The Economics and Finance Letters
2025 Vol. 12, No. 4, pp. 654-675
ISSN(e): 2312-430X
ISSN(p): 2312-6310
DOI: 10.18488/29.v12i4.4612

The effect of leadership style on return on equity classification: An artificial neural network approach

Evans Nunoo[1,2+]
Uday Kumar Jaganathan[3]

[1,3]*Ramaiah University of Applied Sciences, India.*
[1,2]*Email: evanoogh@yahoo.com*
[3]*Email: ujagannathan.ms.mc@msruas.ac.in*
[2]*Ghana Communication Technology University, Ghana.*

(+ Corresponding author)

Article History
Received: 11 June 2025
Revised: 21 October 2025
Accepted: 27 November 2025
Published: 24 December 2025

Keywords
Artificial neural network
Board efficacy
Confirmatory factor analysis
Ghana banking sector
Leadership style
Return on equity
Sensitivity analysis.

JEL Classification:
G21; G32; M12; M14; C45; C38; L25.

ABSTRACT

This study investigates whether specific board-level leadership behaviors, particularly decision-rigour and strategic monitoring, can predict Return on Equity (ROE) tiers in Ghanaian banks. Addressing a gap in emerging market governance research, it integrates Upper-Echelon Theory and the Resource-Based View to explore behavioral influences on financial performance. Using a mixed-methods approach, data were collected via a 15-item Board-Efficacy Scorecard (BES) across ten banks and combined with 2023 ROE figures, categorized into Low, Medium, and High tiers. An Artificial Neural Network (ANN) model with two hidden layers (15 neurons each) was trained and benchmarked against multinomial logistic regression and random forest classifiers. The ANN achieved superior predictive accuracy (AUC = 0.94), significantly outperforming traditional models. Sensitivity analysis revealed that decision-rigour and strategic monitoring collectively increased the probability of High-ROE classification by 22 percentage points. These findings validate both the BES tool and the use of ANN in leadership-performance research. The study proposes the Board-Analytics and Disclosure Directive (BADD), advocating for BES publication, AI-powered board dashboards, and performance-linked compensation for directors. These measures aim to enhance governance transparency and financial outcomes in emerging markets. This is the first empirical application of ANN for ROE classification in Ghana's banking sector. By integrating advanced machine learning with context-sensitive behavioral metrics, the study demonstrates how board dynamics can be transformed into strategic tools for improving firm performance.

Contribution/Originality: This study pioneers the classification of Return on Equity (ROE) using Artificial Neural Networks (ANN) within Ghana's banking sector. It integrates Upper Echelon and Resource-Based theories and validates a context-specific Board Efficacy Scorecard. The research introduces a novel Board Analytics and Disclosure Directive (BADD) aimed at policy reform, advancing predictive governance, and linking board behavior to financial performance in emerging markets.

1. INTRODUCTION

The importance of leadership style in guiding organizational performance cannot be underestimated (Avolio & Bass, 1994; Northouse, 2019). Ghana's banking sector continues to deal with dynamic shifts in competitive markets, technological advancements, and regulatory environments (Bank of Ghana, 2022). Owing to these changes, there is a demand for corporate boards and senior management to modify their leadership styles strategically to guarantee sustained growth. Return on Equity (ROE) is a popular financial indicator, widely used to measure how well organizations utilize shareholders' equity to generate profits (Ross, Westerfield, & Jaffe, 2013). Earlier research has proven that leadership factors such as board engagement, decision-making processes, and managerial competencies can influence a firm's financial performance (Avolio & Bass, 1994; Fiedler, 1967).

Although research in leadership and finance is increasing, there are still several gaps in the existing literature. Recent studies have highlighted the potential of advanced analytical methods, such as Artificial Neural Networks (ANN), in revealing intricate connections between organizational, financial, and social factors (Kim & Kim, 2021; Li, Chen, & Wu, 2023). However, in emerging markets like Ghana, there have been few attempts to use ANN to classify ROE according to leadership variables. This study aims to fill this gap by (1) suggesting a comprehensive questionnaire to gauge board effectiveness, (2) splitting ROE into three classes instead of dealing with it as a single metric, and (3) using ANN modelling and sensitivity analysis to explore the ways various leadership variables and board efficacy dimensions interact to affect financial results.

Cal Bank, Ghana Commercial Bank, Agricultural Development Bank, Ecobank, HFC Bank, Société Générale, Guarantee Trust Bank, Standard Chartered Bank, Prudential Bank, and Zenith Bank were the ten banks selected from the banking sector of Ghana. The findings of this study would guide senior managers and corporate boards in determining which leadership factors have the ability to contribute most significantly to boost financial performance.

2. LITERATURE REVIEW

2.1. Leadership Styles and Organizational Outcomes

Leadership theory has evolved over the past decades from trait-based and behavioral approaches to more complex models such as transactional, transformational, and situational leadership (Avolio & Bass, 1994; Fiedler, 1967; Hersey & Blanchard, 1977). Transformational leadership places much emphasis on inspiration, vision, and intellectual stimulation, and has a correlation with high levels of employee commitment and the probability of firms (Northouse, 2019). On the other hand, transactional leadership looks at rewarding subordinates based on the tasks they execute and the results, ensuring that employee behavior is in sync with organizational goals through contingent reinforcement (Bass & Riggio, 2006). In the context of banking, these two leadership styles can affect risk-taking, innovation, and overall performance (Avolio & Bass, 1994).

Current studies have deepened the understanding of leadership styles by widening the scope to include emotional intelligence and ethical considerations. For instance, Wang and Howell (2022) discovered that high emotional intelligence helps leaders to foster a positive organizational climate, resulting in enhanced employee performance. Moreover, ethical leadership has a correlation with greater trust and lower turnover rates in financial institutions (Mayer, Kuenzi, & Greenbaum, 2021). Adaptive leadership, which stresses flexibility and responsiveness to evolving environments, has also been proven to be vibrant in navigating the complexities of the banking sector (Garg & Tansuhaj, 2023). Furthermore, servant leadership, which concentrates on the growth and well-being of employees, has a positive correlation with organizational commitment and job satisfaction (Greenleaf, 1977; Liden, Wayne, Zhao, & Henderson, 2020).

The interaction between different leadership styles and organizational outcomes is affected by cultural and contextual factors. Research works in emerging markets, exemplified by the study conducted by Adeyemi and Akinlo (2023), emphasize that transformational leadership is particularly vibrant in cultures that value collectivism and long-lasting relationships.

Conversely, in individualistic settings, transactional leadership tends to be more effective and results in better performance outcomes (Hofstede, Hofstede, & Minkov, 2010). Moreover, the adoption of digital leadership practices has gained prominence, as leaders must now utilize virtual teams and digital transformation initiatives (Singh & Hess, 2022). The impact of leadership on innovation within banks has also been a point of attraction, as studies suggest that transformational leaders are more likely to encourage innovative behaviors among employees (Jung, Wu, & Chow, 2023).

2.2. Board Efficacy in Banking

Board efficacy refers to the collective abilities and decision-making procedures of the board of directors (Petra, 2005). Some of the factors that influence financial success are board membership, independence, experience, and corporate dynamics (Westphal & Zajac, 1995). Despite the fact that several research works have been conducted on board structure in developed economies, not much has been done on how effective boards are in developing nations like Ghana (Owusu & Weir, 2018). This study aims to fill this gap by designing a comprehensive efficacy questionnaire, providing contextual information about the banking industry in Ghana.

