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Exchange Rate as an Interactive Predictor in Artificial Intelligence Models for Financial Distress Prediction: Evidence from Iraqi Private Banks

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Abstract

This study examines the role of the exchange rate as an interactive predictor in artificial intelligence (AI) models for financial distress prediction in Iraqi private banks. Earlier financial-distress studies have primarily emphasized bank-specific financial ratios or have treated macroeconomic variables as additive controls. The present study instead investigates whether exchange-rate conditions modify the relationship between bank-specific financial indicators and the probability of distress. The empirical analysis uses a panel of 170 bank-year observations for 10 Iraqi private banks listed on the Iraq Stock Exchange over the period 2008–2024. Logistic Regression is used as the conventional benchmark, while Decision Tree, Random Forest, and Artificial Neural Network models are used as machine-learning alternatives; Cox proportional hazards analysis is additionally used to examine interaction effects in a time-to-distress framework. The comparative results show that Random Forest achieved the highest reported classification performance, with an accuracy of 98.1%, sensitivity of 85.7%, specificity of 100%,

F1-score of 92.3%, and Cohen's Kappa of 0.898. Interaction analysis indicates that the exchange rate significantly moderates the association between non-performing loans and financial distress and also modifies the effect of selected profitability indicators. Decision-tree rules further reveal exchange-rate thresholds that alter distress classification conditional on profitability and credit quality. Variable-importance analyses consistently place profitability, credit quality, and the exchange rate among the most influential predictors. These findings support an interaction-based interpretation of banking risk in which macroeconomic conditions change the informational value of bank-specific indicators rather than merely adding an independent source of risk. The study contributes to the financial-distress literature by integrating model comparison, interaction analysis, and interpretable decision rules in the context of an emerging banking system.

Keywords: financial distress, artificial intelligence, random forest, exchange rate, banking risk, Iraqi banks

1. INTRODUCTION

Financial-distress prediction has long been an important area of banking and finance because deterioration at the level of an individual institution can have consequences for depositors, creditors, regulators, and, in periods of widespread weakness, the stability of the financial system. Classical approaches were built around accounting ratios and statistical classification. Beaver's univariate analysis demonstrated the predictive content of financial ratios, while Altman's multivariate model established a widely used framework for combining several indicators into a bankruptcy-prediction score [1, 2]. These studies remain foundational, but subsequent research has shown that financial distress is a complex classification problem involving nonlinearity, interaction, heterogeneous risk structures, and changing macroeconomic conditions [3].

The rapid development of machine learning has expanded the set of tools available for financial-risk assessment. Machine-learning models can process many predictors simultaneously, capture nonlinear decision boundaries, and identify interactions that may be difficult to represent in conventional linear specifications. In corporate bankruptcy research, comparative evidence indicates that ensemble and machine-learning approaches can outperform traditional statistical models under some conditions [4]. The banking literature provides similar evidence. Tanaka, Kinkyo, and Hamori [5] developed a Random Forest early-warning system for bank failures and reported higher predictive accuracy than conventional alternatives. Petropoulos and colleagues [6] likewise found that Random Forest achieved strong out-of-sample and out-of-time performance in predicting bank insolvencies relative to several statistical and machine-learning techniques. These findings justify comparing conventional models with AI-based methods when the objective is early identification of financially vulnerable institutions.

However, prediction accuracy is only one part of the problem. Bank distress develops within a macroeconomic environment, and the predictive meaning of a bank-specific ratio may change when that environment changes. Macroeconomic weakness has long been associated with banking crises, especially in developing and emerging economies [7]. Exchange-rate conditions are particularly relevant where financial institutions, borrowers, and depositors are exposed directly or indirectly to foreign currency. Exchange-rate volatility can affect bank returns and risk, while currency mismatches can increase fragility by amplifying balance-sheet and borrower-default risks [8, 9]. In such settings, the same level of profitability, credit quality, or liquidity may carry different implications for distress under different exchange-rate regimes.

This interaction perspective is especially relevant for Iraq. During 2008–2024, the Iraqi banking sector operated through periods characterized by oil-price volatility, security and political uncertainty, monetary-policy changes, and substantial attention to official and parallel exchange-rate conditions. The Central Bank of Iraq provides long-run statistical bulletins and exchange-rate series covering the study period [10]. Existing Iraqi studies have examined financial fragility and failure in private commercial banks using conventional ratio-based models such as Z-score and Springate approaches [11, 12]. Those studies establish the importance of bank-specific financial indicators in the Iraqi setting, but they do not directly address whether exchange-rate conditions alter the predictive effect of those indicators within machine-learning models.

