“Funding gap and bank stability in ASEAN emerging markets: Evidence from explainable machine learning for stability forecasting”

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FUNDING GAP AND BANK STABILITY IN ASEAN EMERGING MARKETS: EVIDENCE FROM EXPLAINABLE MACHINE LEARNING FOR STABILITY FORECASTING

Abstract

The study analyzes the role of the Funding Gap (FGAP) as a dynamic structural liquidity indicator that influences bank financial stability in emerging markets, particularly amid heightened post-COVID-19 financial volatility. It aims to forecast banking stability by integrating advanced econometric and machine-learning techniques using a balanced panel dataset of 63 commercial banks from six ASEAN countries over the period 2010–2023. The methodological framework combines Ridge regression for variable selection, Particle Swarm Optimization (PSO) for hyperparameter tuning, and SHapley Additive exPlanations (SHAP) for interpretability within a Gradient Boosting model. The PSO-optimized specification achieves an R^2 of 92.2%, substantially outperforming traditional fixed-effects and random-effects regressions. Empirical results indicate that persistent negative FGAP values significantly reduce Z-scores, confirming that structural liquidity imbalances constitute a key transmission channel from funding stress to systemic fragility. The analysis further reveals the moderating role of macroeconomic shocks, particularly inflation and the COVID-19 pandemic, in amplifying liquidity-induced instability. The proposed framework functions as an operational early warning system that enhances forecasting accuracy, model interpretability, and regulatory transparency, while repositioning FGAP as a forward-looking liquidity metric and offering both theoretical and practical contributions to financial risk management and supervisory practices in emerging economies.

Keywords funding gap, bank stability, liquidity risk, machine learning, SHAP, emerging markets

JEL Classification C45, C53, G21, G28

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INTRODUCTION

The post-COVID-19 period has intensified liquidity pressures across banking systems in emerging markets, where inflationary shocks, weakening growth, volatile capital flows, and global monetary tightening have combined to increase financial fragility. In such environments, bank stability depends not only on the volume of liquid assets held at a given point in time, but also on banks' capacity to manage structural mismatches between funding sources and asset allocation under persistent uncertainty. This makes liquidity risk a central issue in the broader problem of banking-sector resilience in emerging economies.

The difficulty, however, lies in the fact that conventional liquidity indicators often provide only a static view of banks' balance-sheet conditions and therefore do not fully capture the dynamic pressures arising from mismatches in cash inflows and outflows across maturities. As a result, an important dimension of structural liquidity vulnerability may remain insufficiently reflected in the assessment of bank stability, particularly when banking systems are exposed to macroeconomic shocks and abrupt changes in funding conditions. In this context, the funding gap represents a more forward-looking indicator of liquidity imbalance, as it reflects the extent to which banks rely on unstable or insufficient funding to support asset expansion.

The scientific problem addressed in this study, therefore, arises from the need to understand whether structural liquidity imbalances, as captured by the funding gap, constitute a meaningful source of bank instability in emerging markets and whether this channel becomes more pronounced under conditions of elevated macro-financial volatility. This problem is especially relevant in ASEAN emerging markets, where banking sectors play a dominant role in financial intermediation, while institutional constraints and external vulnerability make liquidity stress more difficult to absorb. Clarifying this problem is essential for improving how bank stability is interpreted, monitored, and anticipated in environments characterized by recurrent shocks and asymmetric adjustment capacity.

1. LITERATURE REVIEW

Bank stability has emerged as a central concern in the post-crisis and post-pandemic era, particularly in emerging markets where banking systems remain highly exposed to macroeconomic volatility, inflationary pressures, and external shocks (Pham et al., 2021). A substantial body of literature establishes that liquidity conditions are not merely operational constraints but fundamental drivers of bank resilience and systemic fragility (Borio et al., 2001; Brunnermeier & Pedersen, 2009; Drehmann & Nikolaou, 2013). Within this framework, the role of liquidity extends beyond short-term funding adequacy, shaping the transmission of risk across balance sheets and ultimately determining the stability of financial institutions.

The theoretical foundation of this relationship lies in the maturity transformation function of banks. By funding long-term, illiquid assets with short-term liabilities, banks inherently expose themselves to liquidity risk and rollover pressure (Freixas & Rochet, 2008; Saunders & Cornett, 2020). Under adverse market conditions, tightening funding constraints can rapidly propagate into declining profitability, weakened solvency, and elevated default risk, reinforcing systemic fragility (Brunnermeier & Pedersen, 2009). Empirical evidence consistently supports this mechanism. Across both developed and emerging markets, liquidity risk is negatively associated with bank performance and stability, particularly during periods of financial stress (Demirgüç-Kunt & Huizinga, 2010; Ghenimi et al., 2017; Khan et al., 2017). Banks with weaker liquidity positions exhibit lower survival probabilities and heightened vulnerability to shocks, especially when compounded by credit risk and insufficient capital buffers (Ghenimi et al., 2017).

These dynamics are more pronounced in emerging economies, where banks rely more heavily on unstable funding sources and operate within less developed financial infrastructures. In such environments, liquidity conditions influence not only profitability but also risk-taking behavior and long-term resilience (Nguyen & Du, 2022; Vuong et al., 2024). Recent evidence further indicates that liquidity creation and funding structures play a critical role in shaping bank stability, with excessive reliance on fragile funding increasing systemic risk, particularly under macroeconomic shocks (Tran, 2024; Vazquez & Federico, 2015; Vuong et al., 2024). At the same time, the literature highlights a structural trade-off: while higher liquidity buffers reduce insolvency risk, excessive liquidity may suppress profitability due to opportunity costs (Berger et al., 2009; Demirgüç-Kunt & Huizinga, 2010b). However, most empirical studies operationalize liquidity through static ratios, which capture balance sheet positions at a given point in time but fail to reflect dynamic cash-flow mismatches and evolving funding pressures (Brunnermeier & Pedersen, 2009; Drehmann & Nikolaou, 2013).

This limitation has motivated a growing interest in structural liquidity measures that explicitly account for maturity mismatch. Among these, the Funding Gap (FGAP) provides a direct representation of the imbalance between expected cash inflows and outflows across different maturities, thereby capturing a bank's reliance on unstable

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funding relative to asset expansion (Drehmann & Nikolaou, 2013; Saunders & Cornett, 2020). From an asset–liability management perspective, such a mismatch constitutes a primary source of liquidity stress, as it constrains the bank's ability to meet obligations without costly adjustments or emergency funding. Bank risk theory further links these imbalances to insolvency risk, while the efficiency hypothesis suggests that more efficient banks are better equipped to absorb and manage such pressures (Berger & Humphrey, 1997; Freixas & Rochet, 2008). Taken together, these perspectives imply a coherent transmission mechanism whereby structural liquidity imbalance weakens financial resilience and amplifies the impact of external shocks on bank stability.

