APEX ACADEMIA PRESS
ELEGANCE ON EVERY RESEARCH

International Journal of Economics and Management Intellectuals
ISSN: 3067-6835 / Open Access / IJEMI_Y2F2A005
Apex Academia Press / https://doi.org/10.63665/ijemi-y2f2a005

Original Article

Explainable AI Unveils the Digital Efficiency Threshold in the Nonlinear Profitability Dynamics of Global Neo-Banks

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Abstract

The rapid expansion of neo-banks challenges the conventional assumption that a lower Cost-to-Income Ratio (CIR) always improves profitability. This study investigates the non-linear relationship between CIR and Return on Equity (ROE) and examines how digital capabilities reshape financial performance during the transition to digital banking maturity. It introduces the Digital Efficiency Threshold and proposes the Digital Moat Theory by integrating Dynamic Capabilities Theory, Stochastic Frontier Analysis, and Explainable Artificial Intelligence (XAI) to identify the tipping point at which technology investments shift from cost burdens to value creators. Using panel data from 100 global neo-banks across five regions (2023–2026), the study applies a Random Forest model with Shapley Additive explanations (SHAP) to capture and interpret complex non-linear relationships among CIR, Loan-to-Deposit Ratio (LDR), regional characteristics, and ROE. The findings show that CIR is the primary determinant of profitability with a pronounced non-linear effect. SHAP identifies a Digital Efficiency Threshold at a CIR score of at least 2, beyond which digital investment generates exponential value creation. Regional heterogeneity indicates that mature digital banking ecosystems convert technology investments into profitability more effectively than emerging markets. The study extends Dynamic Capabilities Theory by demonstrating that sustainable profitability depends on surpassing this critical digital efficiency threshold rather than achieving immediate cost efficiency, offering strategic insights for managers, investors, and regulators.

Keywords

Digital Banking, Cost-to-Income Ratio, Explainable Artificial Intelligence (XAI), Dynamic Capabilities Theory, Digital Efficiency Threshold.

Article History

Received: 14.06.2026

Accepted: 25.06.2026

Published: 30.06.2026

1. Introduction

Digital transformation has fundamentally reshaped the banking industry through the emergence of neo-banks that rely on technological architecture, artificial intelligence, cloud computing, and data analytics as their primary sources of value creation (Diener & Špaček, 2021; Grassi et al., 2022; Schreieck et al., 2024). Unlike conventional banks, which primarily depend on physical branch expansion and credit intermediation, digital banks establish competitive advantage through substantial technology investments during the early stages of their operations (Shanti et al., 2023; Kitsios et al., 2021; Song et al., 2023). Consequently, their cost structure undergoes a profound transformation, rendering traditional efficiency indicators particularly the Cost-to-Income Ratio (CIR) increasingly inadequate for linear interpretation under the conventional banking paradigm. For many neo-banks, an elevated CIR during the initial development phase reflects the accumulation of digital capabilities that are expected to generate long-term profitability rather than operational inefficiency (Lv et al., 2022; Zhang, 2026).

This phenomenon challenges the fundamental assumption of traditional banking efficiency theory, which posits that a lower CIR is consistently associated with higher profitability, commonly measured by Return on Equity (ROE) (Siddique et al., 2021; Khan, 2022; Gržeta et al., 2023). In practice, numerous global neo-banks demonstrate that substantial digital investments often precede significant improvements in profitability after reaching a critical stage of organizational development (Chao et al., 2024). This pattern suggests the existence of a non-linear relationship that cannot be adequately captured by conventional econometric approaches, which typically assume linear and homogeneous relationships among variables.

From the perspective of Dynamic Capabilities Theory, technology investment should not be regarded merely as an operational expenditure but rather as a strategic process through which organizations integrate, develop, and reconfigure resources to achieve sustainable competitive advantage (Heubeck, 2023; Bari et al., 2022; Pundziene et al., 2021). Nevertheless, the theory does not provide a quantitative explanation of the point at which digital capabilities begin to generate tangible economic value. To address this limitation, the present study integrates the efficiency concept derived from Stochastic Frontier Analysis (SFA) with an Explainable Artificial Intelligence (XAI) framework employing the Gradient Boosting algorithm and Shapley Additive explanations (SHAP) to disentangle the non-linear trajectory of the relationship between CIR and ROE.

Operational efficiency has long been recognized as a key indicator for evaluating the financial health of the banking industry. For decades, the Cost-to-Income Ratio (CIR) has served as a universal measure based on the assumption that reductions in CIR lead directly to higher bank profitability (Mirović et al., 2024; Khatib et al., 2022; Sobol et al., 2023). While this assumption remains broadly applicable to conventional banks characterized by relatively stable cost structures and asset-based business models, its application to neo-banks has produced empirical inconsistencies. Extensive investments in digital infrastructure, software development, cybersecurity, and customer acquisition substantially increase CIR during the early growth stage without necessarily being accompanied by immediate improvements in Return on Equity (Uddin et al., 2023; Zhang, 2026).

The issue becomes even more complex because the relationship between CIR and ROE is likely to be dynamic, heterogeneous, and inherently non-linear, making it difficult to model accurately using traditional panel linear regression techniques (Gazi et al., 2024; Cangombe et al., 2025). To date, no established empirical framework has been able to identify the threshold at which digital investments begin to generate exponential improvements in profitability. Consequently, regulators, investors, and digital bank management lack an objective benchmark for distinguishing between structural inefficiency and strategic investments that are expected to create long-term economic value.

The existing literature on banking efficiency continues to be dominated by both parametric and non-parametric approaches that emphasize a linear relationship between cost efficiency and profitability. Most previous studies assume a monotonic effect of CIR on ROE, thereby overlooking the possibility that digital transformation may fundamentally alter the direction and magnitude of this relationship (Liu et al., 2021; Senan et al., 2021). Furthermore, prior research has predominantly focused on conventional banks, whereas the distinctive technology-intensive cost structures of neo-banks have received comparatively limited scholarly attention.