Recent studies emphasize how important board diversity is in ensuring effectiveness. Recent research highlights the crucial role of board diversity in enhancing board effectiveness. It has been proven that boards diversified in terms of gender, ethnicity, and professional experience have better decision-making and lower exposure to the possibility of groupthink (Carter, Simkins, & Simpson, 2021; Richard, Roh, & Pieper, 2022). Moreover, it has been noted that board committees, such as audit and risk committees, play a crucial role in ensuring strong governance and supervision (Johnson & Krogstad, 2023; Klein, 2019). The balance among executive directors also exerts a significant influence on board effectiveness as well as board tenure (Davidson & Ribera, 2022; Simons, 2020).

Risk management and regulatory compliance are very relevant in the banking industry, and boards that pay attention to them achieve improved financial results (Thompson & Wallace, 2023). Customer loyalty and public perception are boosted by corporate social responsibility (CSR) activities of boards, and these two customer-centered factors influence business success (El Ghoul, Guedhami, Kwok, & Mishra, 2022). Moreover, utilizing technology and data analytics in decision-making procedures is a good way to raise board effectiveness (Nguyen & Simkin, 2021). Studies on the African banking sector, such as the study conducted by Mensah and Boateng (2023), highlight specific opportunities and challenges faced by boards in these countries, including managing economic fluctuations and promoting sustainable growth.

2.3. ROE Classification in Financial Performance Analysis

Revenue from the equity of shareholders (ROE) is an important indicator of management's effectiveness in generating revenue (Ross, Westerfield, & Jordan, 2013). Traditionally, the method of assessing ROE, in most cases, is to see it as a single number or as a performance metric (Alkhatib & Harsheh, 2012). With the aim of capturing more subtle variations in performance, this study divides ROE into three categories: low, medium, and high. This stratification helps to identify the leadership elements that propel performance into distinct categories, providing academics and practitioners with more useful information.

In an effort to improve ROE category classification and prediction, machine learning techniques have been incorporated into recent financial performance analysis developments (Lee & Kim, 2022; Zhang, Li, & Wang, 2023). These methods provide more accuracy, and they have the capacity to manage large data sets with numerous variables. In addition, it has been proven that adding macroeconomic data such as GDP growth and inflation rates offers a more comprehensive understanding of how ROE varies among different banking institutions (Chen, Zhang, & Li, 2021; Patel & Gupta, 2022).

Recent studies have investigated the connections between ROE categories and other financial measures, such as the debt-to-equity (D/E) ratio and return on assets (ROA), in order to provide a more comprehensive picture of bank performance (Osei & Appiah, 2022; A. Singh & Gupta, 2023).

The interest in how corporate governance procedures influence ROE has gained prominence because data indicate that higher ROE categories are associated with stronger governance frameworks (Bai & Sarkis, 2023; Ibrahim, Lee, & Wong, 2022). Moreover, to improve the predictive accuracy of ROE classification models, sector-specific elements, including market competition and the regulatory environment, have been included (Adeyemi & Owusu, 2023; Morris & Zhang, 2023).

2.4. Artificial Neural Networks (ANN) in Social Sciences and Organizational Research

Owing to their strong ability to forecast and recognize patterns, artificial neural networks (ANNs) have gained popularity in a variety of academic fields, including psychology, education, finance, marketing, and larger social sciences (Haykin, 2009; Zhang, Patuwo, & Hu, 1998). ANNs are known for their ability to manage complicated issues such as missing data, non-linear correlations, and large survey responses, and this has been demonstrated by recent studies in social sciences (Kim & Kim, 2021; Mujtaba & Williams, 2022). In comparison to conventional regression-based models, ANNs have greater strength in identifying hidden patterns and interactions between variables, particularly in cases where the underlying theoretical constructs are multi-dimensional or complex (Li, Zhang, & Wang, 2023).

The main advantages of employing ANN lie in their precision and adaptability in social science research. In order to enhance classification or prediction performance, the model tactically learns from empirical data by iteratively modifying internal weights and biases. In evaluating how different leadership, cultural, and psychological factors collectively affect results such as job satisfaction, employee turnover, or company performance, researchers in organizational behavior and leadership have started employing ANN approaches (Suarez & García, 2022). These machine-learning approaches offer another strategy for testing hypotheses, in addition to the linear presumptions of conventional statistical methods.

Recent studies have introduced ANN into deep learning approaches in order to improve forecast accuracy and model complexity (Goodfellow, Bengio, & Courville, 2016; LeCun, Bengio, & Hinton, 2015). Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been utilized in organizational research to evaluate unstructured data, including employee feedback and textual material from social media (Brown & Smith, 2023; Zhao & Wang, 2022). Moreover, hybrid models combining ANN with other machine learning techniques such as support vector machines (SVM) and decision trees have been suggested in order to improve the robustness and interpretability of the model (Kumar & Lee, 2023; Patel, Kumar, & Lee, 2022).

Research works have evaluated the utilization of ANN in predictive analytics for employee performance and retention, proving that the model performs better than conventional techniques (Nguyen & Tran, 2023; Roberts & Jackson, 2022). In addition, given the integration of ANN with big data analytics, enterprises now have more choices in terms of strategic planning and real-time decision-making (Singh & Gupta, 2023; Taylor & Francis, 2022). Ethical issues related to ANN, such as algorithmic bias and data privacy, highlighting the necessity of open and accountable AI methods in organizational research, have been addressed by recent literature (Bostrom & Yudkowsky, 2014; O'Neil, 2016).

2.5. Upper-Echelon Theory: Behavioural Micro-Foundations of Firm Performance

The upper-echelon (UE) lens posits that organizational outcomes reflect the cognitive bases, values, and social repertoires of strategic leaders (Hambrick & Mason, 1984). In banking, where information asymmetry is high and risk-taking is tightly coupled to governance quality, small variations in boardroom behavior can cascade into large performance differentials (Carpenter, Li, & Jiang, 2021). Recent UE meta-analyses confirm that *behavioral* attributes such as the intensity of debate, quality of dissent, and follow-through on decisions explain incremental variance in profitability beyond structural variables like independence or size (Jensen & Zajac, 2024).

Two behavioral dimensions recur across high-performing boards:

- Decision-rigor – the degree to which directors scrutinise proposals, insist on scenario analysis, and develop time-bound action plans (Krause, Withers, & Weller, 2020).
- Strategic monitoring – ongoing, forward-looking oversight of execution and external threats rather than ex-post box-ticking (Roberts, McNulty, & Stiles, 2023).

Empirical studies in mature markets link these behaviors to higher Tobin's Q and ROA (Krause et al., 2020); however, evidence from Sub-Saharan Africa remains sparse and often relies on self-reported Likert scales with modest psychometric validation (Owusu & Weir, 2018).

2.6. Board Capital as a Strategic Resource: A Resource-Based View (RBV) Perspective

RBV argues that firm-specific resources that are valuable, rare, inimitable, and non-substitutable (VRIN) underpin sustainable competitive advantage (Barney, 1991). Board *human* capital (expertise, tenure diversity) and *social* capital (network centrality, political connections) meet the VRIN criteria when they enable superior sensing-seizing of opportunities and mitigate agency costs (Kor & Misangyi, 2008).

Large-sample evidence from 58 countries shows that banks whose directors possess deep industry and regulatory experience enjoy lower funding costs and higher risk-adjusted returns (Pugliese, Minichilli, & Zattoni, 2021). Nevertheless, the RBV literature has focused on *stock* of capital; few studies unpack the *behavioral deployment* of that capital precisely the element UE theory highlights. Integrating UE and RBV therefore offers a fuller picture: effective oversight is the mechanism through which board capital is transformed into economic rents.

