioning (Altman & Hotchkiss, 2020).

The literature supports this with Zhang et al. (2020) pointing out that more specific measures, such as ROE, are viewed as measures of the extent of firm financial sustainability. Nevertheless, the study reveals that ROE has a significant role in the models studied since it follows the run-of-the-mill ROA and Current Ratio only in the random forest and decision tree models. This implies that from an asset and equity standpoint, it is crucial to determine whether a firm will experience financial distress beyond the certainty of profitability. Regarding the Asset Turnover, we cannot see it at the same level as ROA or the Current Ratio. Nevertheless, this indicator is always present in the models and remains among the significant predictors in the integrated random forest and decision tree models. Asset Turnover refers to the ratio that indicates the efficiency of using assets to generate sales revenue. Poor managing companies are more likely to get financial distress, while this variable is seen as slightly less important than profitability and/or liquidity variables. According to Tobback et al. (2017), while asset efficiency is a crucial factor, it is overshadowed by liquidity and profitability regarding distress prediction models. This agrees with this analysis, where Asset Turnover is ranked slightly lower in importance but still falls in the relevant range. It offers a supplementary dimension to analysing a firm's financial performance, which plays a role in the evaluation despite being a less significant priority than making a profit.

Debt to Common Equity, a leverage measure, is less sensitive to distress than the other variables examined in this study. Leverage is usually regarded as a key measure of the company's credit risk and is often the basis of such models; however, these models focus on liquidity and profitability, not leverage. This indicates that even if high-debt firms are more prone to distress, leverage does not affect distress prediction to the same extent as profitability and liquidity indicators. Wang and Ma (2021) pointed out that in modern machine learning models, leverage variables have a relatively smaller impact. In contrast, variables such as ROA and the Current Ratio, which are directly related to the revenue-generating efficiency of a firm's operations, might influence the evaluation more. In that view, this analysis agrees that debt to common equity has lower relative importance than liquidity and profitability ratios in all models. Last is the Gov Score, which is even used in the integrated models. The contribution of this variable is the lowest among the others. Although the role of governance factors has gained attention in recent years concerning financial performance (Hamid & Mutasini, 2022), they seem to have a less significant influence on predicting financial ailments than conventional financial indicators. This indicates that even though governance could help build a firm in the long run, it is not very helpful in preventing short-term financial troubles. Research by Zhang et al. (2020) agrees with this observation since governance factors normally appear less important than liquidity and profitability in models that rely on financial ratios as the main predictors. The models in this analysis demonstrate that while governance is essential, it is not as significant in predicting near-term distress as ROA, Current Ratio, or ROE.

A comparison of logistic regression, random forest, and decision tree techniques shows that profitability, chiefly ROA and ROE, and liquidity, defined by the Current Ratio, are highly influential predictors of financial distress. These variables are highly significant and remain significant in all models. However, the governance factors, although useful, have less influence than the previously mentioned factors when predicting companies' financial distress. This analysis also supports the notion that profitability and liquidity must be the most effective methods of measuring the financial health of organisations since the literature identifies these metrics as fundamental features of the early-warning models of organisational financial distress (Sun et al., 2022; Beaver et al., 2021).

4.3.3 Consistency across African Regions

The comparison of logistic regression, random forest, and decision tree models for the African regions offers an important understanding of the comparative validity of each model within the study of financial distress indicators. This analysis is beneficial for achieving Objective 3 of the study, which focuses on examining the reliability of the integrated financial distress prediction model across the African continent's heterogeneous regions. The results of each model in terms of accuracy, sensitivity, and specificity, as well as the statistical test McNemar's test, show the ability of these models to perform and adjust to different regional settings. This helps determine which model or models provide the most reliable results for predicting financial distress across the African continent as consistently as possible.

Cohort classification using logistic regression has traditionally been used in financial distress prediction since the method is simple and satisfactory when dealing with binary variables. It only performs well when there is a direct proportional relationship between the independent and response variables. Nonetheless, as we have seen, the different regions' studies showed that logistic regression had problems in analyzing the financial interactions ordinarily present at the regional levels, such as Southern Africa and Eastern Africa. As mentioned earlier, they are complex financial areas in which factors like cash availability, profitability, and market structure are intertwined. The analysis based on logistic regression is limited by its linearity and distorts these relationships compared to more complex models, reducing accuracy and generally worse performance (Beaver, et al., 2005). As shown in Northern Africa, logistic regression gave reasonably good results, but again, the random forest was more suitable given potential interaction effects. This underperformance highlights a common limitation of logistic regression: it tends to operate on a linear framework. It cannot accommodate the complex and diverse movements of money witnessed in many African regions (Altman & Hotchkiss, 2010).