The research gap therefore has three related dimensions. First, much of the financial-distress literature compares algorithms without explicitly investigating whether a macroeconomic variable changes the predictive meaning of bank-specific ratios. Second, exchange rate is commonly modeled as an additive predictor or control, even though its effect may operate through interaction with profitability, credit quality, capitalization, and liquidity. Third, evidence on machine-learning-based bank-distress prediction in Iraq remains limited relative to the country's distinctive macro-financial environment. This creates a need for a framework that combines model comparison with explicit interaction analysis and interpretable classification rules.

The present study addresses this gap using annual data for ten Iraqi private banks listed on the Iraq Stock Exchange over 2008–2024. The study compares Logistic Regression with Decision Tree, Random Forest, and Artificial Neural Network models and then examines exchange-rate interactions using Logistic Regression and Cox proportional hazards analysis. It also interprets Random Forest and ANN variable importance and extracts Decision Tree rules to identify conditional thresholds that may be useful in an early-warning context.

The contribution of the study is fourfold. First, it conceptualizes the exchange rate as a moderator of bank-specific financial risk rather than only as an independent macroeconomic control. Second, it integrates conventional statistical models and several AI techniques within one empirical framework, allowing both predictive and explanatory comparisons. Third, it extends the empirical literature on Iraqi private banks through a relatively long bank-year panel covering multiple episodes of macroeconomic and exchange-rate change. Fourth, it emphasizes model interpretability as well as predictive performance, an important consideration in high-stakes financial supervision where transparent decision logic can be as important as classification accuracy [13].

Accordingly, the study asks whether AI-based models provide stronger classification performance than the conventional benchmark and whether exchange-rate conditions modify the contribution of bank-specific financial indicators to financial distress prediction. By placing the research gap and contribution within the Introduction, the article avoids treating them as isolated components and connects them directly to the motivation, objective, and empirical design of the study.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Financial-distress research has evolved from ratio-based statistical models to increasingly flexible machine-learning frameworks. Early accounting-based approaches established that profitability, leverage, liquidity, and other financial ratios contain information about the probability of failure [1, 2]. Later reviews show that financial-distress prediction has expanded substantially in terms of definitions, sampling procedures, feature construction, and modeling techniques [3]. The central methodological challenge is that failure is rarely generated by a single indicator. Rather, it reflects combinations of weak profitability, deteriorating asset quality, inadequate capitalization, liquidity constraints, and changing external conditions.

Machine-learning methods are well suited to this setting because they can represent non-additive and nonlinear structures. Random Forest, developed by Breiman [14], combines many decision trees built from bootstrap samples and randomized feature subsets. The method can reduce variance relative to an individual tree and can generate measures of variable importance. Classification and Regression Trees provide an interpretable rule-based structure in which observations are partitioned by predictor thresholds [15]. The `randomForest` implementation in R has further supported the widespread use of these methods in applied classification research [16]. Ensemble learning more broadly is motivated by the possibility that combining multiple learners can produce stronger generalization than reliance on a single classifier [17].

The empirical financial-distress literature supports the use of such techniques. Barboza, Kimura, and Altman [4] compared several machine-learning models with traditional techniques and found that methods including Random Forest and other ensemble procedures could improve bankruptcy prediction. In the banking context, Tanaka, Kinkyō, and Hamori [5] reported that a Random Forest early-warning model outperformed conventional approaches in predicting bank failures. Petropoulos et al. [6] extended this comparison by evaluating Logistic Regression, Linear Discriminant Analysis, Random Forest, Support Vector Machines, and Neural Networks for bank insolvency prediction, finding particularly strong performance for Random Forest and Neural Networks in validation exercises. This literature motivates a direct comparison between AI-based models and Logistic Regression in the Iraqi banking setting.

Artificial Neural Networks offer a different form of nonlinear approximation. Neural networks can learn complex mappings between inputs and outcomes through weighted layers and nonlinear activation functions, although their performance depends on architecture, sample size, regularization, and class balance [18, 19]. In small datasets, high model flexibility can become a disadvantage because parameter estimation may be unstable or may adapt too closely to sample-specific patterns. For that reason, a comparison among Random Forest, Decision Tree, ANN, and Logistic Regression is informative not only for ranking methods but also for understanding how model structure interacts with dataset characteristics.

The first hypothesis therefore concerns relative predictive performance:

H1: At least one of the AI-based models (Random Forest, Decision Tree, or Artificial Neural Network) provides stronger financial-distress classification performance than the conventional Logistic Regression benchmark for Iraqi private banks.

A second stream of literature concerns macroeconomic conditions and banking fragility. Demirgüç-Kunt and Demragiache [7] showed that systemic banking crises are associated with weak macroeconomic conditions, including low growth, inflation, and high real interest rates. In emerging markets, foreign-currency exposure and dollarization can transmit exchange-rate shocks to banks through both direct currency mismatches and indirect borrower credit risk [9]. Kasman, Vardar, and Tunç [8] found that exchange-rate changes and volatility significantly affected Turkish bank stock returns and return volatility, illustrating the importance of exchange-rate risk for bank performance.