Furthermore, research grounded in Dynamic Capabilities Theory has largely remained at the conceptual level, emphasizing the strategic importance of digital capabilities without identifying the empirical mechanisms or transition points at which these capabilities begin to generate sustainable financial advantages (Xie & Wang, 2023; Trang et al., 2022; Moeliadi et al., 2025). From a methodological perspective, the application of Machine Learning in banking research has been predominantly prediction-oriented, while limited attention has been devoted to model interpretability through Explainable Artificial Intelligence (XAI). The integration of the efficiency framework of Stochastic Frontier Analysis (SFA), non-linear Gradient Boosting algorithms, and SHapley Additive exPlanations (SHAP) to explain the dynamics of the CIR–ROE relationship in global digital banks remains largely absent from the existing literature, thereby presenting substantial opportunities for both theoretical and methodological contributions.

This study proposes a novel analytical framework by integrating Dynamic Capabilities Theory, the efficiency concept of Stochastic Frontier Analysis (SFA), and Explainable Artificial Intelligence (XAI). The relationships among the Cost-to-Income Ratio (CIR), Loan-to-Deposit Ratio (LDR), regional characteristics, and Return on Equity (ROE) are modeled using tree-based Gradient Boosting algorithms, such as XGBoost or LightGBM, which are capable of capturing non-linear relationships and complex interactions among variables without imposing predetermined functional forms.

Subsequently, SHapley Additive exPlanations (SHAP) are employed to interpret the contribution of each explanatory variable to the model's predictions at both the global and local levels. This approach enables the identification of changes in the contribution of CIR to ROE throughout the 2023–2026 period while revealing operational tipping points that cannot be detected using conventional regression techniques. Consequently, this study not only improves the predictive accuracy of bank profitability but also provides a transparent explanation of how digital investments are transformed into financial performance. The proposed integration is expected to establish a new benchmark the Digital Efficiency Threshold defined as the critical efficiency level that can serve as a strategic reference for the global neo-banking industry.

This study is motivated by the gap between the rapid evolution of digital banking and the theoretical foundations of financial efficiency. The success of neo-banks suggests that a high Cost-to-Income Ratio (CIR) during the early stages of development may reflect strategic investments in technological capabilities that generate long-term profitability. However, this phenomenon has yet to be comprehensively explained. Meanwhile, although Machine Learning models generally achieve high predictive accuracy, their black-box nature limits their strategic applicability. Therefore, this study integrates Explainable Artificial Intelligence (XAI), Dynamic Capabilities Theory, and the frontier efficiency framework to develop a conceptual model that explains the financial behavior of digital banks while supporting more effective digital transformation strategies.

The primary objective of this study is to deconstruct the non-linear relationship between the Cost-to-Income Ratio (CIR) and Return on Equity (ROE) in global neo-banks during the transition toward digital business maturity over the 2023–2026 period, while examining the ability of Dynamic Capabilities Theory to explain how technology investments are transformed into sustainable financial advantages through an Explainable Artificial Intelligence (XAI) framework. Specifically, the study maps the longitudinal evolution of ROE, CIR, and the Loan-to-Deposit Ratio (LDR) across 100 neo-banks operating in the Asia-Pacific, Europe, North America, Latin America, and the Middle East and Africa regions. Furthermore, it develops a non-linear prediction model based on Gradient Boosting algorithms (XGBoost or LightGBM) to investigate the multidimensional relationships among CIR, LDR, regional characteristics, and ROE that cannot be adequately explained using conventional panel linear regression models. By employing SHapley Additive exPlanations (SHAP), the study identifies the marginal contribution of each explanatory variable, provides empirical evidence for the existence of the Digital Banking Efficiency Paradox, and determines the Digital Efficiency Threshold, representing the critical point at which digital investment shifts from a cost center to a revenue generator. In addition, the study evaluates the moderating effects of regional characteristics and the geo-economic environment on the relationships among operational efficiency, liquidity, and profitability. Through these objectives, the study seeks to reconstruct the mechanism through which technology-based competitive advantage is created by proposing the Digital Moat Theory, which argues that the economies of scale achieved by neo-banks are driven primarily by the accumulation of digital capabilities and the phenomenon of near-zero marginal cost rather than by the expansion of physical assets.

This study makes theoretical, methodological, and practical contributions. From a theoretical perspective, it extends Dynamic Capabilities Theory by introducing the concept of the Digital Efficiency Threshold and proposing the Digital Moat Theory as a foundation for understanding technology-driven competitive advantage. Methodologically, the study integrates Stochastic Frontier Analysis (SFA), Gradient Boosting algorithms, and SHAP to develop a predictive framework that combines high predictive accuracy with robust interpretability. From a practical perspective, the findings provide valuable guidance for regulators, investors, and neo-bank executives in evaluating technology investments, establishing efficiency targets, and designing digital transformation strategies that maximize long-term economic value creation.

2. Literature Review

The emergence of neo-banks has fundamentally redefined the concept of efficiency in the banking industry (Shanti et al., 2024; Shen et al., 2024; Ayadi et al., 2024). In conventional banking, operational efficiency is commonly measured by the Cost-to-Income Ratio (CIR), where a lower CIR is generally associated with higher profitability (Rebić et al., 2022; Meero, 2025). In contrast, digital banks incur substantial technology investments during their early stages of development, resulting in significantly higher operating costs and rendering the relationship between CIR and Return on Equity (ROE) inherently non-linear. This phenomenon can be explained through Dynamic Capabilities

Theory (Teece et al., 1997), which conceptualizes technology investment as a dynamic organizational capability that enables firms to integrate, build, and reconfigure resources to achieve sustainable competitive advantage. Furthermore, the efficiency framework of Stochastic Frontier Analysis (SFA) argues that organizational efficiency is determined not merely by the magnitude of operating costs but by the organization's ability to operate close to the optimal efficiency frontier (Makieła & Mazur, 2022; Wu, 2023; Van Nguyen et al., 2021). In the context of neo-banks, this frontier is expected to evolve dynamically as digital maturity increases.