Despite its theoretical relevance, the empirical treatment of FGAP remains limited. The existing literature has largely focused on funding structures, liquidity creation, and regulatory liquidity measures, while rarely positioning FGAP as a central explanatory variable in bank stability models. Studies show that unstable funding structures significantly increase bank fragility, particularly during systemic crises (Vazquez & Federico, 2015; Yang et al., 2021), and that excessive liquidity creation may elevate failure risk when not supported by stable funding (Berger et al., 2009; Tran, 2024; Vuong et al., 2024). These findings implicitly underscore the importance of structural liquidity imbalance, yet they stop short of explicitly modeling its dynamic effect on stability indicators such as the Z-Score. This gap is especially critical in emerging markets, where exposure to macroeconomic shocks and reliance on short-term funding amplify the consequences of maturity mismatch (Khan, 2022; Khan et al., 2017; Yang et al., 2021). Under such conditions, persistent negative FGAP values may serve as early warning signals of structural fragility, capturing risk accumulation before it becomes visible in conventional indicators.

Parallel to these developments, the increasing complexity of financial systems has driven a methodological shift toward machine learning approaches. Traditional econometric models, while theoretically grounded, often struggle to capture nonlinear relationships, high-dimensional interactions, and structural instability inherent in financial data (Brynjolfsson & McAfee, 2017; Mashrur et al., 2020; Pham et al., 2025). In contrast, machine learning techniques have demonstrated superior predictive performance across a wide range of financial applications, including credit risk assessment, fraud detection, and early warning systems (Huang et al., 2024; Mashrur et al., 2020; Wang et al., 2022). Algorithms such as Random Forest, Gradient Boosting, XGBoost, and Support Vector Regression are particularly effective in modeling complex financial relationships that evolve under changing macroeconomic conditions (Climent et al., 2019; Pham, 2025; Pham & Ho, 2021; Tan et al., 2023).

However, the adoption of machine learning in banking remains constrained by two key challenges. First, the lack of interpretability limits its applicability in regulatory and policy contexts. Explainable AI techniques, particularly SHAP, address this limitation by decomposing model predictions into variable-level contributions (Arrieta et al., 2020; Tang et al., 2024), thereby enhancing transparency and supporting decision-making (Lundberg & Lee, 2017; Pham, 2025; Yeo et al., 2025). Second, the presence of multicollinearity and high-dimensional data necessitates robust feature selection methods such as Lasso, Ridge, and Elastic Net, which improve model stability and generalizability (Feng et al., 2020; Tibshirani, 1996; Zou & Hastie, 2005). While these methodological advances have significantly improved predictive performance, their integration with structural liquidity analysis remains underdeveloped. In particular, existing studies rarely examine whether dynamic liquidity indicators such as FGAP emerge as key predictors within nonlinear modeling frameworks, or whether machine learning can meaningfully enhance the forecasting of bank stability in emerging markets (Duarte & Barboza, 2020; Giglio et al., 2016; Gu et al., 2020).

Taken together, the literature converges on three key insights. Liquidity risk is a fundamental determinant of bank stability; structural funding conditions play a critical but underexplored role in shaping this relationship, and machine learning offers a powerful yet insufficiently integrated tool for capturing complex financial dynamics. These observations reveal three persistent gaps: the limited use of FGAP as a central explanatory variable, the reliance on linear empirical frameworks, and the absence of integrated, explainable predictive models tailored to emerging market conditions.

Addressing these gaps, this study investigates the impact of the Funding Gap on bank financial stability and evaluates the effectiveness of explainable machine learning models in forecasting Z-Score.

Based on the above research objectives, the following hypotheses are proposed.

H1: Persistent structural liquidity imbalances, reflected by a more negative Funding Gap, significantly reduce bank financial stability, as measured by the Z-Score.

H2: Machine learning models, when properly optimized and interpreted, provide superior predictive performance in modeling bank financial stability compared to traditional linear panel models.

2. DATA AND METHODOLOGY

This study employs a balanced panel dataset of 63 commercial banks across six ASEAN economies – Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam – over the period 2010–2023. The dataset is constructed from audited financial statements and supplemented by macroeconomic indicators obtained from international sources, including the International Monetary Fund (IMF) and the World Bank. The empirical design is structured to capture the multidimensional determinants of bank stability by integrating structural liquidity conditions, bank-specific characteristics, and macroeconomic factors within a unified analytical framework.

Bank financial stability is proxied by the Z-Score, which measures the distance to insolvency based on profitability, leverage, and volatility. This indicator is particularly suitable in emerging market contexts where high-frequency market data required by structural models such as the Merton Distance to Default are often unavailable or unreliable. Compared to supervisory composite indicators such as CAMELS, which rely on discretionary assessments and lack consistent time-series availability, the Z-Score provides a transparent, replicable, and empirically robust measure for longitudinal analysis. Its widespread application in prior studies further supports its suitability for machine learning frameworks requiring stable and comparable inputs over time (Berger et al., 2009; Demirgüç-Kunt & Huizinga, 2010; Pham, 2025).

The explanatory variables are constructed along three key dimensions. Structural liquidity conditions are captured by the Funding Gap (FGAP), complemented by conventional indicators such as the Loan-to-Assets ratio (LTA) and the Liquidity Coverage Ratio (LIQ). Bank-level characteristics, including size (SIZE), capitalization (ETA), growth dynamics (GROWTA), income diversification (IDI), leverage (DAR, DER), market power (LERNER), and market share (MS), are incorporated to control for institutional heterogeneity. In addition, macroeconomic conditions are represented by GDP growth, inflation (INF), and the COVID-19 shock, reflecting the external environment within which banks operate.

A rigorous data preprocessing procedure is implemented to ensure reliability and consistency. Outliers are identified using the interquartile range (IQR) method and treated through Winsorization at the 1st and 99th percentiles, thereby mitigating the influence of extreme values without discarding economically meaningful observations. Missing data are handled through a two-stage strategy: variables with substantial missingness are excluded to preserve statistical integrity, while remaining gaps are imputed using the Expectation–Maximization (EM) algorithm, which has been shown to better preserve multivariate distributions than conventional imputation techniques (Hair et al., 2019). Following preprocessing, all variables are normalized using the MinMaxScaler method to ensure comparability across scales and to facilitate convergence in machine learning algorithms (Hair et al., 2019; Han et al., 2022).

