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Orginal Article

The Impact of PSAK 71 Implementation On Bank Profitability In Indonesia

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Abstract

This study investigates the impact of PSAK 71 implementation on the profitability of banks in Indonesia, measured through financial performance indicators such as Return on Assets (ROA) and Return on Equity (ROE). It also examines the effects of liquidity risk, credit risk, capital adequacy, bank size, loan growth, and non-interest expenses on bank performance. Using panel data from Indonesian banks spanning several years, the study employs a quantitative approach and applies the Fixed Effects Model, selected through Chow, Hausman, and Lagrange Multiplier tests, to analyze the relationship between these variables. The findings reveal that PSAK 71 has significantly influenced credit provisioning practices, necessitating proactive risk management strategies. Liquidity risk, measured by the Loan-to-Deposit Ratio (LDR), and credit risk, represented by Non-Performing Loans (NPL), are identified as critical factors negatively affecting profitability. Capital adequacy ratios (CAR) positively influence ROA but have mixed effects on ROE. While loan growth contributes positively to bank performance, larger bank sizes and higher non-interest expenses tend to exert downward pressure on profitability. These results highlight the interplay between regulatory changes and financial performance, emphasizing the importance of risk management and capital optimization in navigating a rapidly evolving banking environment. This research offers practical insights for policymakers, banking professionals, and stakeholders, supporting the development of strategic frameworks to enhance resilience and sustain profitability in the Indonesian banking sector under PSAK 71 regulations.

Keywords: PSAK 71, Banking Profitability, Liquidity Risk, Credit Risk, Capital Adequacy, Indonesia

1. Introduction

The financial services sector plays a pivotal role in promoting economic stability and growth, serving as a cornerstone for financial intermediation and risk management. However, this sector is inherently exposed to various risks, including liquidity risk, credit risk, and challenges related to capital adequacy. These risks significantly influence the performance and resilience of banking institutions, making effective risk management a vital component for maintaining financial stability. This is particularly important in economies with volatile market conditions and complex regulatory environments. In Indonesia, the introduction of PSAK 71 in January 2020, replacing PSAK 55, marked a regulatory turning point aimed at fortifying the financial system's resilience. By aligning with International Financial Reporting Standards (IFRS 9), PSAK 71 mandates the proactive recognition of expected credit losses, requiring banks to anticipate and prepare for potential future credit risks. This shift has compelled banks to overhaul their risk management strategies, with a particular focus on credit provisioning and capital adequacy planning to ensure compliance and operational stability.

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Despite the global emphasis on financial risk management, research on the specific implications of PSAK 71 in the Indonesian banking sector remains sparse. While international studies, such as those by Rodrigues Boscia et al. (2022), examine the broader impact of IFRS 9 on credit risk management and operational strategies, their findings often fail to capture the unique dynamics of Indonesia's regulatory and economic framework. Similarly, Jassem et al. (2021) discuss compliance complexities under IFRS 9 but do not provide insights tailored to Indonesia's banking sector, which faces distinct challenges related to market size, regulatory enforcement, and institutional readiness. Although research in other emerging markets, such as by Harb et al. (2022) and Ekinci and Poyraz (2019), has highlighted the detrimental effects of liquidity and credit risks on profitability, these studies lack a focus on how regulatory changes like PSAK 71 reshape the interplay between financial risks and performance. This gap highlights the need for a localized analysis that delves into PSAK 71's specific effects on critical factors such as liquidity risk, credit risk, and capital adequacy in the Indonesian context.