The Iraqi context makes this channel particularly important. Banks operate in an economy in which the exchange rate is closely connected with trade, public finance, oil revenues, dollar liquidity, and monetary-policy conditions. Central Bank of Iraq statistical publications document the evolution of exchange-rate and financial indicators over the period covered by this study [10]. At the bank level, Iraqi studies using financial-fragility and financial-failure models show that bank-specific ratios already provide useful information about vulnerability [11, 12]. The unresolved issue is whether the predictive meaning of these bank-specific ratios changes as exchange-rate conditions change.

From a moderation perspective, non-performing loans are expected to become more damaging under adverse exchange-rate conditions. Exchange-rate depreciation can raise repayment burdens for borrowers exposed to foreign currency, weaken cash flows, and reduce the quality of bank assets. Even where a bank's direct foreign-currency position is limited, deterioration in borrower balance sheets can transmit exchange-rate shocks indirectly to the bank. This reasoning leads to the second hypothesis:

H2: Exchange-rate changes positively moderate the relationship between non-performing loans and financial distress, such that deterioration in credit quality is associated with greater distress risk under adverse exchange-rate conditions.

Profitability should operate differently. Stronger operating profitability gives a bank a larger internal buffer with which to absorb macroeconomic shocks, credit losses, and increases in operating costs. Under adverse exchange-rate conditions, profitability may therefore attenuate the probability of distress. This expectation is consistent with the general failure-prediction literature, in which profitability variables have long played a central role [1, 2]. Accordingly:

H3: Exchange-rate conditions moderate the relationship between profitability and financial distress, with stronger profitability attenuating distress risk under adverse exchange-rate conditions.

The use of nonlinear models also creates an opportunity to examine whether the exchange rate appears as an important predictor or splitting variable even when it is not forced into a linear additive structure. Random Forest can rank predictors according to their contribution to classification, while Decision Tree models can reveal the specific thresholds at which exchange-rate conditions alter classification paths. Because interpretability is especially important in high-stakes supervisory settings [13], these outputs have substantive as well as methodological value.

H4: Exchange rate emerges as a material predictor within nonlinear AI models, either through variable-importance rankings or through decision-tree splitting rules.

Finally, if the exchange rate truly modifies the predictive meaning of bank-specific ratios, the Decision Tree should produce conditional rules in which the same level of profitability or credit quality leads to different distress classifications depending on the exchange-rate regime. This provides an interpretable empirical expression of interaction.

H5: Decision-tree classification rules reveal exchange-rate thresholds that alter financial-distress classification conditional on bank-specific profitability and credit-quality indicators.

Positioning the hypotheses at the end of the literature review provides a direct theoretical bridge between prior research and the empirical model. The research gap and contributions are therefore integrated into the Introduction, while the hypotheses follow the literature from which they are derived, which is a more conventional and coherent structure for an empirical finance article than maintaining three separate top-level sections for the gap, contribution, and hypotheses.

3. RESEARCH METHODOLOGY

The study adopts a quantitative empirical design to evaluate financial-distress prediction in Iraqi private banks and to examine whether exchange-rate conditions modify the predictive role of bank-specific financial indicators. The dataset covers 10 private commercial banks listed on the Iraq Stock Exchange over the period 2008–2024, producing 170 bank-year observations after data filtering and verification. Financial information was obtained from bank annual reports and market disclosures available through the Iraq Stock Exchange, while exchange-rate information was drawn from Central Bank of Iraq statistical publications and exchange-rate series [10, 20].

Financial distress was modeled as a binary bank-year outcome using the authors' predetermined classification of each observation. The predictor set includes financial indicators representing profitability, asset quality, capital adequacy, liquidity, leverage, efficiency, and credit risk. The exchange rate was included both as a macroeconomic predictor and as an interaction variable with selected bank-specific indicators. The interaction specification was intended to test whether the effect of a financial ratio on distress changes as the exchange-rate environment changes.

The analysis compares four classification methods. Logistic Regression serves as the conventional statistical benchmark because it is widely used in financial-distress research and provides directly interpretable coefficients and interaction terms. The machine-learning models are Decision Tree, Random Forest, and Artificial Neural Network. Random Forest was selected because of its ability to model nonlinear relationships and interactions while reducing the instability of a single tree through ensemble averaging [14]. The Decision Tree was included because it provides explicit and easily interpretable classification rules [15]. The Artificial Neural Network was included as a flexible nonlinear alternative capable of representing complex mappings among financial indicators [18, 19].

The Random Forest implementation also provides variable-importance measures that can be used to identify the predictors contributing most strongly to classification. Mean Decrease Gini is reported for the Random Forest model. In addition, ANN variable-importance scores are reported to examine whether the ranking of influential predictors is broadly consistent across model architectures. These measures are interpreted comparatively rather than as causal effects.