Given the high dimensionality and potential multicollinearity inherent in financial datasets, the study first employs penalized regression techniques to identify the most informative predictors. Specifically, Lasso, Ridge, and Elastic Net regressions are implemented to balance model parsimony and explanatory power under correlated covariates. Lasso performs variable selection by shrinking coefficients toward zero, Ridge stabiliz-

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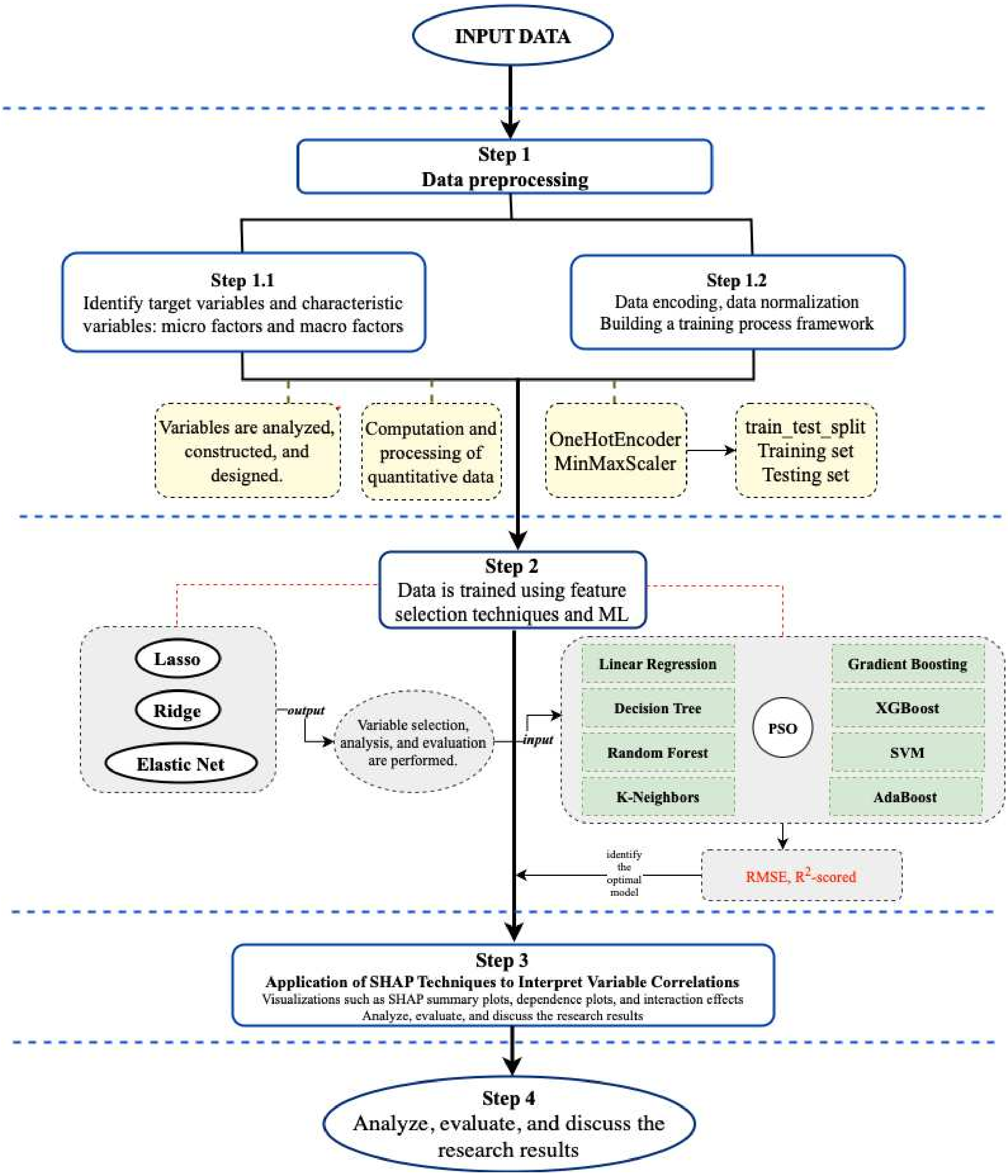

Figure 1. Machine learning workflow for financial stability forecasting

es estimates by penalizing coefficient magnitude under multicollinearity, and Elastic Net combines both mechanisms to handle high-dimensional correlated structures (Tibshirani, 1996; Zou & Hastie, 2005). Model performance is evaluated using R2 and Root Mean Squared Error (RMSE), and the optimal specification is determined through five-fold cross-validation. The calibration of the regularization parameter (alpha) is conducted iteratively to minimize out-of-sample prediction error, yielding an optimal value of 0.004. The results indicate that Ridge regression provides the most stable and generalizable variable set, reflecting its superior ability to retain information from correlated predictors while controlling estimation variance.

Building on this feature selection stage, the study implements a comprehensive suite of machine learning algorithms, including Random Forest, Decision Tree, Gradient Boosting, AdaBoost, Support Vector Regression, K-Nearest Neighbors, and XGBoost. These models are selected for their capacity to capture nonlinear relationships, interaction effects, and complex data structures that are not adequately addressed by conventional econometric approaches. To further enhance model performance, Particle Swarm Optimization (PSO) is employed for hyperparameter tuning, enabling efficient exploration of high-dimensional parameter spaces and convergence toward optimal solutions under non-convex conditions (Eberhart & Kennedy, 1995).

To address the interpretability challenge associated with machine learning models, the SHAP (SHapley Additive exPlanations) framework is integrated into the analysis. This approach decomposes model predictions into the marginal contributions of individual variables, thereby providing transparent and economically meaningful insights into the drivers of bank stability. By combining predictive accuracy with interpretability, the proposed framework overcomes the traditional "black-box" limitation and enhances the applicability of machine learning in regulatory and policy contexts (Lundberg & Lee, 2017; Pham, 2025).

All models are evaluated using a five-fold cross-validation strategy to ensure robustness and mitigate overfitting. This approach provides a reliable internal validation mechanism by assessing model performance across multiple data partitions. However, it should be noted that no independent hold-out test set is reserved for final evaluation. While cross-validation enhances internal consistency, future research should adopt a three-way data split (e.g., training, validation, and testing sets) to further strengthen out-of-sample generalizability and improve the credibility of model deployment in real-world financial monitoring and regulatory applications.

The overall analytical workflow is summarized in Figure 1, which illustrates the sequential process of data preprocessing, feature selection using penalized regression techniques, model training and optimization across multiple machine learning algorithms, and post-estimation interpretation using SHAP. The optimal model is identified based on predictive performance metrics, including RMSE and R^2, ensuring a systematic and replicable approach to financial stability forecasting.