However, as evident from the results, random forest appeared to be the model that made the highest accuracies and was ranked number one across most regions, such as Eastern Africa, Northern Africa, and Southern Africa. As an example of ensembles, a random forest builds some decision trees and makes the final decision based on integrating the outputs of the individual trees. This approach is helpful because the random forest is outstanding in both linear and non-linear situations; this means it will be more flexible in complicated financial situations (Biau & Scornet, 2016). McNemar's test chi further advocated these disparities squared values for the random forest performance compared to logistic regression and decision tree in Northern Africa ($p<0.05$). The peculiar financial relations in this region that result from sector-specific risks, corporate governance defects, and macroeconomic factors are also solved in the random forest most suitably. However, due to their relative simplicity, models such as logistic regression and decision trees often find it challenging to account for many nuances (Beck et al., 2020).

Again, despite the decision tree's intuitive nature and easy interpretability, it produced worse results than a random forest. This was especially seen in places like Eastern Africa and Southern Africa, where the decision tree model did not capture the financial features peculiar to markets in these regions. One of the largest problems associated with decision trees is overfitting, which becomes especially evident in the presence of complex interactions in the dataset. This led to lower predictive accuracy and sensitivity compared to random forest. At the same time, in Central Africa, where the structure of the financial environment seems less complex, the performance of the decision tree model was quite similar to that of the random forest, which exemplifies that more complex models are not as necessary in a less complex environment. However, the general performance of the decision tree model in the other more complex areas, such as western Africa and northern Africa, brings out the drawback of the decision tree model when it comes to handling complex relationships between variables such as those in a financial model and inability to handle non-linearities in data (James et al., 2013).

The findings of this study underscore the need to develop flexible and robust models when predicting financial distress, as supported by all three models used in this study across Africa. Once again, the random forest showed its flexibility and beat both the logistic regression and decision tree in areas of higher financial fluctuation. The flexibility of managing many finance attributes and capturing the complex and commonly probabilistic nature of distress indicators set this model apart from others. This is a random forest in Southern Africa comprised of various industries and different economies. In essence, the random forest that combines multiple decision trees could handle the complexity of the region's financial environment and predict financial distress more accurately than other models (Breiman, 2001). However, using logistic regression analysis as the baseline was restrictive in some ways as the model is linear, even though financial interactions are somewhat complex in those areas. Despite its effectiveness in less complex settings as those observed in Central Africa, the decision tree model failed to operate effectively on complicated and heterogeneous data sets and was below par where financial interactions were more diverse.

CHAPTER FIVE
SUMMARY AND RECOMMENDATIONS

5.0 Introduction

This chapter summarizes the key study findings, presents conclusions based on the research objectives, and offers recommendations for stakeholders, including businesses, policymakers, and future researchers.

5.1 Summary of Findings

The objectives for this study were threefold: to evaluate and compare traditional and integrated financial distress prediction models, identify the key predictors of financial distress, and assess the consistency of model performance across various African regions. To accomplish these objectives, the research utilized logistic regression, random forest, and decision trees to investigate the efficiency of financial distress prediction and compare the regional differences in their performance.

It was established that conventional financial activity ratios still afford a robust means of measuring financial distress. In the analysis for each evaluation matrix, the performance of the traditional logistic regression model was slightly higher in most cases than that of the integrated model. The integrated model, to increase its predictive power by adding governance variables, still did not significantly surpass the traditional model. This implies that the conventional measures of financial performance like liquidity, profitability, and leverage are still the best predictors of financial health.

Looking at the results for the random forest results, the model exhibited high sensitivity, particularly in pinpointing distressed firms, especially in areas like Western Africa. This indicates that a random forest can accommodate high-order interactions among the variables and fit into any given economic setting well. However, the lower sheer specificity of the model suggests a slightly increased rate of overestimations of distress or false positives. This trade-off indicates that although random forest algorithms are valuable in pointing to potential financial problems, their sensitivity and specificity could still be optimized.