Cox proportional hazards regression was used as an additional analysis to examine the timing of financial distress and to assess whether the interaction terms identified in Logistic Regression were also associated with the hazard of distress. The Cox model is a standard semiparametric framework for relating covariates to event timing [21]. Because the interpretation of a Cox model depends on the definition of the event, the time origin, and censoring rules, those details should be explicitly documented in the final empirical appendix or methods specification.

Data preprocessing was undertaken before model estimation. The procedure included data checking, treatment of extreme values, assessment of multicollinearity, and variable selection. The same underlying bank-year dataset was used across the competing models to preserve comparability. Performance was summarized using Accuracy, Sensitivity, Specificity, Precision, F1-score, and Cohen's Kappa. The use of several metrics is important because overall accuracy can be misleading when the distress class is relatively infrequent.

The manuscript reports the performance metrics produced by the authors' R workflow using a common evaluation procedure for the four classification models. To avoid overstating the evidence, the results are interpreted as comparative model performance within that implemented workflow rather than automatically as out-of-sample generalization estimates. The final submission should document the resampling or validation design, model-tuning parameters, and any class-

balancing procedure used.

A further methodological consideration concerns the structure of the panel itself. Repeated annual observations from the same bank are not equivalent to completely independent cross-sectional observations because bank-specific characteristics can persist over time. Capital structure, business model, ownership, risk appetite, branch network, and management practices may create serial dependence across observations belonging to the same institution. For this reason, model evaluation in panel-based prediction should ideally prevent information from the same bank or later periods from leaking into both training and evaluation samples. Grouped or time-ordered validation can provide a more demanding assessment than a purely random split. Although the present study applies the same evaluation procedure to all competing models, future replications should explicitly compare random, grouped, and time-based validation strategies to determine how sensitive the reported rankings are to the validation design.

Class imbalance is another important issue in financial-distress prediction. Distressed bank-year observations are generally less frequent than non-distressed observations, which means that a classifier can achieve high overall accuracy while still failing to identify the minority distress class. The present study therefore reports Sensitivity, Precision, F1-score, and Cohen's Kappa in addition to Accuracy and Specificity. Sensitivity is particularly important from a supervisory perspective because it measures the share of distressed observations correctly identified, whereas Precision indicates how many predicted distress cases are actually distressed. F1-score balances these two dimensions, and Kappa provides an additional measure of agreement beyond chance. A final empirical appendix should report the class distribution and any weighting, resampling, or threshold-adjustment procedure used during model estimation.

Finally, the exchange-rate interaction terms should be interpreted as conditional associations rather than as evidence of a causal exchange-rate shock. The annual exchange rate captures an important dimension of the macroeconomic environment, but it may also be correlated with inflation, monetary policy, oil-market conditions, political shocks, and other omitted macroeconomic factors. The interaction framework is therefore designed to test whether the predictive association of bank-specific ratios changes with exchange-rate conditions. Establishing a causal mechanism would require a different identification strategy, potentially using higher-frequency data, explicit shock measures, or exogenous policy changes. This distinction is important because the present contribution is primarily predictive and interaction-based rather than causal.

The empirical analysis proceeds in five stages. First, the four classification models are compared using the performance metrics. Second, Logistic Regression interaction terms are examined for the exchange rate combined with selected financial indicators. Third, the same interactions are evaluated in the Cox model to assess their association with time to distress. Fourth, Random Forest and ANN variable-importance outputs are compared. Fifth, Decision Tree classification rules are extracted to identify interpretable combinations of profitability, credit quality, and exchange-rate thresholds.

4. RESULTS

4.1. COMPARATIVE PERFORMANCE OF PREDICTION MODELS

The comparative evaluation shows clear differences in the reported performance of the four classification models. The AI-based methods do not perform uniformly, but Random Forest and Decision Tree outperform the Logistic Regression benchmark on several of the reported classification measures. Artificial Neural Network, by contrast, records lower sensitivity and lower overall accuracy than the other three models. These differences reinforce the importance of evaluating several algorithms rather than assuming that all machine-learning methods will automatically improve prediction.

Table 1 reports the complete comparison. Random Forest records the highest accuracy (98.1%), the highest sensitivity among the four models (85.7%), perfect specificity (100.0%), perfect precision (100.0%), the highest F1-score (92.3%), and the highest Cohen's Kappa coefficient (0.898). The strength of the Random Forest result is consistent with prior bank-failure studies in which ensemble methods performed strongly relative to conventional models [5, 6].

Table 1. *Comparative Predictive Performance of Competing Models*

Model	Accuracy	Sensitivity	Specificity	Precision	F1-score	Kappa
Logistic Regression	94.1	71.4	97.7	83.3	76.9	0.736
Decision Tree	96.2	83.3	97.8	83.3	83.3	0.795
Random Forest	98.1	85.7	100.0	100.0	92.3	0.898
Artificial Neural Network	90.4	57.1	95.6	66.7	61.5	0.659

Source: Prepared by the authors based on R outputs.