3. RESULTS

The empirical results are presented in a sequential manner, beginning with the benchmark panel estimations, followed by the variable selection stage, and culminating in the comparative performance of machine learning models and the identification of the main drivers of bank stability. This structure allows the findings to be read as an integrated analytical progression from baseline inference to predictive validation.

The analysis first estimates conventional panel regressions using both the Fixed Effects Model (FEM) and the Random Effects Model (REM) to establish a baseline relationship between the explanatory variables and bank stability, proxied by the Z-Score. As reported in Table 1, the Hausman test strongly favors the FEM specification (Prob > F = 0.0000), indicating the presence of significant unobserved heterogeneity across banks and confirming that fixed effects provide the more appropriate linear benchmark for the dataset. Across both specifications, several variables display stable and statistically significant effects. In particular, the equity-to-assets ratio (ETA) is positively associated with Z-Score, while COVID-19, inflation (INF), GDP, and the debt-to-equity ratio (DER) are consistently significant in both models. These results indicate that capitalization strengthens bank stability, whereas adverse macroeconomic conditions and leverage deterioration weaken it. By contrast, other variables exhibit unstable coefficients or lose significance across specifications, reflecting the limits of linear panel methods in handling more complex relationships. Most notably, FGAP is not statistically significant in either FEM or REM, despite its expected theoretical relevance. Market share (MS) also changes sign across models, while variables such as LERNER and SIZE are significant only under one specification. Taken together, these results suggest that standard panel regressions provide useful benchmark evidence but may fail to detect structural liquidity effects when the underlying relationships are nonlinear or conditional.

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Table 1. Comparative results of Fixed Effects and Random Effects models on Z-Score

Variable	FEM coef.	FEM p-value	REM coef.	REM p-value	Significant in Both?
ETA	1.924	0.000	2.101	0.000	Yes
COVID_19	–0.532	0.000	–0.563	0.000	Yes
INF	–1.553	0.000	–1.281	0.000	Yes
GDP	–3.931	0.000	–3.627	0.000	Yes
MS	1.051	0.000	–0.111	0.026	No (opposite sign)
FGAP	–0.019	0.351	–154.061	0.511	No
GROWTA	0.024	0.155	0.017	0.314	No
DER	–0.060	0.000	–0.059	0.000	Yes
LERNER	0.045	0.227	0.091	0.005	No (only REM)
SIZE	–0.078	0.000	–0.009	0.255	No (only FEM)
LTA	0.014	0.212	0.011	0.336	No
IDI	–0.0001	0.856	–0.0001	0.733	No
DAR	0.083	0.010	–154.0	0.511	No
LIQ					

The next stage of the analysis evaluates the relative performance of Lasso, Ridge, and Elastic Net as alternative feature-selection methods under potential multicollinearity and high-dimensionality. The comparative results are summarized in Table 2, which shows clear differences in the number of retained variables and in predictive performance. Lasso selects 7 variables and produces an R2 of 0.7091 with an RMSE of 0.3092, while Elastic Net retains 9 variables with an R2 of 0.7074 and an RMSE of 0.3051. Ridge regression performs best among the three methods, preserving 14 variables and yielding the highest R2 (0.7194) together with the lowest RMSE (0.2988). These results indicate that Ridge is better able to preserve relevant information when explanatory variables are strongly correlated, thereby offering the most stable basis for downstream prediction. The parameter tuning process displayed in Figure 2 reinforces this conclusion: across the cross-validation path, Ridge exhibits greater stability and more favorable performance than both Lasso and Elastic Net on the relevant prediction metrics. On this basis, the set of variables selected by Ridge is retained as the final input space for machine learning estimation.

Table 2. Comparative performance of Lasso, Ridge, and Elastic Net in variable selection

Method	Number of Selected Variables	Z-Score	
		R^2	RMSE
Lasso	7	0.7091	0.3092
Ridge	14	0.7194	0.2988
Elastic Net	9	0.7074	0.3051

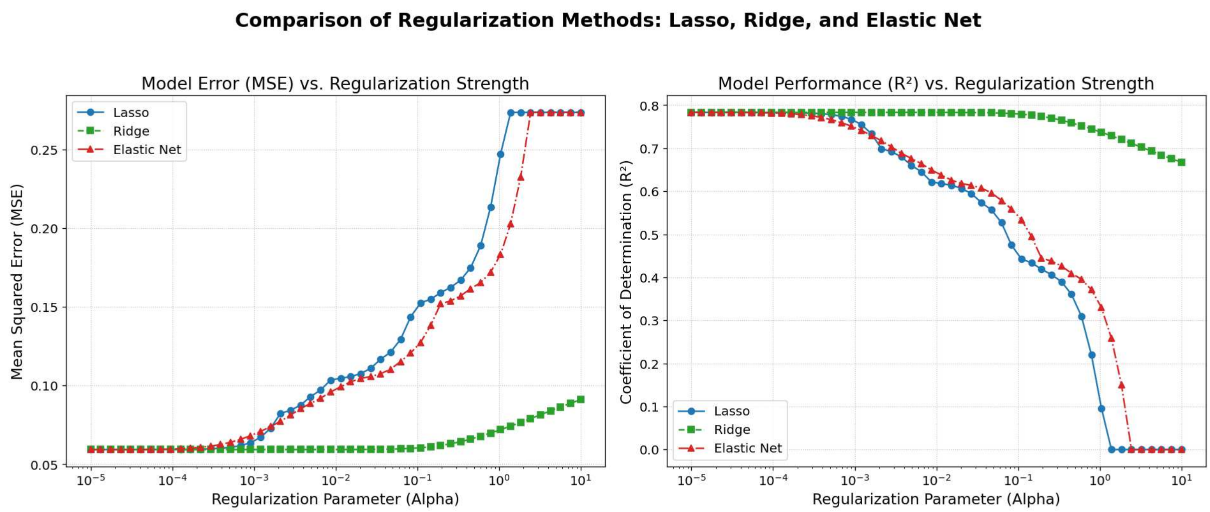

Figure 2. Cross-validation performance of Lasso, Ridge, and Elastic Net in variable selection

Using the Ridge-selected features, seven machine learning algorithms are then trained and validated to forecast the Z-Score. The comparative model performance is reported in Table 3. Among the competing models, XGBoost attains an R^2 of 0.825 with an RMSE of 0.056, while Gradient Boosting records an R^2 of 0.822 with an RMSE of 0.057. Random Forest also performs strongly, with an R^2 of 0.760 and an RMSE of 0.076, whereas Decision Tree, AdaBoost, Support Vector Regression, and K-Neighbors generate lower predictive accuracy. These results show that ensemble-based machine learning models consistently outperform simpler algorithms, indicating that bank stability in this setting is driven by nonlinear interactions and complex variable dependencies that are not adequately captured by conventional linear approaches.