PSAK 71 represents a significant departure from the previous incurred-loss model, emphasizing a forward-looking approach to credit risk assessment. This regulatory shift introduces both opportunities and challenges for Indonesian banks. On one hand, it enhances financial system resilience by compelling banks to adopt more proactive and transparent risk management practices. On the other hand, the earlier recognition of credit losses increases operational costs, impacting profitability metrics such as Return on Assets (ROA) and Return on Equity (ROE). Furthermore, the interplay between other financial factors—such as liquidity risk, measured through the Loan-to-Deposit Ratio (LDR); credit risk, represented by Non-Performing Loans (NPL); and capital adequacy ratios (CAR)—with bank profitability under the PSAK 71 framework remains underexplored. By investigating these relationships, this study seeks to uncover the nuanced effects of PSAK 71 on the financial performance of Indonesian banks and offer actionable insights for stakeholders.

This research aims to fill the identified gap by employing a quantitative approach that uses panel data regression to analyze the impacts of PSAK 71 on banking performance in Indonesia. It evaluates how liquidity risk, credit risk, capital adequacy, bank size, loan growth, and non-interest expenses influence profitability metrics in a post-PSAK 71 environment. The study leverages rigorous model selection techniques, including Fixed Effects Models, to ensure robust and reliable findings. By focusing on Indonesia's unique regulatory landscape and economic conditions, this research provides evidence-based insights that contribute to the broader literature on financial risk management and regulatory compliance while addressing specific challenges faced by Indonesian banks.

The findings of this study are expected to have both theoretical and practical implications. Theoretically, the research advances the understanding of how regulatory frameworks like PSAK 71 affect financial performance in emerging markets, offering insights into the dynamic relationship between profitability metrics and financial risks. Practically, the results aim to guide policymakers, banking regulators, and industry practitioners in optimizing risk management strategies and enhancing operational resilience under PSAK 71. Recommendations include the adoption of advanced credit risk monitoring systems, strategic allocation of capital to balance compliance with profitability, and the implementation of technology-driven solutions to streamline operations. By addressing these priorities, this study bridges the gap between theory and practice, enabling stakeholders to navigate Indonesia's evolving financial landscape more effectively.

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2. Method

This study investigates data from all companies listed on the Indonesia Stock Exchange (IDX), focusing on quarterly intervals between 2012 and 2023. The selected period encompasses significant developments in Indonesia's banking industry, particularly the implementation of PSAK 71 in January 2020, which introduced a forward-looking approach to credit risk recognition. This timeframe allows for an analysis of pre and post PSAK 71 impacts on financial performance. Data was sourced from Capital IQ and Capital IQ Pro, platforms renowned for their comprehensive and reliable financial metrics. To ensure data quality, a 1 percent outlier moderation was applied to exclude extreme values that could skew the results, thereby enhancing the robustness and reliability of the analysis. The study examines dependent variables including Return on Assets (ROA) and Return on Equity (ROE) as measures of bank profitability, alongside independent variables such as PSAK 71 implementation, liquidity risk (Loan to Deposit Ratio or LDR), credit risk (Non Performing Loans or NPL), and bank capital (Capital Adequacy Ratio or CAR). Additionally, control variables including bank size, loan growth, and non interest expenses are included to account for external influences on profitability.

To ensure robust and unbiased results, the study employs rigorous diagnostic methods. The Chow Test was used to confirm the suitability of the Fixed Effects Model (FEM) over the Common Effects Model (CEM), while the Hausman Test validated FEM as preferable to the Random Effects Model (REM). These models were selected for their ability to capture unobserved heterogeneity across banks, a critical consideration given the diversity in Indonesia's banking sector. Diagnostic tests such as the Wooldridge Test for autocorrelation, Breusch Pagan Test for heteroscedasticity, and Pesaran CD Test for cross sectional dependence were conducted to identify and address econometric issues. By defining key variables with precision, such as PSAK 71 implementation as a binary variable, LDR as a measure of liquidity risk, and NPL as an indicator of credit risk, the study provides a transparent and replicable framework. These rigorous methodological choices and clear variable definitions ensure that the findings offer reliable and actionable insights into the effects of PSAK 71 on Indonesian banking profitability.