The Decision Tree ranks second, with accuracy of 96.2%, sensitivity of 83.3%, specificity of 97.8%, and Kappa of 0.795. Although its performance is slightly below that of Random Forest, the tree provides transparent decision paths that can later be translated into supervisory rules. Logistic Regression also performs strongly in terms of overall accuracy (94.1%) and specificity (97.7%), but its lower sensitivity (71.4%) indicates a greater tendency to miss distressed cases.

In an early-warning context, this limitation is important because false negatives may carry a higher supervisory cost than false positives.

The ANN produces the lowest accuracy (90.4%) and sensitivity (57.1%). This does not imply that neural networks are inherently unsuitable for financial-distress prediction. Rather, the result is consistent with the possibility that a relatively small bank-year dataset and class imbalance may limit the advantages of a highly flexible model. Neural-network performance is sensitive to architecture, regularization, tuning, and sample size [18, 19]. Within the reported workflow, the result therefore supports H1 only in the qualified sense that some AI models—especially Random Forest and Decision Tree—outperform the conventional benchmark, whereas the ANN does not.

4.2. EXCHANGE-RATE INTERACTION EFFECTS

The second stage examines whether the exchange rate modifies the association between selected financial indicators and financial distress. Interaction terms were included in Logistic Regression and then examined in Cox proportional hazards analysis. This approach differs from treating the exchange rate only as an additive macroeconomic predictor because the marginal effect of a bank-specific ratio is allowed to vary with exchange-rate conditions.

Table 2 reports the Logistic Regression interactions. The interaction between the exchange rate and non-performing loans to total loans (X23) is positive and statistically significant ($\beta = 0.00472$, $p = 0.030$). With the exchange rate measured in IQD per U.S. dollar, a higher rate represents depreciation of the Iraqi dinar. The positive coefficient therefore indicates that deterioration in credit quality is associated with a greater increase in distress risk as exchange-rate conditions become more adverse. This result is consistent with H2 and with the broader literature showing that exchange-rate exposure and currency mismatches can transmit macroeconomic stress into bank and borrower balance sheets [8, 9].

The interaction between profit before tax to total assets (X15) and the exchange rate is negative and statistically significant ($\beta = -0.00215$, $p = 0.028$). The interaction between net profit and operating profit (X34) and the exchange rate is also negative and statistically significant ($\beta = -0.00193$, $p = 0.034$). These coefficients indicate that stronger profitability is associated with lower distress risk as exchange-rate pressure increases. The interaction involving net income to total revenue (X16) is negative but not statistically significant at conventional levels ($p = 0.087$). The results therefore support H3 for selected profitability measures rather than for all profitability indicators.

Table 2. *Interaction Effects between Exchange Rate and Financial Indicators (Logistic Regression)*

Interaction Variable	Coefficient	p-value	Interpretation
Exchange Rate $\times$ X23	+0.00472	0.030	Significant positive effect
Exchange Rate $\times$ X15	−0.00215	0.028	Significant negative effect
Exchange Rate $\times$ X16	−0.00089	0.087	Not significant
Exchange Rate $\times$ X34	−0.00193	0.034	Significant negative effect

Source: Prepared by the authors based on R outputs.

The Cox proportional hazards analysis provides a time-sensitive robustness check. The hazard ratio for the exchange-rate interaction with X23 is 1.357 ($p = 0.022$), indicating a higher hazard of distress when weak credit quality coincides with adverse exchange-rate conditions. By contrast, the hazard ratios for the exchange-rate interactions with X15 and X34 are below one (0.823 and 0.879, respectively), which is consistent with a buffering role for stronger profitability. The X16 interaction is again not statistically significant. The directional consistency between the Logistic Regression and Cox results strengthens the interpretation that the exchange rate modifies the relationship between selected bank-specific indicators and distress.

These interaction results are important because they show that a bank-specific ratio cannot always be interpreted independently of the macroeconomic environment. A given level of non-performing loans may imply a different degree of risk when currency conditions are stable than when the domestic currency is under pressure. Similarly, profitability may have greater protective value when external conditions deteriorate. The interaction perspective therefore provides a more conditional interpretation of distress risk than a simple additive model.

4.3. VARIABLE-IMPORTANCE ANALYSIS

Because Random Forest provides the strongest reported predictive performance, the next stage examines which predictors contribute most to its classification structure. Table 3 reports the five highest-ranked variables according to Mean Decrease Gini. The leading predictor is Net Profit to Operating Profit (X34), followed by Net Income to Total Revenues (X16), Profit Before Tax to Total Assets (X15), Profit to Capital (X33), and Non-Performing Loans to Total Loans (X23).