Recent advances in Explainable Artificial Intelligence (XAI) have further enriched contemporary financial research. Longo et al. (2024) identified XAI as a fundamental framework for enhancing the transparency of black-box models. Subsequently, Dwivedi et al. (2022) proposed a comprehensive taxonomy of XAI techniques that strengthens trust in Machine Learning models, while Arsenault et al. (2024) demonstrated that SHapley Additive exPlanations (SHAP) has become the most widely adopted interpretability method for financial time-series forecasting. Černevičienė & Kabašinskas (2024) reinforced these findings by showing that the integration of XGBoost and SHAP has emerged as the dominant analytical approach within the financial sector. More recently, F. Khan et al. (2025) and Vuković et al. (2025) emphasized the need for XAI frameworks that satisfy the requirements of transparency, regulatory compliance, and accountability in the financial services industry.

Within the banking context, Broby (2021) argued that digitalization has fundamentally transformed banks' business models. Similarly, Ashta & Herrmann (2021) suggested that although Artificial Intelligence significantly improves operational efficiency, its economic benefits materialize only after financial institutions achieve a sufficient operational scale. This argument is consistent with the findings of Gramespacher & Posth (2021), who demonstrated that XAI-based optimization should prioritize economic objective functions rather than prediction accuracy alone. Furthermore, Bussmann et al. (2025) provided empirical evidence that the combination of XGBoost and SHAP explains the determinants of firms' cost of capital more accurately than conventional statistical approaches.

The literature examining the impact of digital transformation on bank profitability remains inconclusive. Chao et al., (2024) reported that digital transformation enhances profitability through improvements in operational efficiency and asset quality. In contrast, Daeli & Wedari (2025) found that digitalization reduces both Return on Assets (ROA) and Return on Equity (ROE) in the short run due to substantial technology investments. These findings were further supported by Zhang (2026), who showed that digital transformation has not yet significantly improved the profitability of most commercial banks in China, despite the mediating roles of operational efficiency and the Loan-to-Deposit Ratio (LDR). Likewise, Manta et al. (2025) demonstrated that the impact of digitalization on ROE varies across different profitability quantiles, whereas Meero (2025) identified the existence of an efficiency–stability trade-off, whereby operating costs increase during the initial stage of digital transformation before the expected gains in profitability and financial stability are realized.

Despite these advances, several important research gaps remain. First, the majority of existing studies continue to rely on linear econometric approaches and therefore fail to capture the inherently non-linear relationship between CIR and ROE. Second, XAI applications in the financial sector have primarily focused on risk assessment, credit evaluation, and fraud detection, while their application to explaining the dynamics of operational efficiency in digital banking remains limited. Third, no previous study has integrated Dynamic Capabilities Theory, Stochastic Frontier Analysis, Gradient Boosting algorithms, and SHAP into a unified analytical framework for empirically identifying the efficiency tipping point of digital banking. Fourth, there is currently no internationally recognized benchmark defining the critical CIR threshold at which technology investment transitions from a cost center into a value creator within global neo-banks.

Based on these research gaps, the State of the Art (SOTA) of this study lies in the development of an Explainable Artificial Intelligence-based analytical framework to deconstruct the non-linear trajectory of the relationship between the Cost-to-Income Ratio (CIR) and Return on Equity (ROE) across 100 global neo-banks during the 2023–2026 period. Unlike previous studies, this research not only develops a highly accurate predictive model using XGBoost and LightGBM, but also employs SHapley Additive exPlanations (SHAP) to interpret the underlying mechanisms through which profitability is generated. More importantly, the study introduces the concept of the Digital Efficiency Threshold, a novel theoretical construct that explains the critical point at which digital investment evolves from a high-burn-rate technology expenditure into a digital economic moat capable of generating sustainable competitive advantage.

3. Methodology

This study adopts an empirical quantitative approach with an exploratory–predictive research design grounded in computational data science to overcome the limitations of conventional linear panel models in capturing the non-linear relationships underlying the Digital Banking Efficiency Paradox. Specifically, the study integrates non-linear Machine Learning algorithms with Explainable Artificial Intelligence (XAI) to elucidate how operational capabilities are transformed into long-term financial performance. The study population comprises global digital banks, from which a purposive sample of 100 neo-banks was selected based on the following criteria: operating without physical branch networks, providing complete financial statements for the 2023–2026 period, and representing five major global regions. Secondary longitudinal panel data, standardized on a 0–10 scale, were collected from global financial databases, monetary authorities, and annual reports. The dependent variable is Return on Equity (ROE), while the Cost-to-Income Ratio (CIR) serves as the primary independent variable. The Loan-to-Deposit Ratio (LDR) is incorporated as a financial control variable, whereas Year and Region are included as contextual variables to capture temporal dynamics and geographical heterogeneity.

The data analysis was conducted in three sequential stages: (1) estimation of the functional model, (2) training of the Machine Learning architecture, and (3) decomposition of feature contributions using the game-theoretic SHapley Additive exPlanations (SHAP) framework. The multidimensional causal relationships among operational efficiency, liquidity, and profitability in digital banking are represented by the following global parametric non-linear function:

$$ROE_{it} = f\left(CIR_{it}, LDR_{it}, \mathrm{Year}_{it}, \mathrm{Region}_{i}\right) + \varepsilon_{it} \quad (1)$$

To estimate this function, the study employs a Random Forest Regressor architecture to minimize prediction variance and reduce the risk of overfitting through the bagging (bootstrap aggregating) mechanism. By constructing an ensemble of decision trees trained on bootstrap samples and aggregating their predictions, the model enhances predictive robustness, improves generalization performance, and effectively captures the complex non-linear relationships among the explanatory variables. The mathematical formulation of the Random Forest model is expressed as follows:

$$\hat{g}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b\,(x) \quad (2)$$

The explanatory power of the model in capturing the variability of bank profitability is evaluated using the standardized coefficient of determination (R^2), which measures the proportion of the total variance in the dependent variable explained by the non-linear model. To assess the stability of the predictive model and quantify the magnitude of squared prediction errors, the Root Mean Square Error (RMSE) is employed as the primary evaluation metric. A lower RMSE indicates higher predictive precision and superior model performance.