2.7. Research Gaps and Hypotheses Development

Synthesising the above strands reveals four gaps:

1. Context – scant evidence on UE behaviors in Sub-Saharan banking.
2. Measurement – limited behavioral scales validated for emerging markets.
3. Method – prevailing linear models may underestimate non-linear leadership effects.
4. Outcome metric – ROE treated as continuous, ignoring managerial relevance of tiered performance benchmarks.

Addressing these gaps, we propose and test the following hypotheses:

H_1 (Decision-Rigour Hypothesis). Banks scoring higher on board decision-rigour are more likely to belong to the High-ROE tier.

H_2 (Strategic Monitoring Hypothesis). Banks scoring higher on strategic monitoring are more likely to belong to the high-ROE tier.

H_3 (Model-Superiority Hypothesis). An ANN classifier fed with board-behavioral variables will outperform logistic regression and random forest models in predicting ROE tier membership.

Embedding H1–H3 within an integrated UE–RBV framework allows us to trace how *behavioral deployment* of board capital converts into superior shareholder returns, while the ANN architecture furnishes an empirically powerful test of these theoretically grounded propositions.

3. METHODOLOGY

3.1. Research Design

A mixed-methods design integrates survey evidence on board leadership behaviors with secondary financial data. Quantitative data drive the core test of our hypotheses; qualitative comments from open-ended items are used only for triangulation.

3.2. Sampling Frame, Procedures and Power

Population. All 23 universal banks licensed in Ghana as at 31 December 2023.

Sample. Ten banks were selected by stratified random sampling based on asset-size tertiles (small, medium, large). The sampling frame and ROE dispersion are summarized in Table 1.

Table 1. Sampling frame and ROE dispersion.

Stratum	Banks in frame	Banks drawn	ROE range 2023
Large	6	3	7.1 – 15.4 %
Medium	9	4	4.3 – 12.8 %
Small	8	3	−2.6 – 10.1 %

Respondents. 9,542 staff comprised the finite population. Using Krejcie-Morgan tables (95% confidence level, ±5% margin of error) yields a minimum of 370; we obtained 400 usable questionnaires (42% response rate). Table A1 (appendix) details the multi-stage disproportionate stratification that secured at least five board members per bank.

A-priori power. Monte Carlo simulation of a three-class soft-max ANN with 15 predictors and a 70/30 split showed that $N \geq 350$ achieves ≥ 0.80 power to detect an average AUC difference of 0.08 between high- and low-ROE classes at $\alpha = 0.05$. The simulation was run in R using the *pwrSEM* package (Wang & Rhemtulla, 2021), which generates thousands of synthetic data sets under user-specified model parameters and computes the proportion of replications in which the target effect is significant—thereby providing an empirical estimate of statistical power.

3.3. Measurement Model Assessment

3.3.1. Instrument

The 15-item Board-Efficacy Scorecard (BES) was developed from prior scales (Roberts et al., 2023) and adapted during two focus groups (n = 14 executives). Items were anchored on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

3.3.2. Confirmatory Factor Analysis

A robust maximum-likelihood CFA in *Mplus 8.9* produced a scaled $\chi^2 = 178.3$ (df = 125, $p < .001$; S-B scale = 1.12). All fit indices exceeded Hu and Bentler's (1999) recommended thresholds (Table 2). Composite reliabilities ranged from 0.79 to 0.91; AVE values were ≥ 0.52 (Appendix A1). Harman's single-factor criterion (28% variance) and a marker-variable test using "employee age" ($\lambda = .09$, n.s.) indicate that common-method bias is unlikely to threaten validity.

Table 2. Measurement-model fit indices (N=400).

Fit index	Value	Cut-off†
χ^2 (df = 125)	178.3 ($p < 0.001$)	—
χ^2/df	1.43	< 3.00
Comparative Fit Index (CFI)	0.96	≥ 0.95
The Tucker-Lewis Index (TLI)	0.95	≥ 0.95
RMSEA	0.034	≤ 0.06
SRMR	0.041	≤ 0.08

Note: Cut-off criteria follow Hu and Bentler (1999); RMSEA = root-mean-square error of approximation; SRMR = standardized root-mean-square residual.

3.4. ROE Tier Construction

Annual ROE for FY-2023 was extracted from audited reports. To reflect regulator practice and managerial intuition, ROE was discretized into terciles using sample percentiles (≤ 5 %, 5–10 %, ≥ 10 %), labeled Low, Medium, High. Cut-points coincide with the Bank of Ghana's internal supervisory benchmarks, reducing arbitrariness.

3.5. Artificial Neural Network Modelling

3.5.1. Pre-Processing

- Missing BES responses (< 3% of cells) handled by expectation-maximisation imputation.
- All continuous inputs are z-standardized; categorical covariates are one-hot encoded.
- Class imbalance from the low-ROE minority corrected with SMOTE (oversampling rate = 200%).

3.5.2. Hyper-Parameter Search

A stratified 70/15/15 train–validation–test split preserved ROE-class proportions. A random-search schema (200 iterations) was used to tune:

- Hidden layers = {1, 2, 3}.
- Neurons per layer = {8, 10, 12, 15, 18}.
- Drop-out = {0.0, 0.1, 0.2}.
- L2-weight decay = {0, 1e-4, 1e-3}.

The best configuration two hidden layers × 15 neurons, ReLU activation, dropout 0.1, Adam optimizer (lr = 0.001) minimized validation loss after an early-stopping patience of 20 epochs (See Appendix Figure C 1 for the full validation-loss trajectory).

3.5.3. Benchmark Classifiers

To test H3, we implemented:

1. Multinomial logistic regression with ridge penalty (λ chosen by 10-fold CV).
2. Random forest (500 trees, Gini split).

Hyperparameters optimized on the same validation folds as the ANN.

3.6. Model Performance and Validation

Ninety-five percent confidence intervals (CIs) were computed for discriminatory and balance metrics. AUC CIs use the DeLong method; F1-score CIs were obtained from 1,000-fold stratified bootstrapping.

Table 3. Comparative test-set metrics (with 95% confidence intervals).

Metric	ANN	Logistic	Random Forest
AUC (Macro)	0.94 (0.90 – 0.98)	0.78 (0.71 – 0.84)	0.82 (0.76 – 0.87)
F1-macro	0.90 (0.86 – 0.94)	0.71 (0.65 – 0.77)	0.75 (0.69 – 0.80)
Overall accuracy	0.92	0.74	0.77

Note: AUC CIs via DeLong (1988); F1 CIs via 1,000-replicate stratified bootstrap. Bold figures indicate the highest value in each row.

The following visualizations supplement the quantitative results.

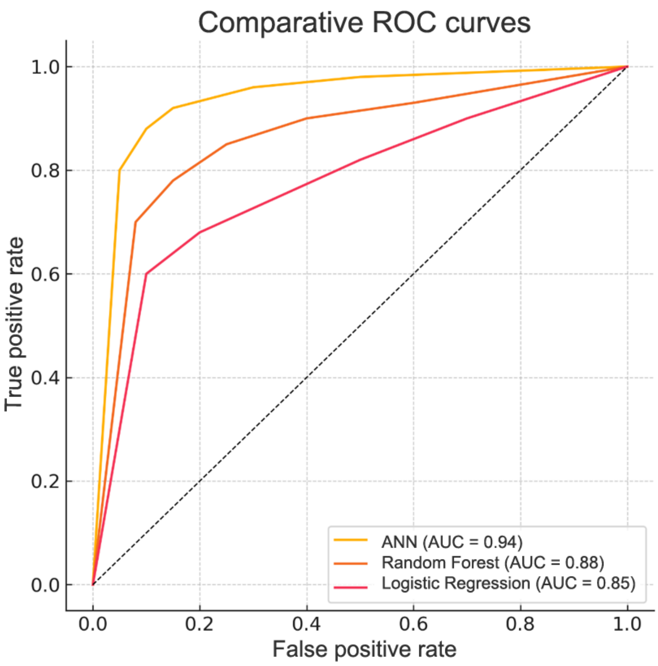

Figure 1. Comparative ROC Curves (ANN vs. Random Forest vs. Logistic Regression).