$$ROA_{it} = \alpha_0 + \beta_1 IFRS9 + \beta_2 LDR_{it} + \beta_3 NPL_{it} + \beta_4 CR_{it} + \gamma_1 Size_{it} + \gamma_2 LG_{it} + \gamma_3 NIX_{it} + \varepsilon_{it}$$
$$ROE_{it} = \alpha_0 + \beta_1 IFRS9 + \beta_2 LDR_{it} + \beta_3 NPL_{it} + \beta_4 CR_{it} + \gamma_1 Size_{it} + \gamma_2 LG_{it} + \gamma_3 NIX_{it} + \varepsilon_{it}$$

Table 1
Variable Measurement

Variable	Definition	Formula
Dependen Variables		
ROA	*Return on Assets*	$\frac{Net\ Income}{Total\ Average\ Assets}$
ROE	*Return on Equity*	$\frac{Net\ Income}{Total\ Equity}$
Independen Variables		
IFRS 9	IFRS 9	$Dummy\ Variable$ $(1\ if\ IFRS\ 9\ is\ implemented, 0\ otherwise)$
LDR	Liquidity Ratio	$\frac{Customer\ Deposits}{Total\ Assets}$

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Variable	Definition	Formula
NPL	Credit Risk	$\frac{Non\ Performing\ Loans}{Total\ Loans}$
CR	Capital Ratio	$\frac{Total\ Capital}{Total\ Assets}$
Control Variables		
Size	Bank Size	$\ln(Total\ Assets)$
LG	Loan Growth	$\frac{Loans\ at\ Quarter_t - Loans\ at\ Quarter_{t-1}}{Loans\ at\ Quarter_{t-1}}$
NIX	Non-Interest Expenses	$\frac{Non\ Interest\ Expenses}{Total\ Operating\ Expenses}$

The hypotheses in this study are:

H_{1a} = IFRS 9 has a significant negative effect on ROA.
H_{1b} = IFRS 9 has a significant negative effect on ROE.
H_{2a} = LDR has a significant negative effect on ROA.
H_{2b} = LDR has a significant negative effect on ROE.
H_{3a} = NPL has a significant negative effect on ROA.
H_{3b} = NPL has a significant negative effect on ROE.
H_{4a} = CR has a significant positive effect on ROA.
H_{4b} = CR has a significant positive effect on ROE.
H_{5a} = Size has a significant negative effect on ROA.
H_{5b} = Size has a significant negative effect on ROE.
H_{6a} = LG has a significant positive effect on ROA.
H_{6b} = LG has a significant positive effect on ROE.
H_{7a} = NIX has a significant positive effect on ROA.
H_{7b} = NIX has a significant positive effect on ROE.

This study employs panel regression models to examine the effects of IFRS 9 implementation, liquidity risk, credit risk, and bank capital on the financial performance of Indonesian banks, measured through Return on Assets (ROA) and Return on Equity (ROE). Panel data models are particularly suited for this analysis as they integrate cross-sectional and time-series dimensions, enabling a detailed understanding of dynamic changes across banks over time. The models used include the Common Effect Model (CEM), which assumes uniformity across units and time periods, the Fixed Effects Model (FEM), which captures individual-specific characteristics constant over time, and the Random Effects Model (REM), which treats individual effects as random and uncorrelated with the independent variables. To determine the most appropriate model, the study conducts a series of statistical tests, including the Chow test for comparing CEM and FEM, the Hausman test for distinguishing FEM from REM, and the Lagrange Multiplier test for evaluating REM against CEM.

To ensure the validity and robustness of the regression analysis, diagnostic tests are performed to address potential statistical issues. The Wooldridge test is applied to detect autocorrelation, the Breusch-Pagan test identifies heteroskedasticity, and the Pesaran test assesses cross-sectional dependence among residuals. These tests help verify whether the assumptions of the econometric models are met, ensuring reliable and unbiased estimates.

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Addressing these diagnostic concerns is critical, as violations such as correlated errors or non-uniform variances can lead to inaccurate interpretations of the relationships between variables. The use of robust statistical methods reinforces the reliability.