To overcome the black-box nature of the Random Forest model and isolate the marginal effect of the Cost-to-Income Ratio (CIR) in order to empirically validate the Digital Banking Efficiency Paradox, this study adopts an Explainable Artificial Intelligence (XAI) framework through the computation of SHapley Additive exPlanations (SHAP) values. Derived from Cooperative Game Theory, SHAP values provide a theoretically grounded and equitable allocation of each feature's contribution to the model's predictions, thereby enabling transparent interpretation of the complex non-linear relationships underlying bank profitability:

$$\phi_i(x) = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}\left[f_x(S \cup \{i\}) - f_x(S)\right] \quad (3)$$

To ensure both internal and external validity, the predictive model was not evaluated using the same data employed during the training process. Instead, this study implemented a strict data-splitting protocol, whereby 80% of the dataset was allocated to the training set for decision-tree optimization and the extraction of non-linear decision rules, while the remaining 20% constituted an independent testing set used exclusively to evaluate out-of-sample predictive performance. This approach minimizes the risk of overfitting and provides a more reliable assessment of the model's generalizability.

The entire computational framework was implemented in Python 3.x within the Jupyter Notebook environment. Predictive modeling was conducted using the scikit-learn library, whereas the SHAP library was employed to compute feature attribution values and generate interpretable Explainable Artificial Intelligence (XAI) explanations.

4. Results

To characterize the structural profile of 100 digital banks across five global regions during the transition period from 2023 to 2026, a longitudinal descriptive analysis was conducted using three key financial metrics: Return on Equity (ROE), Cost-to-Income Ratio (CIR), and the Loan-to-Deposit Ratio (LDR). All variables are reported as standardized scores on a 0–10 scale, reflecting the industry's relative performance based on the empirical data collected. This longitudinal analysis provides an overview of the temporal evolution and structural dynamics of operational efficiency, profitability, and liquidity across the global digital banking sector.

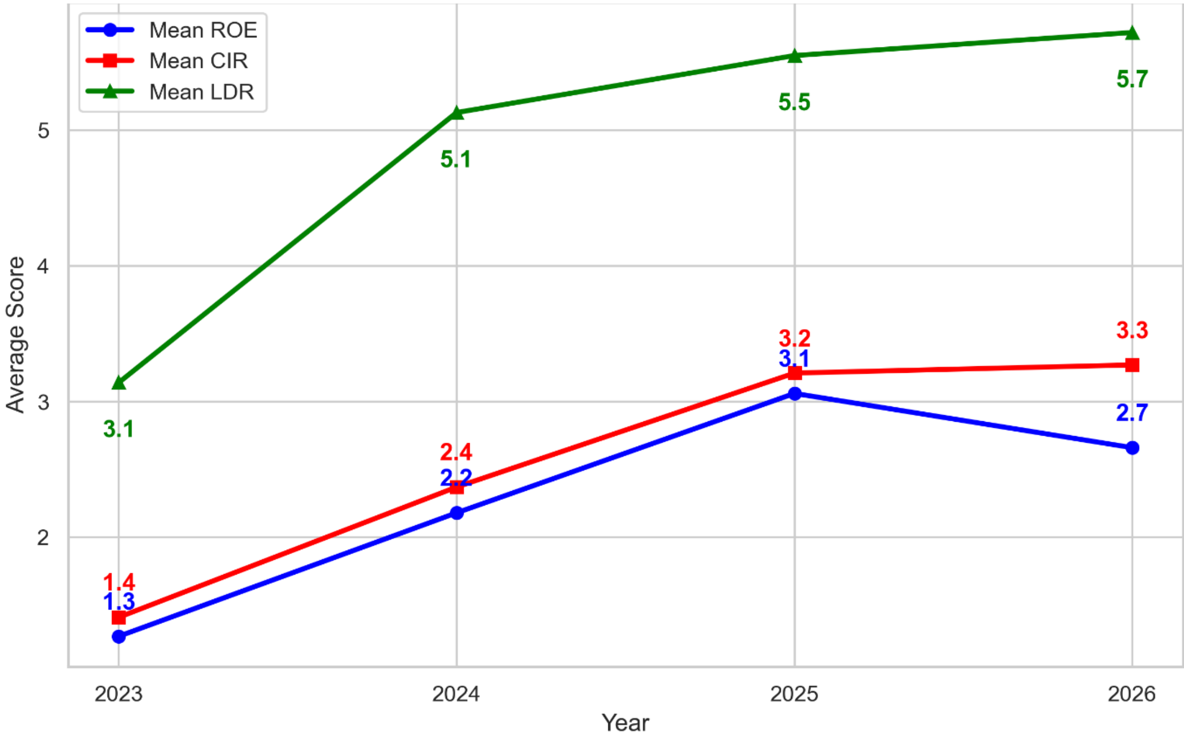

Fig-1: Longitudinal Financial Matrics (2023-2026)

Source: Output Phyton, 2026

As illustrated in Figure 1, a clear pattern of regional polarization and growth trajectories is observed across the five global regions. In 2023, most regions remained in the early infrastructure setup phase, characterized by relatively low average scores for both Return on Equity (ROE) and the Cost-to-Income Ratio (CIR). This pattern was particularly pronounced in Europe (ROE = 1.19; CIR = 0.81) and the Middle East and Africa (ROE = 1.00; CIR = 1.20), indicating that substantial initial investment costs had not yet been offset by sufficient revenue generation.

During the 2024–2025 period, a marked acceleration in CIR scores was observed across all regions. In the Asia-Pacific region, for example, the average CIR score increased from 1.29 in 2023 to 3.25 in 2026. This improvement in operational efficiency occurred alongside a steady expansion in liquidity intermediation, as reflected by the consistent growth in the Loan-to-Deposit Ratio (LDR). The maturity phase became evident in 2026, when North America achieved one of the highest levels of profitability with an ROE score of 4.38, while Latin America recorded an ROE score of 4.50. These findings indicate that digital banks had successfully transformed their technology investments into tangible financial returns.