Table 3. Model training performance results using machine learning algorithms

Models	Z-Score	
	R^2	RMSE
XGBoost	0.825	0.056
Gradient Boosting	0.822	0.057
Random Forest	0.760	0.076
Decision Tree	0.647	0.093
AdaBoost	0.628	0.095
Support Vector Regression	0.617	0.112
K-Neighbors	0.509	0.156

To improve learning efficiency and hyperparameter configuration, Particle Swarm Optimization (PSO) is then applied to the machine learning models. The optimization exercise yields visible gains in performance across all algorithms, as illustrated in Figure 3. The most notable improvement is observed for the Gradient Boosting model, whose predictive power rises substantially after PSO tuning and reaches an R2 of approximately 92.2%. The optimization process converges with a best cost of 0.0219 and an alpha value of 0.004, while the interaction parameters are set at c1 = 0.5, c2 = 0.3, and inertia weight w = 0.9, allowing convergence to be reached within 20 iterations. These results indicate that PSO materially enhances the adaptive capacity of the model in a nonlinear financial environment and substantially reduces the error structure relative to the untuned specification. The gains reported in Figure 3, therefore, confirm that hyperparameter optimization is not merely a technical refinement but a decisive component of predictive performance in this setting.

The comparison between the benchmark panel models and the optimized machine learning estimators provides a direct basis for hypothesis assessment. The panel results show that FEM is preferable to REM as a linear estimator, but the explanatory power of both models remains limited, with R^2 values below 60%, and FGAP does not emerge as statistically significant in that framework. By contrast, the machine learning results demonstrate substantially stronger predictive accuracy, especially after PSO optimization, with the Gradient Boosting model achieving the best overall performance. These findings provide clear support for H2, which states that machine learning models, when properly optimized and inter-

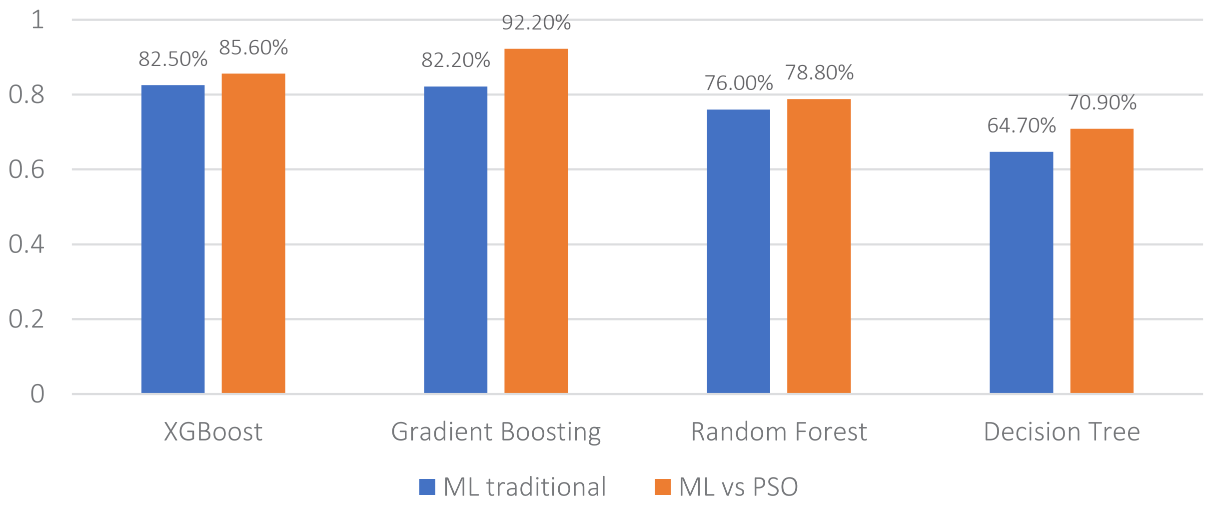

Figure 3. Comparative performance of machine learning models before and after PSO optimization

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preted, offer superior predictive performance in modeling bank financial stability relative to traditional linear panel models.

The final step of the results analysis examines the internal contribution of the predictors to the best-performing forecasting structure using SHAP-based interpretation. The SHAP summary displayed in Figure 4 identifies the variables that contribute most strongly to the predicted Z-Score. The most influential predictors include the equity-to-assets ratio (ETA), the COVID-19 shock, inflation (INF), GDP growth, and market share (MS). Importantly, FGAP also emerges as a pivotal variable in the machine learning specification, despite its insignificance in the linear panel results. This contrast is one of the most important empirical outcomes of the study. The SHAP values indicate that more persistent negative FGAP positions are associated with lower predicted Z-Scores, implying that structural liquidity imbalance exerts a systematic downward pressure on bank stability. In other words, when funding mismatch deepens, the probability of fragility rises in a way that becomes visible only when a nonlinear structure is allowed to enter the model. This result is consistent with the theoretical importance of liquidity transmission channels emphasized by Brunnermeier and Pedersen (2009) and Drehmann and Nikolaou (2013), and it provides direct empirical support for the proposition that structural liquidity conditions materially shape financial resilience. In substantive terms, the evidence supports H1: persistent structural liquidity imbalances, reflected in more negative FGAP values, significantly reduce bank financial stability as measured by the Z-Score.

The SHAP distribution in Figure 4 also shows that the influence of FGAP is not confined to a narrow subset of observations but extends across the broader prediction range, with stronger effects under weak liquidity positions. This result suggests that liquidity imbalance acts as a systematic rather than incidental source of vulnerability. In the same figure, the role of macroeconomic variables is also prominent, with inflation and the COVID-19 shock contributing negatively to the predicted Z-Score. The results, therefore, show that bank stability is shaped jointly by internal funding structure and external macro-financial conditions. The empirical evidence reported in Table 1, Table 2, Table 3, Figure 2, Figure 3, and Figure 4 consistently points to the same conclusion: once the data are examined through a nonlinear and explainable machine learning framework, structural liquidity risk, captured by FGAP, emerges as a central predictor of banking fragility in ASEAN emerging markets.