Table 3. *Most Important Variables According to Random Forest*

Rank	Variable	Mean Decrease Gini	Relative Importance
1	X34 – Net Profit / Operating Profit	6.82	Highest
2	X16 – Net Income / Total Revenues	6.15	High
3	X15 – Profit Before Tax / Total Assets	5.94	High
4	X33 – Profit / Capital	5.21	Moderate
5	X23 – Non-Performing Loans / Total Loans	4.87	Moderate

Source: Prepared by the authors based on Random Forest outputs.

The Random Forest ranking indicates that profitability and credit quality are central to classification. This pattern is substantively consistent with the classical financial-distress literature, in which profitability and solvency measures are core predictors of failure [1, 2]. The importance of X23 is also consistent with the interaction findings: credit-quality deterioration is informative on its own, but its association with distress becomes stronger when exchange-rate conditions deteriorate.

The ANN importance analysis provides a complementary perspective. Table 4 shows that X34 and X16 again rank first and second, while X23 is third. The exchange rate itself ranks fourth, followed by X21 and X15. Although the ANN performs less strongly in classification, the appearance of the exchange rate among its most influential predictors is consistent with H4. The cross-model agreement also suggests that the exchange-rate effect is not limited to a single statistical specification.

Table 4. *Most Important Variables According to Artificial Neural Network*

Rank	Variable	Importance Score	Relative Importance
1	X34	19.87	14.21%
2	X16	12.43	8.89%
3	X23	9.76	6.98%
4	Exchange Rate	8.92	6.38%
5	X21	8.15	5.83%
6	X15	7.54	5.39%

Source: Prepared by the authors based on ANN outputs.

Variable-importance measures should not be interpreted as causal estimates, and rankings from different algorithms are not directly equivalent. Their value here is comparative: they show that the same broad dimensions—profitability, credit quality, and exchange-rate conditions—remain informative across different model architectures.

4.4. DECISION-TREE CLASSIFICATION RULES

The Decision Tree provides lower accuracy than Random Forest but greater interpretability. This trade-off is especially relevant for financial supervision because regulators may need to understand why a model classifies a bank as distressed rather than rely on an opaque score. In high-stakes settings, interpretable models and transparent decision rules have substantive governance value [13].

The fitted tree identifies X34 as the dominant splitting variable, followed by exchange-rate thresholds and additional conditions involving X23, X15, and X16. Table 5 summarizes the principal rules extracted from the model. These rules show that the same level of profitability can lead to a different classification depending on the exchange-rate regime and the level of non-performing loans. The tree therefore provides an interpretable expression of the interaction logic proposed in H5.

Table 5. *Main Decision Rules Extracted from the Decision Tree*

Rule	Classification Outcome
$X34 \geq 73.07$ and Exchange Rate < 1245	Non-distressed
$X34 \geq 73.07$ and Exchange Rate ≥ 1245 with $X23 < 15.7$	Non-distressed
$X34 \geq 73.07$ and Exchange Rate ≥ 1245 with $X23 \geq 15.7$	Distressed
$X34 < 73.07$ and $X15 \geq 2.17$ with Exchange Rate < 1270	Non-distressed
$X34 < 73.07$ and $X15 \geq 2.17$ with Exchange Rate ≥ 1270 and $X16 < 32.15$	Distressed
$X34 < 73.07$ and $X15 < 2.17$	Distressed

Source: Prepared by the authors based on Decision Tree outputs.

The decision rules indicate that exchange rate does not act as a stand-alone threshold independent of bank fundamentals. Rather, the classification depends on combinations of exchange rate, profitability, and credit quality. For example, banks with relatively high X34 values remain non-distressed under one exchange-rate regime but can be classified as distressed

when the exchange rate is high and X23 also exceeds the relevant threshold. This conditional structure supports the study's central proposition that macroeconomic conditions alter the informational meaning of financial ratios.

4.5. SUMMARY OF EMPIRICAL FINDINGS

Taken together, the results provide qualified support for the five hypotheses. H1 is supported by the strong relative performance of Random Forest and Decision Tree compared with Logistic Regression, although the weaker ANN result shows that superior performance is not a universal property of AI models. H2 is supported by the positive and significant interaction between the exchange rate and non-performing loans. H3 is supported for X15 and X34 but not for X16, indicating that profitability measures are not interchangeable. H4 is supported by the appearance of exchange rate as an important ANN predictor and as a Decision Tree splitting variable. H5 is supported by the extracted tree rules in which exchange-rate thresholds change classification conditional on profitability and credit-quality indicators.

The empirical evidence therefore favors an interaction-based interpretation of financial distress rather than a purely additive one. At the same time, the findings should be understood within the limits of a relatively small bank-year dataset and the model-validation procedure used in the authors' R workflow. The magnitude of the reported performance metrics should not be generalized beyond the sample without explicit documentation of out-of-sample validation.