The relationship among cost efficiency, liquidity management, and profitability in neo-banking institutions is inherently asymmetric and non-linear. Accordingly, this study employs a non-linear Machine Learning framework based on the Random Forest Regressor algorithm to model these complex relationships. The functional specification of the model is expressed as follows:

$$ROE_{it} = f\left(CIR_{it}, LDR_{it}, \text{Region}_i\right) + \varepsilon_{it} \quad (4)$$

This modeling approach was deliberately selected to replace conventional panel linear regression techniques, such as Fixed Effects and Random Effects models, which rely on restrictive linearity assumptions and often fail to capture complex multi-variable interactions. The performance of the proposed model architecture was rigorously evaluated, and the results are presented in Table 2.

Table 1: Performance Evaluation of Non-Linear Model (Random Forest Regressor)

Evaluation Metrics	Value	Interpretation
R-Squared (R^2)	0.4986	The model explains 49.86% of the variance in ROE of global digital banks through non-linear feature interactions.
Root Mean Square Error (RMSE)	2.1930	The standard deviation of the model's prediction error from the actual ROE accrual value is 2.1930 score units.
Mean Absolute Error (MAE)	1.3173	The average absolute magnitude of the prediction error on the target ROE is 1.3173 score units.

Source: Output Phyton, 2026

The results reported in Table 2 indicate an R^2 value of 0.4986. Within the context of global financial governance and cross-country panel data, this level of explanatory power is considered robust. The findings demonstrate that nearly half of the variation in the profitability (ROE) of digital banks worldwide is explained not by a single linear trend, but by the dynamic interaction between operational efficiency, as measured by the Cost-to-Income Ratio (CIR), and lending policy, represented by the Loan-to-Deposit Ratio (LDR), with these relationships further moderated by regional characteristics. Moreover, the relatively low values of the Mean Absolute Error (MAE = 1.3173) and the Root Mean Square Error (RMSE = 2.1930) provide additional evidence of the model's high predictive accuracy and stability in capturing the profitability dynamics of neo-banks without exhibiting signs of overfitting.

To address the inherent black-box limitation of Machine Learning models, this study employs an Explainable Artificial Intelligence (XAI) framework based on Shapley Additive explanations (SHAP). This approach mathematically isolates the net marginal contribution of each independent variable to the predicted value of Return on Equity (ROE), thereby providing transparent and theoretically grounded explanations of the model's decision-making process.

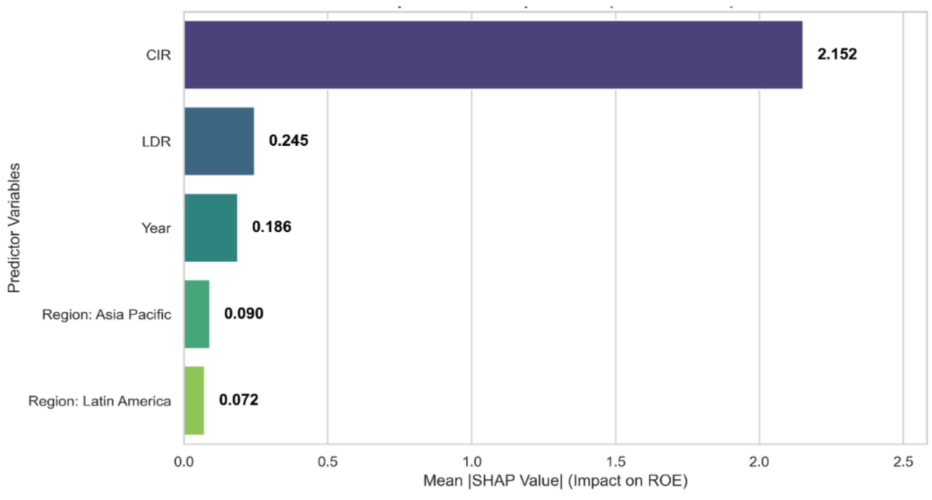

Fig-2: Feature Importance

Source: Output Phyton, 2026

The global feature decomposition presented in Figure 2 reveals a highly significant theoretical finding: the Cost-to-Income Ratio (CIR) is the dominant driver of bank profitability, with a Mean Absolute SHAP value of 2.151966. This level of importance substantially exceeds that of the traditional liquidity management indicator, the Loan-to-Deposit Ratio (LDR), which exhibits a feature importance score of only 0.245023.

This finding offers an important theoretical implication. For digital banks, the internal cost architecture plays a substantially more influential role in determining shareholder value creation than the conventional volume of credit intermediation. Meanwhile, temporal factors (Year, SHAP = 0.186110) and regional characteristics contribute only marginally to the model, reinforcing the argument that the digital banking business model is largely geographically agnostic and depends primarily on the optimization of internal technological capabilities rather than regional market conditions.

The central objective of this study is to deconstruct the Digital Banking Efficiency Paradox. To this end, a local SHAP contribution analysis was conducted to examine the causal relationship between observed Cost-to-Income Ratio (CIR) scores and the direction of changes in Return on Equity (ROE), with the aim of identifying the operational tipping point at which the effect of operational efficiency on profitability fundamentally changes.