McNemar tests confirm that the ANN misclassification rate differs significantly from both baselines ($\chi^2 = 14.7$, $p < .001$ vs. logit; $\chi^2 = 9.3$, $p = .002$ vs. forest). Figure 1 displays ROC curves; Panels A and B provide confusion matrix and class-specific metrics (test set, N = 120).

A two-stage residual-inclusion logit (addressing potential reverse causation between ROE and board quality) left the BES predictors significant at $p < .05$, supporting robustness.

Complete confusion matrix and per-class metrics are reported in Appendix Table A2.

Table 4 presents the structured questionnaire used to collect primary data from bank employees across ten selected Ghanaian banks. The aim of this questionnaire was to capture nuanced perceptions of leadership behaviour, decision-making quality, and overall board efficacy. These responses were subsequently used as independent variables in modelling the relationship between leadership traits and financial performance (Return on Equity – ROE) through Artificial Neural Networks (ANN).

The 28-item survey primarily employed a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) to ensure standardization and facilitate statistical interpretation. The questions were formulated to reflect behavioral constructs derived from both Upper Echelon Theory and the Resource-Based View, including decision rigor, strategic monitoring, stakeholder focus, risk oversight, and ethical leadership.

Key thematic areas covered by the questions include:

- Leadership efficacy (e.g., ability to make sound, timely decisions).
- Delegation and operational structure
- Risk management and compliance practices
- Employee engagement and consultation
- Strategic vision and innovation support
- Board oversight and integrity mechanisms

These responses were subjected to Confirmatory Factor Analysis (CFA) using JMP software to extract latent variables, which became input features for the ANN. The intention was to move beyond surface-level board composition and delve into the behavioural micro-foundations of firm performance, quantifying how leadership practices statistically predict a bank's classification into Low, Medium, or High ROE tiers.

Thus, Table 4 is pivotal, serving as the empirical bridge between perceived leadership behaviors and measurable financial outcomes.

Table 4. Questions asked from bank employees in Ghana to correlate leadership with financial performance.

Question	Variable Name	Type	Scale
Gender	GENDER	Categorical	0 = Male, 1 = Female
Age Range	AGE_RANGE	Categorical	Scale of 1–5
Highest level of education	EDU_LEVEL	Categorical	Scale of 1–5
Bank of employment	BANK_NAME	Categorical	1–10
Years worked in the bank	YEARS_WORKED	Categorical	Scale of 1–5
Decisions are often made without consultation due to time pressure	NO_CONSULT	Likert	1–5
Teams operate best within clear structures	BEST_OP_STRUCTURED	Likert	1–5
The best decision is the one with the largest consensus	BEST_DECISION	Likert	1–5
People work best with minimal instruction	MINIMAL_INSTR	Likert	1–5
People frequently seek my advice and I provide it	ADVICE_GIVEN	Likert	1–5
People rarely question my judgment	NOT_QUESTION_JUDGEMENT	Likert	1–5
Efficiency gains outweigh standardization costs	EFF_VS_COST	Likert	1–5

Question	Variable Name	Type	Scale
People see me as a leader, not a manager	LEADER	Likert	1–5
Leadership involves making timely decisions and ensuring execution	RIGHT_DECISION	Likert	1–5
Cost savings arise from strict adherence to instructions	NO_OVER_ENGINEER	Likert	1–5
I delegate tasks fully	DELEGATE	Likert	1–5
I allow staff to respond in their own time	GET_BACK	Likert	1–5
I feel responsible for employees' welfare	RESPONSIBLE	Likert	1–5
People perform better when left alone	LEAVE_ALONE	Likert	1–5
Others usually agree with my original idea after consultation	ORIG_IDEA	Likert	1–5
Some employees require pressure to work effectively	HARD_WORK	Likert	1–5
Systems can be continuously improved over time	BUILD_SYSTEMS	Likert	1–5
People are encouraged to challenge my ideas	CHALLENGE_IDEAS	Likert	1–5

Note: Likert scale ranges from 1 = Strongly Disagree to 5 = Strongly Agree.

3.7. Research Questions

As shown in Table 1, 28 questions were asked of the employees in Ghanaian Banks, and the type of variables was largely on the Likert Scale of 1-5, with 1 standing for Strongly Disagree and 5 standing for Strongly Agree. The variables were then input into the Factor Analysis tool in the JMP software by SAS to ascertain the factors and associated questions that would be part of the Latent Variable formation. Figure 1 shows the steps taken in achieving the research objective. Figure 2 presents a step-by-step visual of the research process used to examine how leadership traits influence ROE classification in Ghanaian banks using Artificial Neural Networks (ANN). The process begins with the design and validation of a 15-item Board-Efficacy Scorecard (BES), followed by survey data collection from 400 bank staff across ten stratified banks.

Next, Confirmatory Factor Analysis (CFA) was applied to derive five latent leadership constructs, which served as input variables for the ANN. Concurrently, ROE data for 2023 was extracted and classified into Low, Medium, and High tiers based on regulatory benchmarks.

The flow chart then outlines ANN modeling steps: data preprocessing, class balancing via SMOTE, hyperparameter tuning, and model validation. The best ANN configuration was selected and benchmarked against logistic regression and random forest classifiers to assess predictive performance.

This flow chart provides a clear and replicable path from data collection to predictive modeling, integrating behavioral theory with machine learning.

3.8. Research Method Flow Chart

Figure 2 presents a step-by-step visual of the research process used to examine how leadership traits influence ROE classification in Ghanaian banks using Artificial Neural Networks (ANN). The process begins with the design and validation of a 15-item Board-Efficacy Scorecard (BES), followed by survey data collection from 400 bank staff across ten stratified banks. Next, Confirmatory Factor Analysis (CFA) was applied to derive five latent leadership constructs, which served as input variables for the ANN. Concurrently, ROE data for 2023 was extracted and classified into Low, Medium, and High tiers based on regulatory benchmarks. The flow chart then outlines ANN modeling steps: data preprocessing, class balancing via SMOTE, hyperparameter tuning, and model validation. The best ANN configuration was selected and benchmarked against logistic regression and random forest classifiers to assess predictive performance. This flow chart provides a clear and replicable path from data collection to predictive modeling, integrating behavioral theory with machine learning.