At the same time, the exceptionally high performance of the PSO-optimized Gradient Boosting model should be interpreted with caution. Although the model is validated through five-fold cross-validation, no independent hold-out test set is reserved for final evaluation. Accordingly, the

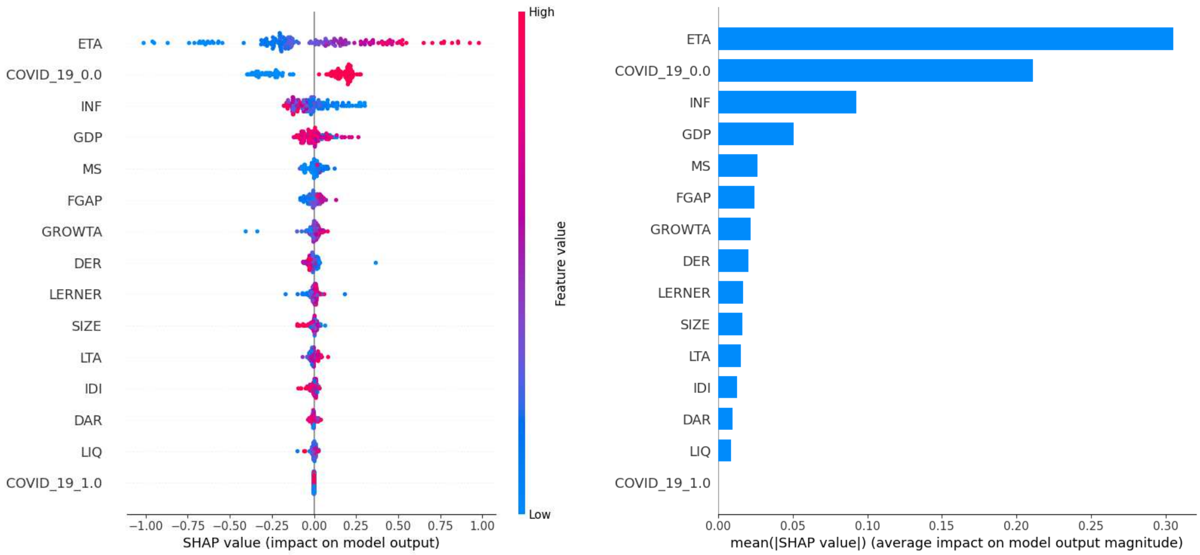

Figure 4. SHAP-based feature importance explaining Z-Score prediction

reported R^2 of 92.2% demonstrates very strong in-sample and cross-validated predictive capacity, but it does not fully eliminate the possibility of overfitting. This does not alter the ranking of model performance or the substantive findings reported above; rather, it qualifies the interpretation of predictive strength and indicates that future validation with a separate test sample would further strengthen the robustness of the forecasting framework.

Overall, the results reveal three main empirical patterns. First, the linear panel estimators identify several conventional determinants of stability but do not detect a statistically meaningful role for FGAP. Second, Ridge regression provides the most effective variable-selection structure for the dataset, outperforming Lasso and Elastic Net in terms of both R^2 and RMSE. Third, machine learning models, and especially the PSO-optimized Gradient Boosting specification, substantially improve forecasting performance and, through SHAP interpretation, reveal FGAP as an economically meaningful predictor of bank stability. These findings collectively confirm the empirical relevance of the study's two hypotheses (H1 and H2) and establish the basis for the subsequent discussion of their theoretical and policy implications.

4. DISCUSSION

The empirical findings of this study provide robust evidence that structural liquidity conditions, captured by FGAP, play a central role in shaping bank financial stability in emerging markets. More importantly, the results not only confirm established theoretical expectations but also reveal important deviations from prior empirical findings when nonlinear modeling frameworks are employed.

First, the consistently negative relationship between FGAP and Z-Score indicates that structural liquidity imbalances significantly weaken bank resilience. Persistent funding mismatches increase refinancing pressure and reduce banks' capacity to absorb shocks, thereby elevating the probability of financial distress. This finding is fully consistent with the funding liquidity mechanism proposed by Brunnermeier and Pedersen (2009), which suggests that funding constraints amplify financial instability through feedback effects between liquidity conditions and asset markets. It also aligns with Drehmann and Nikolaou (2013), who emphasize the importance of funding liquidity risk as a key determinant of banking fragility. However, unlike most previous empirical studies that rely on static liquidity indicators, the present study demonstrates that a dynamic structural measure such as FGAP provides stronger explanatory power in predicting bank stability, particularly in volatile emerging market environments.

These findings provide strong empirical support for H1, confirming that persistent structural liquidity imbalances, as reflected by a more negative FGAP, significantly deteriorate bank financial stability. Compared with earlier studies (Demirgüç-Kunt & Huizinga, 2010; Khan et al., 2017), which primarily focus on liquidity levels, the present results suggest that maturity mismatch – rather than liquidity stock – is the critical driver of instability. Furthermore, while studies on funding structures and liquidity creation (Vazquez & Federico, 2015) highlight the role of unstable funding, they do not explicitly model FGAP as a dynamic transmission mechanism. This study extends the literature by providing direct empirical evidence that FGAP operates as a structural channel through which liquidity stress translates into financial fragility.

Second, the comparison between traditional econometric models and machine learning approaches reveals a substantial divergence in both predictive performance and economic interpretation. The Fixed Effects Model (FEM), although statistically preferred over the Random Effects Model, fails to identify FGAP as a significant determinant of bank stability. This finding contrasts with theoretical expectations and suggests that linear panel models may underestimate the role of structural liquidity risk due to their inability to capture nonlinear relationships and interaction effects. Similar limitations of linear models have been noted in prior studies (Drehmann & Nikolaou, 2013), particularly in high-dimensional and volatile financial environments.

In contrast, the PSO-optimized Gradient Boosting model identifies FGAP as one of the most influential predictors of Z-Score, significantly improving predictive accuracy. This result directly sup-

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ports H2, indicating that machine learning models, when properly optimized and interpreted, provide superior predictive performance compared to traditional linear panel models. This finding is consistent with prior literature demonstrating the effectiveness of ensemble learning techniques in financial forecasting (Mashrur et al., 2020; Pham, 2025; Pham et al., 2025; Wang et al., 2022). However, the contribution of this study goes beyond predictive accuracy. Through SHAP analysis, the model offers a clear economic interpretation, revealing that persistent negative FGAP values exert a strong downward pressure on bank stability. This addresses a key limitation in previous machine learning applications, where predictive power is often achieved at the expense of interpretability (Lundberg & Lee, 2017; Yeo et al., 2025).