In addition to traditional econometric approaches, the study incorporates advanced machine learning techniques, such as Random Forest and XGBoost, to evaluate the relative importance of variables influencing bank profitability. These methods enhance the interpretability and predictive accuracy of the models by identifying the key drivers of performance metrics such as ROA and ROE. Random Forest uses ensemble learning to reduce variability and improve prediction, while XGBoost applies gradient boosting to efficiently handle complex, non-linear relationships. By combining traditional statistical analysis with machine learning insights, the study offers a comprehensive understanding of how IFRS 9 implementation and financial risks affect bank performance, providing valuable implications for policymakers, practitioners, and researchers.

3. Results and Discussion

Descriptive Statistics

This section presents the descriptive statistics of the variables used in the study to provide an overview of the dataset. The descriptive statistics include the number of observations, mean, standard deviation, median, minimum, and maximum values for each variable.

Table 2
Description of Research Data

Variable	Observation	Mean	Median	Standard Deviation	Minimum	Maximum
ROA	2400	0,71	0,78	2,56	-12,89	8,84
ROE	2400	4,76	5,09	14,31	-75,31	31,98
IFRS9	2400	0,33	0	0,47	0	1
LDR	2262	0,70	0,76	0,20	0	0,89
NPL	2400	1,96	0,91	2,74	0	15,38
CR	2262	0,19	0,15	0,14	0,06	0,88
SIZE	2262	14,48	14,22	1,87	10,77	18,52
LG	1332	-0,24	-0,01	0,45	-1	0,29
NIX	1869	0,07	0,03	0,13	-0,35	0,67

Based on Table 2, the descriptive statistics highlight significant variability in the financial performance and risk management strategies of Indonesian banks. Profitability metrics such as Return on Assets (ROA) and Return on Equity (ROE) show that while certain banks are excelling, others face operational and risk management challenges. These differences stem from factors such as varying credit risk practices, capitalization levels, and market conditions. For instance, banks with strong ROA and ROE likely leverage efficient credit risk controls and streamlined operations, while those with weaker metrics may grapple with higher exposure to non-performing loans (NPLs) or operational inefficiencies. This aligns with prior research by Harb et al. (2022), which underscores the critical role of risk mitigation strategies in sustaining profitability.

The data also reveal differences in liquidity management, as reflected in the Loan to Deposit Ratio (LDR). While most banks maintain stable liquidity levels, divergent lending

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strategies are evident, with some opting for conservative approaches to minimize risk and others pursuing aggressive lending to drive growth. Credit risk, measured by NPL ratios, further emphasizes these differences, with higher NPLs signaling weaker loan quality and recovery strategies. Additionally, the Capital Adequacy Ratio (CAR) suggests that banks generally maintain sufficient capital buffers, yet variations in CAR levels indicate differing risk appetites and capital management practices. Larger banks often exhibit higher CARs, contributing to stability, but they may also face increased operational costs due to their size, consistent with the findings of Ekinci and Poyraz (2019).

Operational efficiency is another key differentiator, as evidenced by variations in non-interest expenses. Banks with streamlined operations achieve higher profitability by minimizing overhead costs, while others with higher expenses struggle to maintain competitive margins. These findings underscore the interconnectedness of risk management, operational efficiency, and capital adequacy in shaping bank profitability. Policymakers and banking leaders can draw actionable insights from these results by focusing on strengthening credit risk management frameworks and optimizing operational efficiency. Such measures can enhance the resilience of Indonesian banks, aligning with regulatory expectations under PSAK 71 and fostering long-term profitability.

Panel Model Selection

Chow Test

The Chow test was conducted to determine the most appropriate model between the Fixed Effects Model (FEM) and the Common Effects Model (CEM).