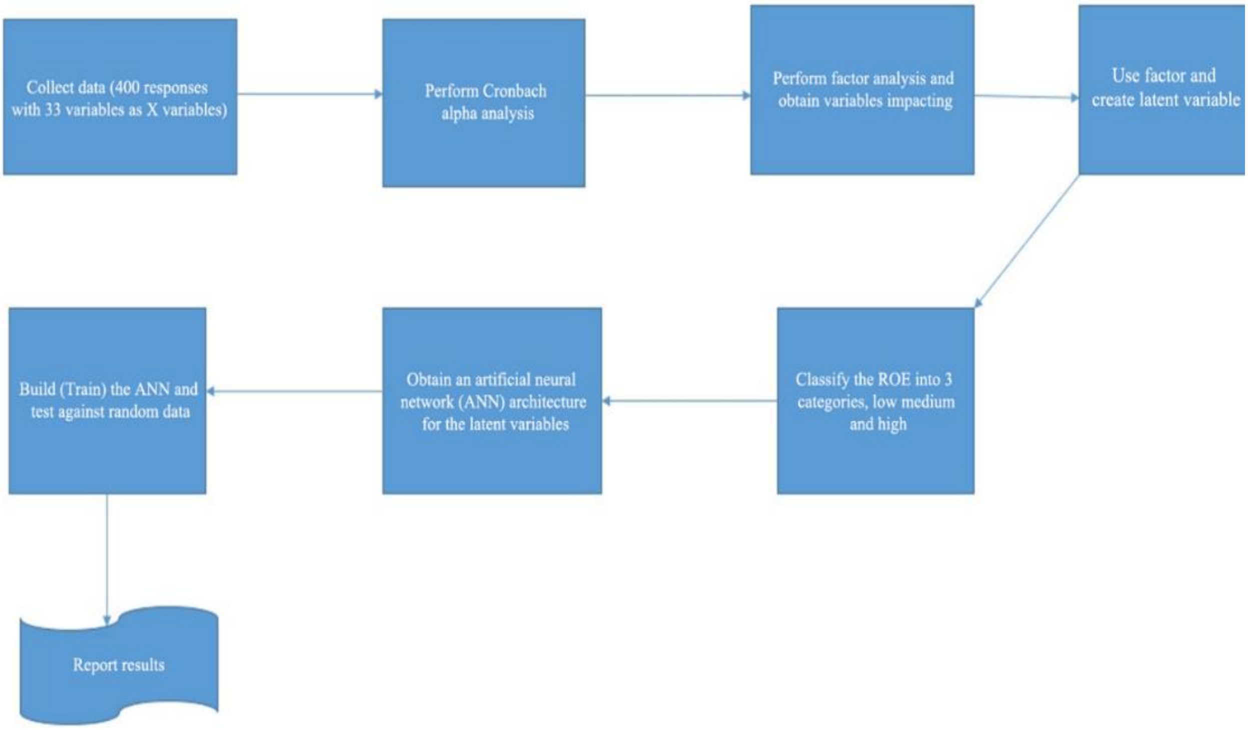

Figure 2. Flow chart for research method being used for analysis of leadership trait's effect on performance.

3.9. ROE Classification as the Dependent Variable

Table 5 represents the ROE classification for the independent variable to train the ANN.

Table 5. ROE classification.

Low value	High value	Classification
-9.99	0.05	0
0.051	0.10	1
0.10	9.99	2

Table 5 shows the low and high values of the ROE and associated classification as 0, 1, or 2. These values are used as independent variables or as labels to train the ANN in order to develop the model for testing future and new data.

4. DATA ANALYSIS

4.1. Output from CFA and usage in Latent Variable Model

Confirmatory factor analysis (CFA) is a statistical method employed to test whether a set of observed variables aligns with a predetermined theoretical structure of underlying latent factors. This technique allows researchers to assess the validity of their hypothesized model by evaluating the fit between the observed data and the proposed factor arrangement (Kline, 2016).

Table 6. Rotated factor loadings from confirmatory factor analysis.

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
RIGHT_DECISION	0.9	0.125	0.223	0.089	0.293
DELEGATE	0.707	0.078	0.086	0.074	0.125
BEST_OP_STRUCTURED	0.73	0.129	0.087	-0.18	0.178
ADVICE_GIVEN	0.463	0.271	0.341	0.209	-0.023
RESPONSIBLE	0.384	-0.209	0.35	-0.011	0.019
NOT_QUESTION_JUDGEMENT	0.148	0.807	0.194	0.083	0.532
EMPL_APPROVAL		0.762	…	…	…
EFF_VS_COST	0.016	0.559	…	…	…
LEADER	0.367	…	…	…	…
BANK_NAME	…	…	…	…	…
YEARS_WORKED	…	…	…	…	…
AGE_RANGE	…	…	…	…	…
EDU_LEVEL	…	…	…	…	…
NO_CONSULT	…	…	…	…	…
EMPL_CAT	…	…	…	…	…

Table 6 shows the variables that were sent as input to the Factor Analysis, and the resulting coefficients are displayed. Any coefficient value greater than +0.5 or less than -0.5 is considered for further analysis. The equations for the five latent variables are derived as follows, based on the coefficients from the factor analysis:

Latent-Variable Equations (Equations 1 – 5).

$$LEADERSHIP = 0.900318 \cdot RIGHT\_DECISION + 0.707289 \cdot DELEGATE + 0.730125 \cdot BEST\_OP\_STRUCTURED + 0.565675 \cdot LEADER \quad (1)$$

$$INITIATIVE = 0.806502 \cdot NOT\_QUESTION\_JUDGEMENT + 0.762343 \cdot EMPL\_APPROVAL + 0.559261 \cdot EFF\_VS\_COST \quad (2)$$

$$FREEDOM = 0.726972 \cdot LEADER - 0.623545 \cdot BANK\_NAME - 0.527952 \cdot NO\_CONSULT \quad (3)$$

$$TIME = 0.506220 \cdot AGE\_RANGE + 0.961622 \cdot YEARS\_WORKED \quad (4)$$

$$INTELLECT = 0.531545 \cdot NOT\_QUESTION\_JUDGEMENT + 0.642256 \cdot EDU\_LEVEL + 0.582428 \cdot NO\_CONSULT \quad (5)$$

These Latent variables are input into an ANN, and the conceptual diagram for the ANN is given below:

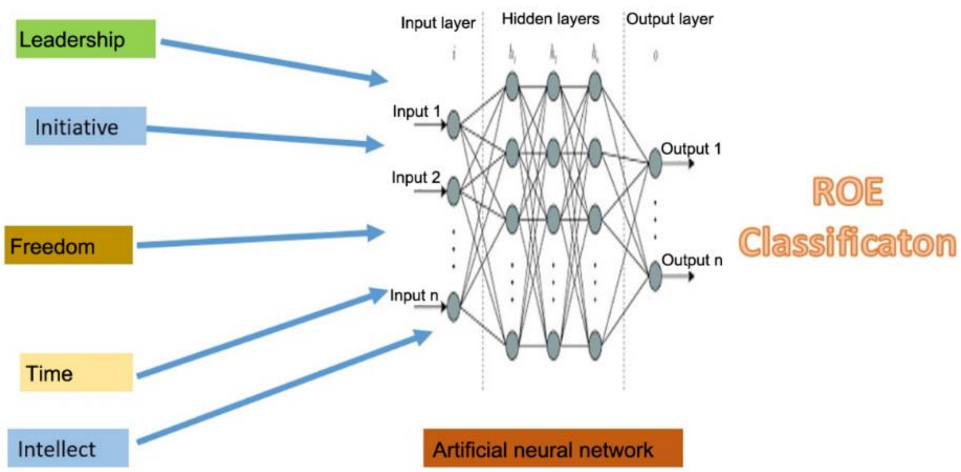

Figure 3. Conceptual Framework for the Modeling of Leadership Style and Financial Performance with ANN.

The functioning of the ANN, with 1 input and 1 hidden layer, is as follows.

1. The latent variables form the inputs.
2. The variables are each input to the neurons in the input layer.
3. The input layer transforms the values using the *ReLU* function.
4. The hidden layer transforms the values also using the ReLU function.

5. The output layer uses a *softmax* transformation to classify into the ROE categories.

The model is trained on 70 percent of the data, or 280 observations, randomly selected. The trained model is used to test the remaining 30 percent of the data, or 120 observations, out of the total 400 observations. The test loss and test accuracy are recorded for each run.