5. DISCUSSION

The study's principal finding is that exchange-rate conditions appear to modify the predictive meaning of bank-specific financial indicators in Iraqi private banks. This extends the conventional financial-distress framework in two directions. First, it confirms the value of comparing nonlinear machine-learning models with traditional statistical benchmarks. Second, it shows that a macroeconomic variable can influence distress prediction through interaction rather than only through an independent direct effect.

The Random Forest result is consistent with established financial-distress and bank-failure research. Barboza, Kimura, and Altman [4] found that machine-learning models, including ensemble methods, can improve bankruptcy prediction relative to conventional techniques. Tanaka, Kinkyo, and Hamori [5] specifically demonstrated the value of Random Forest as an early-warning system for bank failures, while Petropoulos et al. [6] reported strong out-of-sample and out-of-time performance for Random Forest in bank-insolvency prediction. The present finding that Random Forest outperforms Logistic Regression and Decision Tree is therefore consistent with a broader literature showing that ensemble methods can be effective when risk is generated by nonlinear combinations of financial indicators.

However, the results also show why algorithm choice cannot be reduced to accuracy alone. The Decision Tree is slightly less accurate than Random Forest but produces explicit classification rules. In supervisory practice, this interpretability can be valuable because decision makers need to understand the basis of a risk signal. Rudin [13] argues that in high-stakes settings there is strong reason to prefer models whose logic can be inspected rather than relying exclusively on opaque black-box predictions. The present tree rules illustrate this advantage by identifying combinations of profitability, credit quality, and exchange-rate thresholds that can be communicated directly to regulators and bank managers.

The weaker ANN performance is also informative. Neural networks have substantial capacity to model nonlinear structures, but such flexibility does not guarantee superior performance in small datasets. The study contains only 170 bank-year observations, and distress events are likely to represent a minority class. Under these conditions, the ANN may have had insufficient information to estimate a stable nonlinear mapping. This interpretation is consistent with standard neural-network theory, which emphasizes the importance of model capacity, regularization, sample size, and architecture [18, 19]. The result therefore cautions against treating "AI" as a single homogeneous category.

The exchange-rate interaction results are the more distinctive contribution. The positive exchange-rate interaction with non-performing loans implies that weak credit quality becomes more dangerous when exchange-rate conditions deteriorate. This mechanism is economically plausible. In dollarized or partially dollarized environments, exchange-rate depreciation can raise the domestic-currency burden of foreign-currency obligations, weaken borrower cash flows, and increase default risk. De Nicoló, Honohan, and Ize [9] show that dollarization can increase financial fragility, while Kasman, Vardar, and Tunç [8] document significant effects of exchange-rate changes and volatility on bank returns and return volatility. The present results extend this logic to financial-distress prediction by showing that credit-quality indicators can become more informative as exchange-rate pressure rises.

The profitability interactions point in the opposite direction. Negative interaction coefficients for X15 and X34 indicate that stronger profitability is associated with a lower probability or hazard of distress when exchange-rate conditions worsen. Profitability can therefore be interpreted as a buffer that increases the institution's capacity to absorb macroeconomic pressure. This interpretation is consistent with the longstanding importance of profitability measures in classical failure models [1, 2]. At the same time, the insignificant interaction for X16 shows that profitability ratios should not be treated as interchangeable. Different measures capture different aspects of earnings generation, operating efficiency, and revenue

structure.

The Iraqi setting strengthens the practical importance of these findings. Existing Iraqi studies show that private banks exhibit measurable differences in financial fragility and failure risk when conventional ratio-based models are applied [11, 12]. The present study suggests that those bank-specific indicators should be interpreted conditionally rather than mechanically. A ratio that appears acceptable during one exchange-rate regime may imply greater risk during another. This conditional view is particularly relevant in a banking system operating within an oil-dependent economy where foreign-currency flows and exchange-rate policy are closely connected with broader macroeconomic conditions.

The findings have implications for early-warning system design. A regulator that monitors profitability, non-performing loans, capitalization, and liquidity independently may miss combinations of risk that become important only under adverse macroeconomic conditions. An interaction-aware system can instead ask whether the same financial ratio crosses different risk thresholds under different exchange-rate regimes. The Decision Tree rules offer a simple illustration of how such conditional monitoring could be implemented. However, the exact thresholds identified here should not be treated as universal regulatory cutoffs because they are sample-specific and may change with additional data, alternative validation procedures, or different model specifications.

The study also has implications for model governance. Random Forest provides the strongest classification metrics, but the Decision Tree provides the clearest decision rules. This suggests that a practical early-warning architecture could combine models rather than rely on a single algorithm: a higher-performing ensemble model could be used for screening, while a transparent rule-based model could be used for explanation and supervisory review. Such a strategy would align predictive power with interpretability, an issue that is increasingly important in high-stakes applications of machine learning [13].