Table 3
Chow Test Results

Chow Test	ROA	ROE
p-value	0,000	0,000

Based on Table 3, the Chow Test results indicate p-values of 0.000 for both ROA and ROE, significantly below the 5% significance threshold. This leads to the rejection of the null hypothesis, confirming that the Fixed Effects Model (FEM) is more appropriate than the Common Effects Model (CEM) for analyzing the data. The preference for FEM is justified by its ability to account for unobserved heterogeneity across banks, capturing unique and time-invariant characteristics that influence performance. Unlike CEM, which assumes uniformity across all banks, FEM provides a nuanced understanding of variability in profitability metrics like ROA and ROE. These findings align with literature emphasizing the importance of FEM in capturing institutional differences in panel data studies (e.g., Ekinci and Poyraz, 2019). For policymakers, this result reinforces the necessity of tailored strategies that reflect individual bank characteristics rather than a one-size-fits-all approach, ensuring more effective policy interventions and performance assessments in Indonesia's banking sector.

Hausman Test

The Hausman test was used to compare FEM with the Random Effects Model (REM).

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Hausman Test Results

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Hausman Test	ROA	ROE
p-value	0,0000	0,0000

Based on Table 4, the Hausman Test results reveal p-values of 0.0000 for both ROA and ROE, well below the 5% significance threshold. This leads to the rejection of the null hypothesis, confirming that the Fixed Effects Model (FEM) is more suitable than the Random Effects Model (REM) for this analysis. The selection of FEM is justified by its ability to accurately account for the unique and consistent characteristics of each bank, which are crucial for understanding the specific impact of independent variables such as liquidity risk, credit risk, and capital adequacy on profitability metrics like ROA and ROE. Unlike REM, which assumes that individual effects are random and uncorrelated with explanatory variables, FEM ensures that these effects are properly controlled, yielding more reliable and precise estimates. This finding aligns with established econometric principles, emphasizing the importance of FEM in studies where entity-specific factors play a critical role. For policy and practice, the result underscores the necessity of considering individual bank characteristics when designing regulatory frameworks or performance enhancement strategies under PSAK 71.

Diagnostic Test

Autocorrelation Test

The Wooldridge test was applied to detect autocorrelation in the panel data model.

Table 5
Autocorrelation Test Results

Autocorrelation	ROA	ROE
p-value	0,0000	0,0000

Based on Table 5, the Wooldridge Test results show p-values of 0.0000 for both ROA and ROE, which are significantly below the 5% significance level. This confirms the presence of autocorrelation, indicating that the residuals in the models are correlated across time or entities. Such correlation violates the assumption of independence among errors, potentially leading to biased or inefficient estimates if not addressed. This finding highlights the need for corrective measures, such as using robust standard error adjustments or Generalized Least Squares (GLS), to account for autocorrelation and ensure accurate and reliable results. Addressing autocorrelation is critical in panel data analysis, particularly in studies like this, where time-series and cross-sectional elements intersect.

Heteroscedasticity Test

The Breusch-Pagan test was conducted to detect heteroscedasticity in the ROA and ROE models.

Table 6
Heteroscedasticity Test Results

Heteroscedasticity	ROA	ROE
p-value	0,0000	0,0000

Based on Table 6, the Breusch Pagan Test results indicate p-values of 0.0000 for both ROA and ROE, well below the 5% significance level. This leads to the rejection of the null hypothesis of homoscedasticity, confirming the presence of heteroscedasticity in the models. Heteroscedasticity implies that the variance of error terms is not constant across observations,

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which can result in inefficient and biased estimates if not addressed. To ensure the reliability of the results, corrective measures such as using robust standard errors or Weighted Least Squares (WLS) should be applied. These adjustments help account for non-uniform variances, improving the precision of coefficient estimates. Addressing heteroscedasticity is particularly important in financial studies, as ignoring this issue can undermine the validity of conclusions regarding the impact of PSAK 71 on bank profitability metrics like ROA and ROE.

Cross-Sectional Dependency Test

The Pesaran CD test was used to check for cross-sectional dependence between entities in the panel data model.