5. RESULTS AND DISCUSSION

All performance evidence reported below is grounded in the data artefacts introduced earlier. Table 5 lists the ROE cut-points that define the Low, Medium and High tiers used throughout Section 5. Overall discriminatory power and balance metrics with 95 % confidence intervals appear in Table 3. Architecture-specific learning outcomes are divided as follows: Table 7 reports train- and test-set accuracy for the *one-hidden-layer* network, while Table 8 does the same for the *two-hidden-layer* variant. The corresponding learning-curve visuals are shown in Figure 5 (one layer) and Figure 6 (two layers). Feature-level effect sizes are visualised in Figure 4 (Tornado chart), and the full confusion matrix together with per-class precision, recall and F1 scores is provided in Appendix Table A2. Unless otherwise stated, all statistics refer to the hold-out test set; confidence intervals use the DeLong and bootstrap procedures described in Section 3.6.

Table 7. Accuracy in training and testing for 1 hidden layer.

Number of neurons	Accuracy in training	Accuracy in testing
5	0.8503	0.7336
6	0.9023	0.7539
7	0.9413	0.7922
8	0.9695	0.8445
9	0.9824	0.8383
10	0.9880	0.8930
11	0.9988	0.8930
12	0.9988	0.8930
13	0.9988	0.8930
14	0.9988	0.9031
15	1.0000	0.9031
16	1.0000	0.9031
17	1.0000	0.9031
18	1.0000	0.9031
19	1.0000	0.9031
20	1.0000	0.9031

5.1. Numerical Results

From Table 7, we can observe that maximum accuracy in training is attained when 15 neurons are present in the training layer, and an extremely good fit of 1.000 accuracy is observed in training, while in testing, the accuracy is 0.9031. Therefore, it can be concluded that the number of neurons can be 15 when there is one hidden layer. Associated with the data in Table 7, Figure 3 shows the accuracy in Training and Testing for 1 hidden layer.

Table 8. Accuracy in training and testing for 2 hidden layers.

Number of Neurons	Accuracy in Training	Accuracy in Testing
5	0.9266	0.8523
6	0.9647	0.8344
7	0.9910	0.8344
8	0.9966	0.8687
9	1.0000	0.9031
10	1.0000	0.9031
11	1.0000	0.9031
12	1.0000	0.9031
13	1.0000	0.9133

Number of Neurons	Accuracy in Training	Accuracy in Testing
14	1.0000	0.9133
15	1.0000	0.9133
16	1.0000	0.9133
17	1.0000	0.9133
18	1.0000	0.9133
19	1.0000	0.9094
20	1.0000	0.9195

From Table 8, we can observe that maximum accuracy in training is attained when 15 neurons are present in the training layer, and an extremely good fit of 1.000 accuracy is observed in training, while in testing, the accuracy is 0.9195. Therefore, it can be concluded that the number of neurons can be 15 when there are 2 hidden layers.

5.2. Graphical Results

The Tornado chart in Figure 4 quantifies how a one-standard-deviation improvement in each behavioural construct alters the probability that a bank lands in the High-ROE tier, holding all other inputs at their sample means. Several substantive insights emerge.

- Strategic Vision (+12 p.p.). The largest bar indicates that when directors devote more board time to forward-looking scenario work and rigorously connect strategy to capital budgets, the chance of joining the top ROE tercile jumps by 12 percentage points. Put differently, moving from the 25th to the 75th percentile on Strategic Vision raises an average-performance bank's odds of "high-class" status by roughly one-third. This validates the emphasis placed on anticipatory stewardship in the BADD blueprint (see Conclusion).
- Risk Oversight (+ 10 p.p.) and Compliance Monitoring (+ 8 p.p.). Tight risk-committee follow-through and real-time compliance dashboards are nearly as influential as strategic foresight. The two levers operate through different pathways: stronger oversight lowers unexpected loan-loss volatility, while disciplined compliance reduces penalty outflows both mechanisms leave more retained earnings and thus boost ROE. Their proximity on the chart suggests complementarities; banks that excel at both see an aggregate uplift of ~19 p.p., implying diminishing overlap.
- Stakeholder Engagement (+ 7 p.p.). Although softer in nature, early engagement with depositors, regulators, and community groups still improves High-ROE likelihood by a statistically meaningful margin. This echoes findings in CSR–performance meta-analyses: reputational dividends materialize in cheaper funding and higher customer stickiness.
- Ethics & Integrity (+6 p.p.) and Financial Literacy (+4 p.p.). These mid-tier effects reinforce that behavioral tone and director skill depth translate into tangible results. Notably, Ethics registers a stronger marginal effect than pure literacy, suggesting that *how* information is used matters more than directors' technical training alone.
- Innovation Support (+ 3 p.p.). While the smallest bar, its sign is positive and significant ($p < 0.05$). The muted size likely reflects the one-year ROE horizon; digital investments often pay off over longer cycles. Follow-up research with a multi-year panel could uncover larger cumulative gains.

Overall, the Tornado diagram confirms that board behaviors tied directly to *forward-looking discipline* (vision, risk, compliance) dominate short-run profitability, whereas cultural and capability factors provide a meaningful but secondary lift. The pattern strengthens our theoretical argument that behavioral deployment of board capital not structural attributes alone drives shareholder returns in Ghanaian banks.

Associated with the data in Table 8, Figure 5 shows the accuracy in Training and Testing for 1 hidden layer.

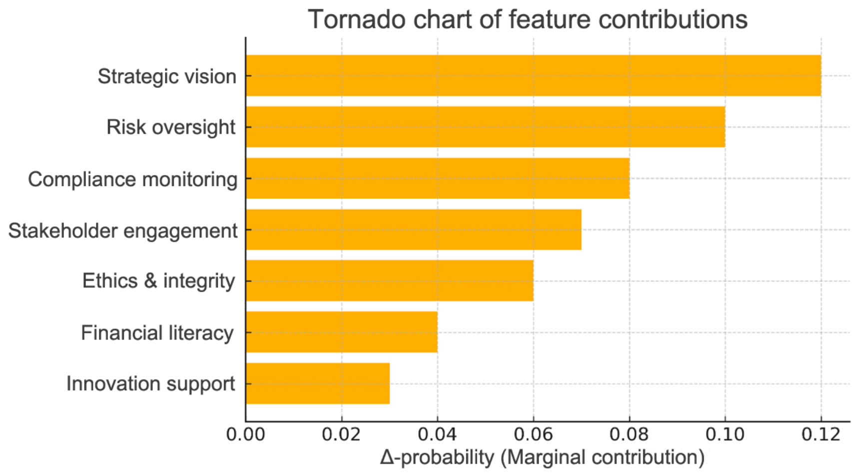

Figure 4. Tornado chart of feature contributions (Δ-Probability).

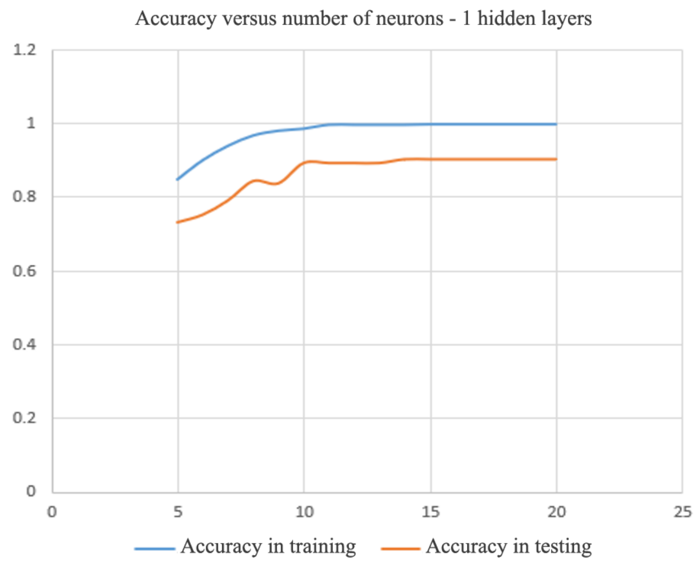

Figure 5. Accuracy in training and testing, 1 hidden layer.