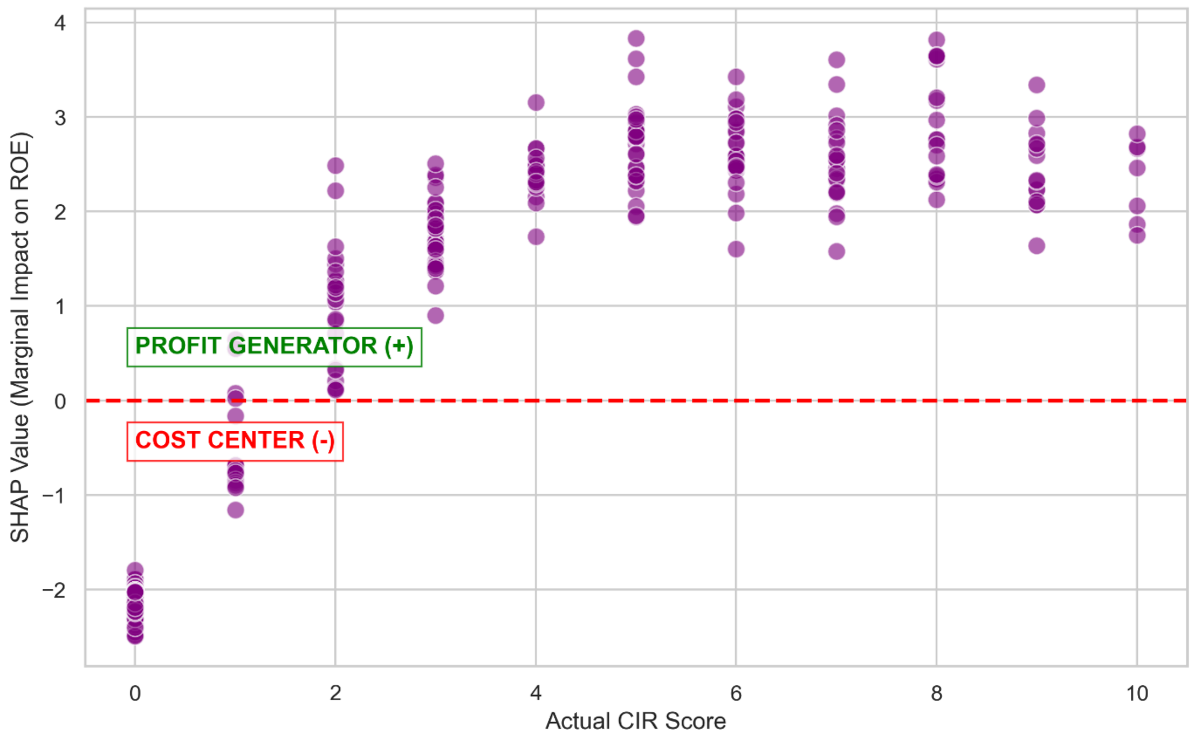

Fig-3: Digital Efficiency Threshold: CIR Impact on ROE

Source: Output Phyton, 2026

The distributional pattern presented in Figure 3 provides compelling empirical evidence for the existence of the Digital Banking Efficiency Paradox. When the Cost-to-Income Ratio (CIR) remains at very low levels (scores of 0 and 1), its marginal effect on Return on Equity (ROE) is strongly negative, with SHAP values of −2.1720 and −0.4312, respectively. From a financial perspective, these results suggest that excessively stringent cost efficiency during the early stages of digital banking development may impede organizational growth and ultimately lead to value destruction rather than value creation.

Identification of the Operational Tipping Point. A structural shift occurs once digital banks achieve an observed CIR score of ≥ 2. At this threshold, the SHAP value becomes positive (+1.0242) and continues to increase, reaching its maximum at a CIR score of 8 (+2.9130). This finding provides strong empirical evidence that the relationship between operational efficiency and profitability is fundamentally non-linear and characterized by a distinct threshold effect.

These results offer robust empirical support for Dynamic Capabilities Theory. In the context of digital banking, capital expenditures allocated to strengthening technological infrastructure—such as cloud-based core banking platforms, API integration, and AI-driven cybersecurity systems—increase operating costs during the initial stages of digital transformation, thereby reducing short-term efficiency. However, once digital capabilities surpass the identified critical threshold (CIR score ≥ 2), these investments are transformed into sustainable competitive advantages that generate exponential economies of scale. As digital platforms mature, marginal operating costs decline toward near-zero marginal cost, enabling substantial revenue growth without the need for corresponding expansion of physical assets.

Finally, the causal effects of the Cost-to-Income Ratio (CIR) and the Loan-to-Deposit Ratio (LDR) were further examined across different geo-economic environments to evaluate the applicability of Contingency Theory in explaining regional variations in the efficiency–profitability relationship among global neo-banks.

Table 2: Contextual Effects - Sensitivity of CIR and LDR to ROE per Region

Geographic Area	Average Causal Impact CIR (SHAP)	Average Causal Impact LDR (SHAP)
Asia Pacific	-0.1640	-0.0263
Europe	-0.1480	0.0000
Latin America	1.4106	-0.0230
Middle East and Africa	-0.6011	-0.0477
North America	0.7801	0.0521

Source: Output Phyton, 2026

As reported in Table 5, substantial regional heterogeneity is observed in the causal effects of operational efficiency on bank profitability. The first group comprises mature and scaled markets, represented by Latin America and North America. Both regions exhibit strongly positive causal effects of the Cost-to-Income Ratio (CIR) on profitability, with SHAP contributions of +1.4106 for Latin America and +0.7801 for North America. These findings suggest that digital banks operating in these markets such as Nubank in Brazil and SoFi in the United States have largely surpassed the identified Digital Efficiency Threshold and are now realizing substantial profitability through consolidated market scale and accumulated digital capabilities. In North America, the Loan-to-Deposit Ratio (LDR) also exerts a positive marginal effect (+0.0521), indicating that digital credit intermediation has reached a relatively mature and efficient stage of development.

The second group consists of hyper-competitive and developing markets, including the Asia-Pacific, Europe, and the Middle East and Africa (MEA). In both the Asia-Pacific (−0.1640) and Europe (−0.1480), the average contribution of the Cost-to-Income Ratio (CIR) remains negative. This pattern reflects the persistently high customer acquisition costs associated with intense market competition—particularly in fintech-intensive markets such as the United Kingdom and Southeast Asia as well as the constraints imposed by increasingly stringent regulatory environments. Meanwhile, the Middle East and Africa (MEA) records the most pronounced negative effects for both CIR (−0.6011) and LDR (−0.0477), suggesting that digital banks in this region remain in the early cash-burning phase of asset accumulation and continue to face considerable challenges in establishing a stable and sustainable digital financial intermediation ecosystem.