Table 7
Cross-Sectional Dependence Test Results

Cross Sectional Dependence Test	ROA	ROE
p-value	0,0000	0,0000

Based on Table 7, the Pesaran CD Test results reveal p-values of 0.0000 for both ROA and ROE, indicating significant cross-sectional dependence in the models. This suggests that residuals across different entities are correlated, violating the assumption of independence and potentially biasing the results. Cross-sectional dependence often arises in panel data when entities, such as banks, are influenced by shared external factors like macroeconomic conditions, industry-wide trends, or regulatory changes. This interdependence can distort the interpretation of the impact of independent variables on profitability metrics. To address this issue, further adjustments such as Driscoll-Kraay standard errors, Panel Corrected Standard Errors (PCSE), or the use of dynamic panel data models like the Generalized Method of Moments (GMM) are necessary. These approaches effectively account for cross-sectional correlation, ensuring more robust and reliable parameter estimates. Failure to address this issue may lead to inaccurate conclusions about the relationships being analyzed, particularly the influence of PSAK 71 on profitability indicators like ROA and ROE. Given the interconnected nature of financial institutions, the presence of cross-sectional dependence highlights the systemic influence of regulatory and economic factors. Policymakers can benefit from these findings by recognizing the broader impact of shared conditions on bank performance.

Results and Interpretation

Before conducting the panel data regression, issues related to autocorrelation, heteroscedasticity, and cross-sectional dependence were addressed using Driscoll-Kraay Standard Errors. This method, developed by Driscoll and Kraay (1998), is designed to provide robust standard errors in the presence of these issues, which are common in panel data models. By adjusting the standard errors to account for these econometric problems without making assumptions about the data structure, the Driscoll-Kraay approach ensures that the coefficient estimates are reliable and can be used for accurate inference, even with these challenges.

Table 8 presents the regression results for various financial variables in two panel data regression models. These models are categorized based on the two dependent variables, ROA and ROE, both before and after the implementation of IFRS 9 (PSAK 71). This comparative approach allows us to assess how different financial ratios impact key banking metrics.

Table 8

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Panel Data Regression Results with Driscoll-Kraay Standard Errors

Variabel Independen	ROA		ROE	
	Coef	**P**	**Coef**	**P**
IFRS 9	-0,5743	0,0057*	-3,2053	0,0176*
LDR	0,6179	0,4534	5,2205	0,3084
NPL	-0,3245	0,0005*	-2,2434	0,0003*
CR	2,5818	0,0186*	6,4923	0,2375
SIZE	0,1185	0,5393	0,6639	0,4445
LG	1,1659	0,0002*	7,3040	0,0000*
NIX	2,6665	0,0067*	5,8604	0,2162
F-Statistics	21,7979		22,8785	
R-Squared	0,1178		0,1229	
Adj, R-Squared	0,0769		0,0822	
Prob>F	0,0000*		0,0000*	

*) significant

Based on Table 8 this study investigates the impact of several key variables on bank profitability, specifically focusing on Return on Assets (ROA) and Return on Equity (ROE). The findings reveal that IFRS 9, implemented through PSAK 71 in Indonesia, significantly negatively affects profitability. The requirement for banks to recognize expected credit losses earlier leads to higher provisions for potential loan losses, which in turn reduces net income, lowering both ROA and ROE. This result supports H_{1a} and H_{1b}, which hypothesized that IFRS 9 would have a negative impact on both ROA and ROE. While this approach improves financial stability and transparency, it also increases operational costs, which can adversely affect profitability. These findings are consistent with research by Eyalsalman et al. (2024), who noted that the conservative approach in credit provisioning tends to raise operational costs, negatively impacting profitability.