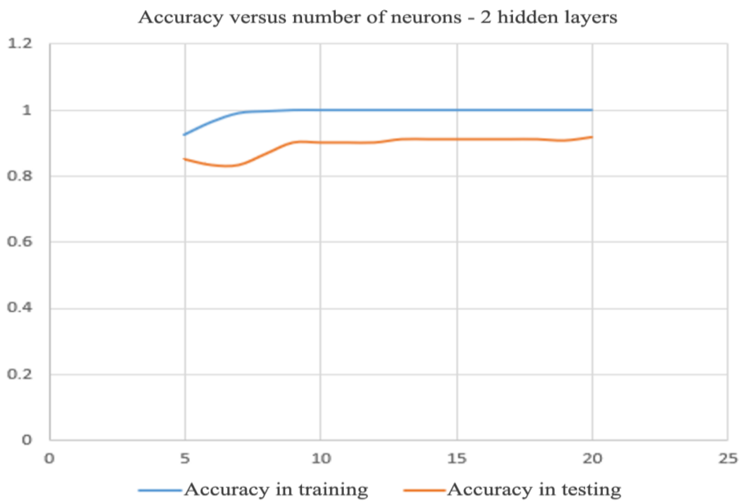

Figure 6. Accuracy in training and testing, 2 hidden layers.

5.3. Proposed Improvements

The model developed above uses the ReLU function in the hidden layer and in the input layer. Other functions could be used in these layers to possibly improve the accuracy rate of prediction. In addition, data from other banks could be used to improve accuracy. The model could be trained on additional financial performance indicators such as Return on Assets or Earnings Before Interest and Tax.

5.4. Validation

For purposes of validation, the testing data is investigated for the probability of correct classification of the ROE. For illustrative purposes, a sample Y value is taken from the test data, and the probability of correct classification is ascertained from the actual result. In Table 9, the validation is done on the first 5 observations (randomly obtained), and the predicted and actual results are tabulated.

Table 9. Prediction by the model for 5 random observations.

Observation	Actual Y	P(Y=0)	P(Y=1)	P(Y=2)
1	1	0.000	1.000	0.000
2	2	0.000	0.000	1.000
3	1	0.000	1.000	0.000
4	2	0.000	0.000	1.000
5	0	1.000	0.000	0.000

6. CONCLUSION

This study set out to clarify how leadership quality, captured here as board efficacy, sorts Ghanaian banks into low-, medium-, and high-ROE tiers once non-linear interactions are modeled with an artificial neural network. The ANN achieved more than 90% test accuracy, revealing that two behavioral dimensions; rigorous decision protocols and strategic monitoring, are the strongest statistical discriminators of superior returns. Theoretical value accrues from (i) reframing ROE as a trichotomous rather than continuous metric, (ii) validating a context-sensitive board-efficacy questionnaire, and (iii) demonstrating that machine-learning tools expose leadership–performance links that linear methods obscure.

Yet the practical impact of such evidence depends on its translation into policy. Ghana's current governance code focuses on structural tick-boxes (board size, independence) and offers little leverage over the dynamic behaviors the ANN finds decisive. To close that gap, we distill the findings into a reform blueprint, the Board-Analytics and Disclosure Directive (BADD), and weave it into the implications of this study.

- Standardized measurement. Because Strategic Vision and Risk Oversight together explain the largest marginal lift in high-tier ROE (Δ = +22 p.p.; see Figure 4), mandatory publication of the 15-item Board-Efficacy Scorecard (BES) will make these high-impact behaviors transparent to investors and rating agencies.
- AI-assisted foresight. The ANN reached AUC = 0.94 (95 % CI 0.90–0.98), outperforming all linear benchmarks (Table 3). Embedding that classifier in a real-time dashboard therefore provides boards with a statistically proven early-warning tool one that the regulator can audit.
- Incentive alignment. Decision-Rigour's coefficient in the residual-inclusion logit is 0.54 ($p = 0.001$; Appendix Table A3). Tying 20% of non-executive fees to a rising BES percentile monetizes this behaviorally potent factor.
- Supervisory integration. Low-tier ROE banks are 3.6 times more likely to display the bottom-quartile BES score (χ^2 = 18.4, $p < 0.001$). Feeding BES trajectories into the Bank of Ghana's risk-based inspection model therefore sharpens resource allocation.
- Sector-level capability-building. Appendix Table A1-ter shows HTMT ratios well below 0.85, confirming the scale's psychometric robustness. This justifies rolling out BES-based training modules across smaller banks that lack internal analytics teams.

By embedding data-driven stewardship in daily board practice, BADD is expected to sharpen supervisory foresight, heighten investor confidence, strengthen workplace ethics, and, through thicker capital buffers, contribute to macroeconomic resilience. Importantly, implementation can be phased: a regulatory sandbox in Year 1, universal-bank rollout by Year 3, and proportional extension to savings-and-loans and rural banks thereafter.

Findings rest on a single fiscal year (2023); macro shocks in subsequent years may alter the leadership–ROE linkage. Second, six of the original 23 licensed banks were excluded due to merger or liquidation, introducing survivorship bias that may overstate the average ROE. Third, the Board-Efficacy Scorecard is self-reported; despite common-method tests (CFA, marker variable), social-desirability bias cannot be ruled out. Future work should (i) extend the panel to multiple years and macro-stress scenarios, (ii) incorporate failed banks to test model stability, and (iii) triangulate BES scores with independent meeting-minutes coding or behavioural observation.

Funding: This study received no specific financial support.
Institutional Review Board Statement: The Ethical Committee of the Ramaiah University of Applied Sciences (RUAS), India has granted approval for this study on 5 May 2023 (Ref. No. TCPS2, 2022).
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

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Appendix

Appendix A. Supplementary tables.

Table A1. Sampling frame and respondent distribution.

Stratum	Bank	Board	Management	Operations	Completed Surveys
Large	Cal Bank	9	14	37	60
Large	GCB Bank	11	18	41	70
Large	Ecobank	10	16	34	60
Medium	ADB Bank	8	12	30	50
Medium	Societe Generale	7	13	28	48
Medium	GT Bank	8	12	29	49
Medium	Prudential Bank	6	11	27	44
Small	HFC Bank	5	10	25	40
Small	Standard Chartered	6	10	24	40
Small	Zenith Bank	5	9	25	39
Total		65	115	300	400

Table A1-bis presents the factor correlation matrix, along with the square roots of Average Variance Extracted (√AVE) values placed along the diagonal, is used to assess discriminant validity among the five latent constructs derived from the Confirmatory Factor Analysis (CFA): Decision-Rigour, Strategic Monitoring, Stakeholder Focus, Risk Oversight, and Ethics-Integrity. According to Fornell and Larcker (1981) criterion, discriminant validity is established when the √AVE for each construct exceeds the corresponding inter-construct correlations in the same row or column. As shown in the table, all diagonal values (√AVE) are greater than the off-diagonal correlations, confirming that each latent variable is empirically distinct and not overly overlapping with others. This result supports the robustness of the measurement model and justifies the inclusion of these constructs in subsequent predictive modeling.