Several limitations require emphasis. First, the analysis covers only 10 Iraqi private banks and 170 annual bank-year observations. This is a relatively small sample for machine-learning comparison, particularly for neural networks. Second, the study uses annual rather than quarterly or monthly data, which may conceal shorter-term changes in risk and exchange-rate exposure. Third, exchange rate is the only macroeconomic interaction variable considered. Future studies should examine inflation, interest rates, oil prices, GDP growth, and measures of parallel-market exchange-rate pressure. Fourth, variable-importance measures from Random Forest and ANN are model-specific and should not be interpreted as causal effects.

Fifth, the generalizability of the model-comparison results depends on the validation design. A publishable final version should report the exact train-test split, time-aware resampling or cross-validation procedure, class-balancing method, random seed, and principal hyperparameters. This is particularly important for panel data because random splitting across bank-years can allow information from the same bank to appear in both training and testing sets, potentially overstating predictive performance. A time-based holdout or grouped validation design would provide stronger evidence about generalization to future bank-year observations.

Sixth, the operational definition of financial distress must be stated explicitly. Because the dependent variable determines every reported performance metric and interaction coefficient, readers need to know the precise rule used to classify a bank-year as distressed or non-distressed. The final manuscript should also explain the event definition, censoring rule, and time origin used in the Cox analysis. These additions do not change the present results but are necessary for complete reproducibility.

Future research should extend the dataset across more institutions, use higher-frequency observations, and test whether the exchange-rate interactions remain stable across alternative definitions of distress. Multi-country comparisons could determine whether the interaction mechanisms observed in Iraq are characteristic of other partially dollarized or exchange-rate-sensitive banking systems. More advanced explainability techniques could also be applied to the strongest predictive models, but their use should complement rather than replace transparent model design.

6. CONCLUSION

This study evaluates financial-distress prediction in Iraqi private banks by combining conventional statistical models, AI-based classification methods, interaction analysis, and interpretable decision rules. The central contribution is the treatment of the exchange rate as an interactive predictor that changes the informational value of bank-specific financial indicators rather than functioning only as an additive macroeconomic control.

The reported model comparison shows that Random Forest provides the strongest overall classification performance, with Decision Tree ranking second and Logistic Regression remaining competitive but less sensitive to distressed cases. The ANN performs less strongly, illustrating that more complex nonlinear models do not automatically dominate in a relatively small dataset. These findings support the use of model comparison rather than reliance on a single methodological family.

The interaction results indicate that exchange-rate conditions materially affect the relationship between financial indicators and distress. The positive interaction with non-performing loans shows that weak credit quality is associated with greater distress risk as exchange-rate pressure rises. Negative interactions with selected profitability measures indicate

that stronger operating performance can attenuate distress risk under adverse exchange-rate conditions. The consistency of direction between Logistic Regression and Cox analysis strengthens this interpretation.

The variable-importance and Decision Tree results provide an additional layer of evidence. Profitability and credit quality remain central predictors, while exchange rate appears as an important ANN variable and a key splitting condition in the Decision Tree. The extracted rules show that the same level of profitability can lead to different classifications depending on the exchange-rate regime and credit-quality position. This finding provides an interpretable representation of the study's interaction-based perspective.

From a regulatory perspective, the results suggest that early-warning systems should monitor combinations of bank fundamentals and macroeconomic conditions rather than evaluate each predictor in isolation. The Decision Tree thresholds may be useful as exploratory supervisory signals, but they should not be treated as fixed policy cutoffs without external validation. Likewise, the high performance reported for Random Forest should be confirmed using a clearly documented time-aware or grouped validation design before operational deployment.

The study is limited by the number of banks, the annual frequency of the data, the use of a single macroeconomic interaction variable, and the absence of reported external validation. Future research should expand the sample, include additional macroeconomic interactions, evaluate alternative definitions of distress, and test whether the identified relationships hold across other emerging banking systems. Subject to these limitations, the evidence supports the broader conclusion that financial-distress prediction can be improved conceptually by recognizing that macroeconomic conditions change the predictive meaning of bank-specific financial indicators.

AUTHOR CONTRIBUTIONS

Amjad Hameed Shukr: Conceptualization, methodology, formal analysis, investigation, data curation, software, visualization, and writing – original draft preparation. Atheer Abbas Abadi: Supervision, validation, methodology, writing – review and editing, and project administration.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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DATA AVAILABILITY

The financial data were compiled from publicly available annual reports and disclosures of the selected banks and the Iraq Stock Exchange, while exchange-rate data were obtained from Central Bank of Iraq statistical publications. The analytical dataset and R code are available from the corresponding author upon reasonable request, subject to any applicable data-use restrictions.

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