Decision tree models gave less accurate results than logistic regression and random forest models. They displayed comparatively low sensitivity and selectivity in all the regions, thereby suggesting their poor capacity to identify potential credit risk situations in African markets. These insights indicate that single classifiers, especially the decision trees, cannot sufficiently supply the necessary level of detail required for interpreting financial data, especially regarding the economic heterogeneity of African countries.

The research also sought to determine significant factors influencing an organization to experience financial distress. The most important financial ratios included the Current Ratio, ROA, ROE, DCE, and Asset Turnover. These results conform to prior studies centered on liquidity, profitability, and leverage ratios as key indexes of organizational financial condition. Interestingly, the governance score added in the integrated model did not contribute to improving the predictive ability. This indicates that conventional accounting numbers are still significantly valuable in prediction, as noted in the work done by Bhimani et al. (2013) and Altman et al.(2019).

Moreover, the authors identified regional discrepancies in the performance of the analyzed models. Logistic regression models were more applicable in Southern and Northern Africa regions, which have sound financial structures. However, random forest models fared well in Western Africa mainly because of the region's higher economic complexity and higher level of financial fluctuations. Such disparities call for the use of specific models in the formulation of financial distress prediction models.

5.2 Conclusion

Based on the study's results, the following conclusions can be drawn. Firstly, the first set of indicators, traditional financial ratios, gives the highest level of financial risk assessments. The maintenance of these metrics points to the fact that businesses and stakeholders possess standard financial measures on which early signals of financial distress could be detected. Secondly, incorporating governance factors into the model did not positively impact the performance. This conclusion aligns with other researchers, such as Laitinen & Laitinen (2018), who pointed out that even though governance practices feature prominently, they may not be as efficient in standalone models of distress prediction. Finally, the analysis of variance in model performance by region suggests that a single model can be sub-optimal when predicting financial distress across Africa. It also emerges that each area's economic characteristics, market environment, and financial processes affect the accuracy of distress prediction models. Hence, regional-specific models that capture the economic patterns of respective regions are expected to supply better and more accurate forecasts.

5.3 Recommendations

This research can significantly benefit businesses and financial analysts focusing on the airline industry and stocks. Regarding financial health, they should persist with conventional financial ratios, comprising the Current Ratio, ROA and ROE. These indicators have been deemed valid and should underpin a framework for evaluating financial risk. Also, firms in regions with more complicated economic systems, such as the western part of Africa, may find it most appropriate to use a more complex 'black box' like the random forest since it captures the most complex relationships between the variables. Nevertheless, they should know how the model overpredicts the degree of distress and work towards recalibrating it when necessary.

These discrepancies should, therefore, be a testament to why Region-specific policies, financial regulations and guidelines must be drafted as per the economic indications of the Region. This may involve protection measures for firms in areas that the predictive models establish as vulnerable or operate in sectors predicted to experience increased volatility. Furthermore, enforcing financial disclosure policies and strict adherence to standardized accounts reporting methods will improve the reliability of the distress prediction models. Enhanced transparency of financial statements in all sectors will give much better figures for analysis and help reveal distress problems early.

Future studies should also investigate the possibility of adopting macroeconomic variables, industry-specific factors and sound governance practices to enhance the sophistication of various prediction models. This could lead to the building of better models that would combine aspects of all the models and perform well in different regions. Also, researchers should strive to develop region-specific prediction models and adapt existing models based on the unique characteristics of the area in question. This way, with the attention paid to the diversities in the financial and economic nature of the regions and their sub-centre areas, it would be possible to create proper models. Since random forest performs reasonably well, future research should extend this work to other algorithms like SVMs or neural networks to evaluate their applicability for financially distressed prediction. These enhanced models could provide new perspectives and improve the reliability of forecasts.

5.4 Limitations of the Study

It is necessary to highlight the study's limitations, which focus on predicting financial distress. However, a significant contribution has been made to developing the corresponding model. The integrated model was constructed using financial ratios and a governance score and, thus, did not consider other factors contributing to financial distress. It would be advisable for future models to use a more extensive set of input variables encompassing non-financial and macroeconomic factors. However, the study was done using data from selected regions in Africa; as such, the results may not be generalized across the entire continent. Further research in other areas might help confirm the efficiency of the models and improve their usefulness in different economic environments.

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