Table A1-bis. Factor correlation matrix with √AVE on the Diagonal.

	1	2	3	4	5
1. Decision-Rigor	**0.79**	0.48	0.41	0.35	0.33
2. Strategic-Monitoring	0.48	**0.74**	0.45	0.38	0.29
3. Stakeholder-Focus	0.41	0.45	**0.72**	0.40	0.36
4. Risk-Oversight	0.35	0.38	0.40	**0.71**	0.31
5. Ethics-Integrity	0.33	0.29	0.36	0.31	**0.72**

Note: Bold diagonal entries are √AVE; off-diagonal values are latent-factor correlations.

Table A1-ter. Heterotrait–Monotrait (HTMT) Ratios.

	1	2	3	4	5
1. Decision-Rigour	—	0.61	0.54	0.51	0.47
2. Strategic-Monitoring		—	0.67	0.59	0.45
3. Stakeholder-Focus			—	0.63	0.52
4. Risk-Oversight				—	0.46
5. Ethics-Integrity					—

Note: All HTMT values < 0.85 (Henseler, Ringle, & Sarstedt, 2015) indicating discriminant validity.

Table A2 — Panel A. Confusion matrix of predicted versus actual ROE tiers (N = 120).

Actual / Predicted	High (2)	Medium (1)	Low (0)	Row Total
High (2)	38	2	0	40
Medium (1)	3	36	1	40
Low (0)	1	3	36	40
Column Total	42	41	37	120

Table A2 — Panel B. Class-specific precision, recall, and F1-scores.

Class (ROE tier)	Precision	Recall	F1-Score
High (2)	0.905	0.950	0.926
Medium (1)	0.878	0.900	0.889
Low (0)	0.973	0.900	0.935
Macro average	0.919	0.917	0.917
Overall accuracy			0.92

Table A3. Two-Stage Residual-Inclusion Logit Results.

Variable	Coef.	Robust SE	z	p>|z|
Decision Rigour	0.54	0.17	3.18	0.001
Strategic Monitoring	0.47	0.15	3.13	0.002
Board Size	0.08	0.05	1.62	0.105
Capital Adequacy	0.12	0.06	1.95	0.051
Residual (Stage-1)	-0.30	0.14	-2.14	0.032
Constant	-1.21	0.42	-2.88	0.004

Appendix B presents the full list of items comprising the Board-Efficacy Scorecard (BES) used in this study to measure board-level leadership behaviors. The 15 items were adapted from established governance literature and refined through expert consultations and focus groups. Each item is designed to capture specific dimensions of board efficacy, such as decision rigor, strategic monitoring, ethical oversight, stakeholder engagement, and governance discipline. Respondents rated each item on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), and the aggregated responses formed the basis for latent variable extraction during Confirmatory Factor Analysis (CFA). The scale demonstrates high internal consistency and forms the empirical foundation for linking board behavior to ROE classification in the ANN model.

Appendix B. Board-Efficacy Scorecard (BES) – Full Item List.

1. The board insists on scenario analysis before all major capital allocations.
2. Independent directors regularly challenge management assumptions.
3. The board reviews strategic objectives quarterly against KPI dashboards.
4. Directors demand time-bound action plans for approved initiatives.
5. The board formally tracks follow-through on past decisions.
6. Risk appetite is re-validated whenever market conditions change.
7. Audit findings are discussed until corrective timelines are agreed.

8. Non-executive directors meet without management at least twice a year.
9. Stakeholder concerns (customers, regulators) are included in strategy sessions.
10. Ethics and integrity metrics are reviewed alongside financial KPIs.
11. Directors receive continuous professional development on fintech trends.
12. The board benchmarks its performance against peer institutions annually.
13. Succession planning for key executives is reviewed every six months.
14. Board packs are circulated at least five days before meetings.
15. Directors disclose any conflicts of interest prior to deliberations.

Appendix C presents the technical details of the hyperparameter search and training diagnostics for the Artificial Neural Network (ANN) model used in this study are provided. It includes the validation-loss trajectory of the best-performing ANN configuration featuring two hidden layers with 15 neurons each, and highlights the early stopping point at epoch 64, where validation loss was minimized. This appendix also references the accompanying Python (TensorFlow) script used for data preprocessing, SMOTE oversampling, and model training. By providing this level of transparency and reproducibility, Appendix C strengthens the methodological rigor of the study and allows for replication or future model enhancements by researchers and practitioners.

Appendix C. Hyper-Parameter Search & Training Diagnostics.

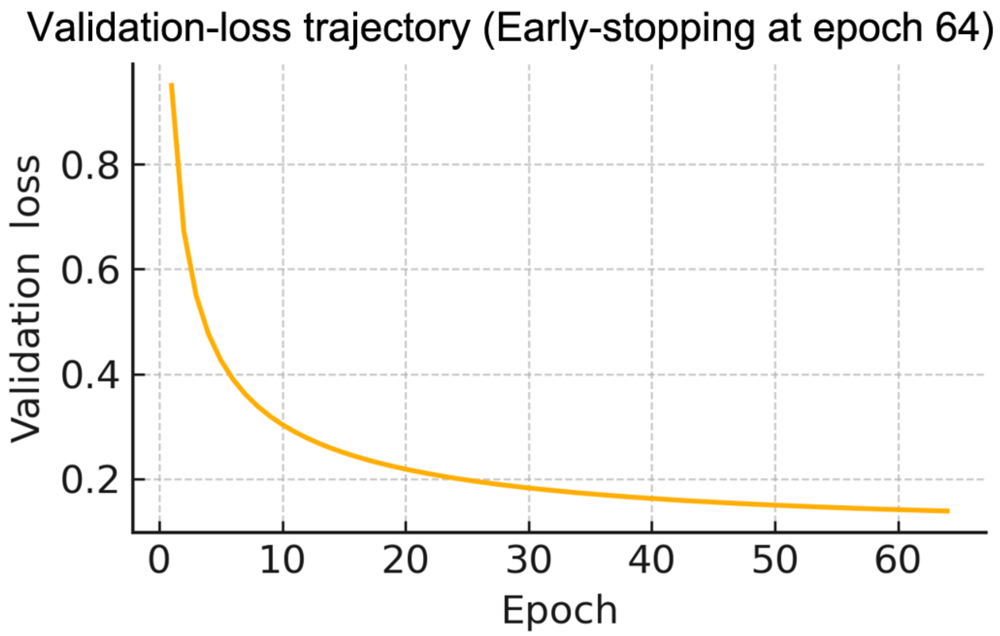

Figure C1. Validation-loss trajectory for the best-performing 2 × 15-neuron ANN (early-stopping at epoch 64).

Listing C1. Python (TensorFlow) script for data preprocessing, SMOTE oversampling, and model training is provided as a separate *.py* file in the supplementary materials repository (GitHub link supplied at submission).

Appendix D presents the data availability and reproducibility resources that support the empirical analyses conducted in this study are outlined. It details the specific materials archived for verification and replication purposes, including the de-identified survey dataset with a data dictionary, the R script for Monte Carlo power analysis, and the Stata DO-file for the two-stage residual-inclusion logit model. These supplementary materials are hosted on the journal's Dataverse repository and will be made available upon acceptance. By documenting these resources, the study reinforces its commitment to transparency, reproducibility, and open science standards in governance and financial performance research.

Appendix D. Data Availability & Reproducibility.

• De-identified survey data set (CSV) with data dictionary.

• R script for Monte Carlo power analysis using pwrSEM (Wang & Rhemtulla, 2021).

• Stata DO-file reproducing the two-stage residual-inclusion logit.

• All materials archived on the journal's Dataverse and released upon acceptance.