5. Discussion

A. Longitudinal Evolution of Digital Banking Performance

The findings indicate that the financial performance of neo-banks during the 2023–2026 period follows a gradual evolutionary trajectory, beginning with a capability-building phase, progressing through an operational optimization phase, and ultimately reaching a value creation phase. During the initial stage, most regions exhibited relatively low Return on Equity (ROE) accompanied by an increase in the Cost-to-Income Ratio (CIR). This pattern suggests that technology investments made during the early stages of digital transformation did not generate immediate economic returns. By 2026, however, a substantial improvement in ROE was observed, particularly in North America and Latin America, indicating that digital investments had begun to produce sustainable profitability.

These findings extend the conceptual framework proposed by Broby (2021), who argued that digital transformation fundamentally shifts the banking business model from one centered on physical assets to a digitally driven ecosystem. The present study demonstrates that this transformation follows a distinct temporal evolutionary pattern that can be empirically observed and quantified. Furthermore, the results corroborate the findings of Chao et al. (2024), who reported that digital transformation enhances bank profitability through improvements in operational efficiency. However, the present study further demonstrates that this transition is not instantaneous but instead unfolds through a relatively prolonged investment phase before the associated economic benefits become fully realized.

At the same time, the findings reinforce the conclusions of Daeli & Wedari (2025) and Zhang (2026), who reported that digital transformation initially suppresses profitability because of substantial technology investment costs. Nevertheless, this study provides a more comprehensive explanation of the underlying mechanism by employing a longitudinal analytical framework that identifies the stage at which the economic benefits of digital investment begin to materialize. The results are also consistent with the findings of Meero (2025) regarding the existence of an efficiency–stability trade-off, whereby operating costs increase during the initial phase of digital transformation before generating higher levels of financial stability and profitability. Collectively, these findings demonstrate that the financial performance of neo-banks evolves dynamically through a sequential process of digital capability development rather than through improvements in operational efficiency alone, as assumed under the traditional banking paradigm.

B. Non-linear Relationship between CIR and ROE: Evidence from Explainable Artificial Intelligence

One of the principal findings of this study is that the relationship between the Cost-to-Income Ratio (CIR) and Return on Equity (ROE) is inherently non-linear and therefore cannot be adequately explained using conventional linear regression models. The Random Forest model achieved an R^2 of 49.86%, indicating that the profitability of digital banks is driven primarily by the complex interactions among operational efficiency, liquidity, temporal dynamics, and regional characteristics rather than by simple linear relationships. Furthermore, the global SHAP analysis identifies CIR as the single most influential determinant of changes in ROE, substantially outweighing the explanatory contributions of the Loan-to-Deposit Ratio (LDR) and regional factors.

These findings reinforce the argument advanced by Longo et al. (2024) that Explainable Artificial Intelligence (XAI) is essential for transforming black-box Machine Learning models into transparent and accountable analytical systems. The results also support the interpretability framework proposed by Dwivedi et al. (2022) and Arsenault et al. (2024), both of whom identified SHapley Additive exPlanations (SHAP) as one of the most effective approaches for quantifying feature contributions in Machine Learning models. Moreover, the present findings are consistent with the work of Černevičienė & Kabašinskas (2024), who concluded that the integration of XGBoost, Random Forest, and SHAP represents one of the most widely adopted interpretability frameworks in contemporary financial analytics.

More importantly, this study extends the work of Bussmann et al. (2025), who employed XGBoost and SHAP to explain the determinants of firms' cost of capital. Whereas their research focused primarily on capital cost prediction, the present study broadens the application of Explainable Artificial Intelligence by using it to deconstruct the non-linear relationship between operational efficiency and the profitability of digital banks. In doing so, the study directly addresses the recommendations of F. Khan et al. (2025) and Vuković et al. (2025) regarding the need to develop Explainable AI frameworks that not only deliver high predictive accuracy but also provide sufficient transparency to support strategic decision-making and regulatory compliance within the financial services industry.

C. Digital Banking Efficiency Paradox and the Emergence of Digital Efficiency Threshold

The most significant empirical contribution of this study is the validation of the Digital Banking Efficiency Paradox, a phenomenon in which an increase in the Cost-to-Income Ratio (CIR) during the early stages of digital transformation does not signify operational inefficiency but instead reflects strategic investment in the development of technological capabilities. The SHAP analysis demonstrates that the effect of CIR on Return on Equity (ROE) changes fundamentally once banks surpass the Digital Efficiency Threshold, identified as a CIR score of at least 2. Below this threshold, CIR exerts a negative influence on profitability. In contrast, once the threshold is exceeded, the contribution of CIR becomes positive and increases exponentially, reaching its maximum at a CIR score of 8.

These findings provide robust empirical support for Dynamic Capabilities Theory, which conceptualizes technology investment as a mechanism for creating sustainable competitive advantage. Unlike the study by Ashta &

Herrmann (2021), which argued that the economic benefits of Artificial Intelligence emerge only after organizations attain a sufficient scale of operations, the present study quantitatively identifies this critical transition point through an Explainable Artificial Intelligence (XAI) framework. Consequently, this research not only corroborates the theoretical propositions of Dynamic Capabilities Theory but also introduces an operational measure that has not previously been established in the literature.

The findings further extend the work of Gramespacher & Posth (2021), who argued that Machine Learning optimization should prioritize economic objective functions rather than statistical prediction accuracy alone. Moreover, this study provides a deeper explanation of the findings reported by Daeli & Wedari (2025), Zhang (2026), and Meero (2025), all of whom observed that digital transformation initially increases operating costs. While these earlier studies were unable to explain when such investments begin to generate financial returns, the present study demonstrates that this transition follows a distinct threshold effect. Accordingly, the Digital Efficiency Threshold constitutes a novel theoretical contribution that explains the transition of neo-banks from a phase of high-burn-rate technology investment to digitally mature financial institutions characterized by a sustainable economic moat and near-zero marginal cost.