Importantly, the divergence between FEM and machine learning results provides a novel insight into the nature of the relationship between liquidity risk and bank stability. The confirmation of H2 implies that this relationship is inherently nonlinear and context-dependent. While linear models fail to detect the significance of FGAP, nonlinear models capture its full effect, including amplification under adverse conditions. This finding helps reconcile inconsistencies in prior empirical studies and suggests that mixed results in the literature may reflect methodological limitations rather than the absence of a true relationship.

Third, the results concerning macroeconomic factors further reinforce the importance of structural liquidity dynamics. The positive effect of GDP growth and the negative effect of inflation on Z-Score are consistent with established findings (Demirgüç-Kunt & Huizinga, 2010). However, the SHAP-based analysis reveals a more nuanced mechanism: macroeconomic shocks do not operate independently but interact with liquidity conditions, amplifying the adverse effects of structural imbalances. In particular, the COVID-19 pandemic significantly intensifies the negative impact of FGAP on bank stability, indicating a conditional relationship that has received limited attention in previous studies (Demirgüç-Kunt & Huizinga, 2010; Goodell, 2020).

This interaction effect represents a key contribution of the study. While earlier research typically treats macroeconomic variables as exogenous controls, the present findings demonstrate that they act as amplifiers of internal vulnerabilities. Structural liquidity imbalance creates latent fragility, which is subsequently activated and intensified by external shocks. This dynamic transmission mechanism provides a more comprehensive understanding of how financial instability evolves in emerging banking systems.

The findings contribute to the literature in three important ways. First, they establish FGAP as a critical structural indicator of bank stability, offering a more informative alternative to traditional liquidity ratios. Second, they demonstrate that the relationship between liquidity and stability is nonlinear and requires advanced modeling techniques to be properly identified. Third, they show that macroeconomic shocks amplify the effects of liquidity imbalance, highlighting the need for integrated and forward-looking risk assessment frameworks. The results suggest that conventional empirical approaches may underestimate the importance of structural liquidity risk, particularly in emerging markets. By integrating dynamic liquidity measurement with explainable machine learning techniques, this study provides a more accurate and policy-relevant framework for understanding and forecasting bank financial stability.

CONCLUSION AND POLICY IMPLICATIONS

This study sets out to examine whether structural liquidity imbalances, captured by FGAP, constitute a critical determinant of bank financial stability in emerging markets and whether advanced, explainable machine learning models can improve the accuracy and interpretability of stability forecasting compared to conventional econometric approaches.

The results demonstrate that structural liquidity imbalance is not merely a secondary balance sheet characteristic but a core transmission channel through which financial fragility materializes. In particular, persistent negative FGAP positions are systematically associated with a deterioration in bank stability, indicating that maturity mismatch plays a more decisive role than static liquidity indicators in explaining vulnerability under volatile conditions. At the same time, the comparison between modeling approaches reveals that the relationship between liquidity structure and stability is inherently nonlinear. While traditional panel models fail to capture the significance of FGAP, machine learning methods, when properly specified and interpreted, identify it as a dominant predictor, thereby uncovering dynamics that remain obscured under linear assumptions.

These findings lead to two principal conclusions. First, measuring liquidity risk in banking research and practice requires a structural and forward-looking perspective. Indicators that explicitly capture funding mismatch provide deeper insight into the mechanisms of instability than conventional ratio-based measures. Second, the empirical analysis of financial stability must move beyond linear frameworks when addressing complex, high-dimensional systems. The integration of explainable machine learning not only enhances predictive performance but also restores interpretability, thereby bridging the long-standing tension between model accuracy and transparency in financial risk analysis.

Beyond these theoretical implications, the results suggest a broader reconsideration of how financial stability is monitored and assessed in emerging markets. Liquidity risk should be understood as a dynamic process shaped by the interaction between internal balance sheet structures and external macroeconomic conditions. In this context, structural indicators such as FGAP can serve as early signals of latent vulnerability, particularly when combined with analytical frameworks capable of detecting nonlinear amplification effects. This perspective supports a shift from static assessment toward adaptive, data-driven monitoring systems.

Several avenues for future research naturally follow from this analysis. First, extending the framework to other emerging regions would allow for testing the external validity of the findings under different institutional and financial conditions. Second, integrating additional dimensions of risk, including ESG-related exposures, technological risk, and market-based indicators, would provide a more comprehensive view of financial fragility. Third, the incorporation of unstructured and high-frequency data, combined with advances in explainable artificial intelligence, offers significant potential for improving real-time risk detection and early warning capabilities. Further work in these directions would contribute to the development of more robust and forward-looking financial stability frameworks in an increasingly complex and uncertain global environment.

AUTHOR CONTRIBUTIONS

Conceptualization: Hoang Thi Thanh Hang, Pham Thuy Tu.
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Visualization: Pham Thuy Tu.
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REFERENCES

1. Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58,* 82-115. https://doi.org/10.1016/j.inffus.2019.12.012
2. Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research, 98*(2), 175-212. https://doi.org/10.1016/S0377-2217(96)00342-6
3. Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank Competition and Financial Stability. *Journal of Financial Services Research, 35*(2), 99-118. https://doi.org/10.1007/s10693-008-0050-7
4. Borio, C., Craig, F., & Philip, L. (2001). Procyclicality of the financial system and financial stability: issues and policy options. In *Marrying the macro- and micro-prudential dimensions of financial stability* (Vol. 1, pp. 1-57). Retrieved from https://www.bis.org/publ/bppdf/bispap01a.pdf
5. Brunnermeier, M. K., & Pedersen, L. H. (2009). Market Liquidity and Funding Liquidity. *Review of Financial Studies, 22*(6), 2201-2238. https://doi.org/10.1093/rfs/hhn098
6. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review*. Retrieved from https://hbr.org/2017/07/the-business-of-artificial-intelligence
7. Climent, F., Momparler, A., & Carmona, P. (2019). Anticipating bank distress in the Eurozone: An Extreme Gradient Boosting approach. *Journal of Business Research, 101,* 885-896. https://doi.org/10.1016/j.jbusres.2018.11.015
8. Demirgüç-Kunt, A., & Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns. *Journal of Financial Economics, 98*(3), 626-650. https://doi.org/10.1016/j.jfineco.2010.06.004
9. Drehmann, M., & Nikolaou, K. (2013). Funding liquidity risk: Definition and measurement. *Journal of Banking & Finance, 37*(7), 2173-2182. https://doi.org/10.1016/j.jbankfin.2012.01.002
10. Duarte, D. L., & Barboza, F. L. de M. (2020). Forecasting Financial Distress With Machine Learning – A Review. *Future Studies Research Journal: Trends and Strategies*, *12*(3), 528-574. https://doi.org/10.24023/FutureJournal/2175-5825/2020.v12i3.533
11. Eberhart, R., & Kennedy, J. (1995). A new optimizer using particle swarm theory. *Proceedings of the Sixth International Symposium on Micro Machine and Human Science* (pp. 39-43). Nagoya, Japan. https://doi.org/10.1109/MHS.1995.494215
12. Feng, G., Giglio, S., & Xiu, D. (2020). Taming the Factor Zoo: A Test of New Factors. *The Journal of Finance, 75*(3), 1327-1370. https://doi.org/10.1111/jofi.12883
13. Freixas, X., & Rochet, J.-C. (2008). *Microeconomics of banking* (2nd ed.). MIT Press.
14. Ghenimi, A., Chaibi, H., & Omri, M. A. B. (2017). The effects of liquidity risk and credit risk on bank stability: Evidence from the MENA region. *Borsa Istanbul Review, 17*(4), 238-248. https://doi.org/10.1016/j.bir.2017.05.002
15. Giglio, S., Kelly, B., & Pruitt, S. (2016). Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics, 119*(3), 457-471. https://doi.org/10.1016/j.jfineco.2016.01.010
16. Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters, 35,* 101512. https://doi.org/10.1016/j.frl.2020.101512
17. Gu, S., Kelly, B., & Xiu, D. (2020). Empirical Asset Pricing via Machine Learning. *The Review of Financial Studies, 33*(5), 2223-2273. https://doi.org/10.1093/rfs/hhaa009
18. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.
19. Han, J., Kamber, M., & Pei, J. (2022). *Data mining: Concepts and techniques* (4th ed.). Morgan Kaufmann.
20. Huang, Z., Zheng, H., Li, C., & Che, C. (2024). Application of Machine Learning-Based K-means Clustering for Financial Fraud Detection. *Academic Journal of Science and Technology, 10*(1), 33-39. https://doi.org/10.54097/74414c90
21. Khan, H. H. (2022). Bank competition, financial development and macroeconomic stability: Empirical evidence from emerging economies. *Economic Systems, 46*(4), 101022. https://doi.org/10.1016/j.ecosys.2022.101022
22. Khan, M. S., Scheule, H., & Wu, E. (2017). Funding liquidity and bank risk taking. *Journal of Banking & Finance, 82,* 203-216. https://doi.org/10.1016/j.jbankfin.2016.09.005
23. Lundberg, S. M., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. *31st Conference on Neural Information Processing Systems (NIPS)*. Retrieved from https://proceedings.neurips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf
24. Mashrur, A., Luo, W., Zaidi, N. A., & Robles-Kelly, A. (2020). Machine Learning for Financial Risk Management: A Survey. *IEEE Access, 8,* 203203-203223. https://doi.org/10.1109/ACCESS.2020.3036322
25. Nguyen, T. D., & Du, Q. L. T. (2022). The effect of financial inclusion on bank stability: Evidence from ASEAN. *Cogent Economics & Finance, 10*(1). https://doi.org/10.1080/23322039.2022.2040126
26. Pham, T. T. (2025). Drivers of bank stability in Vietnam's emerg-

ing economy: an advanced machine learning, regularization and explainable AI approach. *Journal of Economic Studies*, 1-20. https://doi.org/10.1108/JES-04-2025-0237

27. Pham, T. T., Dao, L. K. O., & Nguyen, V. C. (2021). The determinants of bank's stability: a system GMM panel analysis. *Cogent Business & Management, 8*(1). https://doi.org/10.1080/23311975.2021.1963390

28. Pham, T. T., Oanh, D. L. K., & Trang, D. D. (2025). Machine Learning and Parameter Optimization for Banking Stability Prediction and Determinants Identification in ASEAN. *Emerging Science Journal, 9*(3), 1189-1208. https://doi.org/10.28991/ESJ-2025-09-03-04

29. Pham, X. T. T., & Ho, T. H. (2021). Using boosting algorithms to predict bank failure: An untold story. *International Review of Economics & Finance, 76,* 40-54. https://doi.org/10.1016/j.iref.2021.05.005

30. Saunders, A., & Cornett, M. M. (2020). *Financial institutions management: A risk management approach* (10th ed.). McGraw-Hill Education.

31. Tan, B., Gan, Z., & Wu, Y. (2023). The measurement and early warning of daily financial stability index based on XGBoost and SHAP: Evidence from China. *Expert Systems with Applications, 227,* 120375. https://doi.org/10.1016/j.eswa.2023.120375

32. Tang, P., Tang, T., & Lu, C. (2024). Predicting systemic financial risk with interpretable machine learning. *The North American Journal of Economics and Finance, 71,* 102088. https://doi.org/10.1016/j.najef.2024.102088

33. Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological), 58*(1), 267-288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

34. Tran, T. T. N. (2024). Liquidity creation and banking stability: an approach using the Bayes method. *Cogent Economics & Finance, 12*(1). https://doi.org/10.1080/23322039.2024.2417760

35. Vazquez, F., & Federico, P. (2015). Bank funding structures and risk: Evidence from the global financial crisis. *Journal of Banking & Finance, 61,* 1-14. https://doi.org/10.1016/j.jbankfin.2015.08.023

36. Vuong, G. T. H., Nguyen, Y. D. H., Nguyen, M. H., & Wong, W.-K. (2024). Assessing the impact of macroeconomic uncertainties on bank stability: Insights from ASEAN-8 countries. *Heliyon, 10*(11), e31711. https://doi.org/10.1016/j.heliyon.2024.e31711

37. Wang, K., Li, M., Cheng, J., Zhou, X., & Li, G. (2022). Research on personal credit risk evaluation based on XGBoost. *Procedia Computer Science, 199,* 1128-1135. https://doi.org/10.1016/j.procs.2022.01.143

38. Yang, L., Yi, Y., & Wang, S. (2021). Banks' maturity mismatch, financial stability, and macroeconomic dynamics. *Economic Research-Ekonomska Istraživanja, 34*(1), 3038-3063. https://doi.org/10.1080/1331677X.2020.1867212

39. Yeo, W. J., Van Der Heever, W., Mao, R., Cambria, E., Satapathy, R., & Mengaldo, G. (2025). A comprehensive review on financial explainable AI. *Artificial Intelligence Review, 58*(6), 189. https://doi.org/10.1007/s10462-024-11077-7

40. Zou, H., & Hastie, T. (2005). Regularization and Variable Selection Via the Elastic Net. *Journal of the Royal Statistical Society Series B: Statistical Methodology, 67*(2), 301-320. https://doi.org/10.1111/j.1467-9868.2005.00503.x

http://dx.doi.org/10.21511/bbs.21(2).2026.07