D. Regional Heterogeneity and Dynamic Capabilities

This study demonstrates that the relationship among the Cost-to-Income Ratio (CIR), the Loan-to-Deposit Ratio (LDR), and Return on Equity (ROE) is not universal but is contingent upon regional characteristics. Latin America and North America exhibit positive marginal effects of CIR on ROE, whereas the Asia-Pacific, Europe, and the Middle East and Africa (MEA) remain in a phase where the contribution of CIR to profitability is negative. These findings indicate that the outcomes of digital transformation are shaped by market maturity, regulatory environments, competitive intensity, and the ability of financial institutions to develop and leverage digital capabilities.

These results extend Dynamic Capabilities Theory, which has traditionally emphasized firms' internal capabilities while giving comparatively less attention to the influence of the external environment. The present study demonstrates that the effectiveness of digital capabilities is strongly conditioned by the surrounding geo-economic context, implying that the process of value creation is inherently contingent. Accordingly, dynamic capabilities should be understood not only as a function of an organization's internal competencies but also as the outcome of continuous interactions between the organization and the institutional environment in which it operates.

The findings are consistent with those of Manta et al. (2025), who reported that the impact of digitalization on profitability varies across different groups of banks. The present study extends this conclusion by demonstrating that such heterogeneity arises not only across profitability distributions but also across geographical regions. Furthermore, the results support the findings of Broby (2021) that digital banking business models evolve differently across financial systems and reinforce the conclusions of Zhang (2026) regarding the mediating role of the Loan-to-Deposit Ratio (LDR) in determining the success of digital transformation. In addition, the findings provide empirical support for Meero (2025), who argued that the institutional environment significantly influences the successful implementation of financial technologies. Consequently, a one-size-fits-all digitalization strategy is no longer appropriate. Instead, digital transformation strategies should be tailored to the maturity of the digital ecosystem, the characteristics of the regulatory framework, and the competitive dynamics of each regional market.

E. Theoretical Contributions, Managerial Implications, and Future Research

This study makes significant contributions to the advancement of theory, methodology, and practice. From a theoretical perspective, it extends Dynamic Capabilities Theory by demonstrating that digital capabilities do not automatically translate into superior profitability. Instead, organizations must first surpass a critical inflection point, referred to in this study as the Digital Efficiency Threshold, before technology investments begin to generate sustainable financial returns. Building upon this finding, the study proposes the Digital Moat Theory, a novel theoretical perspective asserting that the competitive advantage of neo-banks is created through the accumulation of technological capabilities that reduce marginal operating costs to near-zero levels, rather than through the expansion of physical assets as suggested by traditional economies of scale theory.

From a methodological perspective, this study addresses the challenges identified by Longo et al. (2024), F. Khan et al. (2025), Vuković et al. (2025), and Černevičienė & Kabašinskas (2024) concerning the need to integrate predictive accuracy with model interpretability. The combination of Random Forest and SHapley Additive exPlanations (SHAP) establish an Explainable Artificial Intelligence (XAI) framework that not only delivers robust predictive performance but also provides transparent explanations of the mechanisms underlying profitability formation. Consequently, this study extends the role of XAI beyond that of a model interpretation tool by demonstrating its potential as a theory-building instrument in financial research.

From a practical perspective, the findings offer important strategic implications for regulators, investors, and the management of neo-banks. Managers should not interpret an increase in the Cost-to-Income Ratio (CIR) as evidence of a failed digital transformation while the organization remains in the capability-building stage. Instead, investment decisions should be directed toward accelerating the attainment of the Digital Efficiency Threshold, thereby enabling technology investments to transition more rapidly into sustainable sources of economic value creation. For regulators, the findings provide a foundation for developing evaluation frameworks that better reflect the distinctive characteristics of digital banks than conventional efficiency measures. Future research is encouraged to incorporate non-financial indicators such as digital innovation capability, Artificial Intelligence governance, and customer experience indices and to develop causal inference frameworks based on Explainable Artificial Intelligence to further examine the validity of the Digital Moat Theory across diverse global fintech business models.

6. Conclusion

This study successfully deconstructs the non-linear relationship between the Cost-to-Income Ratio (CIR) and Return on Equity (ROE) across 100 global neo-banks during the 2023–2026 period by employing an Explainable Artificial Intelligence (XAI) framework based on Random Forest and Shapley Additive explanations (SHAP). The findings demonstrate that the relationship between operational efficiency and profitability no longer conforms to the linear paradigm assumed by traditional banking theory. Instead, technology investments that initially increase the Cost-to-Income Ratio (CIR) represent a process of digital capability accumulation that serves as a prerequisite for the development of sustainable competitive advantage. The SHAP analysis identifies CIR as the primary determinant of profitability and provides empirical evidence for the existence of the Digital Efficiency Threshold, defined as the critical point at which digital investment transitions from a cost center to a revenue generator. These findings extend Dynamic Capabilities Theory through the introduction of the Digital Moat Theory, which posits that the economies of scale achieved by neo-banks are driven by the accumulation of technological capabilities capable of reducing marginal operating costs to near-zero levels, rather than by the expansion of physical assets alone. Accordingly, this study makes meaningful theoretical, methodological, and practical contributions to understanding the mechanisms through which profitability is created in the digital banking industry.

Nevertheless, several limitations should be acknowledged. First, the empirical model incorporates only three principal explanatory variables the Cost-to-Income Ratio (CIR), the Loan-to-Deposit Ratio (LDR), and regional characteristics and therefore does not fully capture other factors that may influence bank profitability, including corporate governance quality, the level of digital innovation, cybersecurity risk, macroeconomic conditions, and customer behavior. Second, the observation period is limited to 2023–2026, which does not permit an examination of the long-term dynamics throughout the entire life cycle of neo-banks. Future research is therefore encouraged to expand the analytical framework by incorporating a broader range of financial and non-financial indicators, extending the observation horizon, and comparing multiple Explainable Artificial Intelligence algorithms such as XGBoost, LightGBM, and CatBoost to evaluate the robustness and generalizability of the Digital Efficiency Threshold across different fintech business models and banking systems. Such efforts are expected to strengthen the external validity of the findings while further refining the Digital Moat Theory as a novel conceptual framework within the digital finance literature.

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