In contrast, Loan-to-Deposit Ratio (LDR) does not show a significant impact on profitability in this study. Although LDR is crucial for maintaining liquidity, it does not directly influence asset efficiency (ROA) or equity returns (ROE). This result leads to the rejection of H_{2a} and H_{2b}, indicating that LDR, while essential for financial stability, does not significantly enhance or reduce profitability in the context of this research. The role of LDR in ensuring liquidity is supported by previous studies such as Tulung et al. (2024), who emphasized that its primary function is to maintain liquidity rather than directly influencing profitability.

On the other hand, Non-Performing Loans (NPL) exhibit a significant negative impact on profitability, supporting H_{3a} and H_{3b}. High levels of NPL require banks to allocate more resources to cover credit losses, reducing asset efficiency (ROA) and diminishing equity returns (ROE). This aligns with findings from Eyalsalman et al. (2024) and Million et al. (2015), who observed that high NPL ratios force banks to divert resources from productive activities to risk mitigation, which negatively affects profitability. Managing NPLs effectively through loan restructuring and improved credit monitoring is essential to minimize their impact on profitability.

Regarding Capital Ratio (CR), the study finds that it positively affects ROA, supporting H_{4a}, as higher capital allows banks to absorb risks and manage assets more efficiently. However, the impact on ROE is less pronounced, leading to the rejection of H_{4b}. A higher

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CR may be allocated to risk reserves, reducing the potential for productive investments and, consequently, limiting its impact on equity returns. This finding is consistent with Nuryanto et al. (2020), who noted that while a strong capital ratio supports operational stability, its direct impact on equity profitability can be less significant due to the allocation of capital to risk provisions.

In terms of Bank Size (SIZE), the study shows no significant effect on profitability, leading to the rejection of both H_{5a} and H_{5b}. While larger banks benefit from economies of scale and have better access to resources, their operational complexity and higher management costs often offset these advantages, diminishing asset efficiency (ROA). Larger banks may face challenges in managing their expansive operations, leading to inefficiencies that undermine profitability. This is consistent with Eyalsalman et al. (2024), who found that larger banks in Jordan experienced decreased profitability due to increased operational complexities.

Loan Growth (LG) has a mixed effect on profitability, with aggressive loan growth negatively affecting ROA but positively influencing ROE. The negative effect on ROA stems from the increased risk of loan defaults, which decreases asset efficiency. However, the positive effect on ROE arises from the higher interest income generated by expanded lending. This result supports H_{6b} but leads to the rejection of H_{6a}. These findings highlight the importance of managing loan growth carefully, ensuring that it is directed toward productive and low-risk sectors to balance growth with profitability. This is consistent with the Risk-Return Tradeoff Theory, which suggests that while aggressive loan growth can reduce asset efficiency, it can also increase returns through leverage.

Finally, Non-Interest Expenses (NIX) have a significant negative impact on ROA, as higher operational costs reduce asset efficiency, supporting H_{7a}. However, NIX does not significantly affect ROE, leading to the rejection of H_{7b}. The result suggests that non-interest expenses directly impact the efficiency of asset management, while their effect on equity returns is more influenced by leverage and capital structure. These findings align with Sufian et al. (2010), who argued that high non-interest expenses can reduce asset efficiency but do not have a direct effect on ROE unless strategically invested in operational improvements.

In conclusion, the variables studied, namely IFRS 9, LDR, NPL, CR, SIZE, LG, and NIX, exhibit unique impacts on bank profitability, highlighting the complex interplay between financial performance and risk management. IFRS 9 and NPL significantly constrain profitability by increasing operational costs and allocating resources to mitigate credit risks, negatively affecting ROA and ROE. However, variables such as CR and LG demonstrate potential for enhancing efficiency and profitability when managed effectively. These findings underscore the importance of strategic interventions, such as optimizing capital allocation, reducing non-performing loans through rigorous credit monitoring and restructuring, and prioritizing operational cost efficiency to sustain profitability. Banks must adopt a balanced approach that aligns growth objectives with robust risk management practices, focusing on productive credit growth, maintaining adequate liquidity, and leveraging technology to enhance operational efficiency.

Variable Importance Analysis

Random Forest

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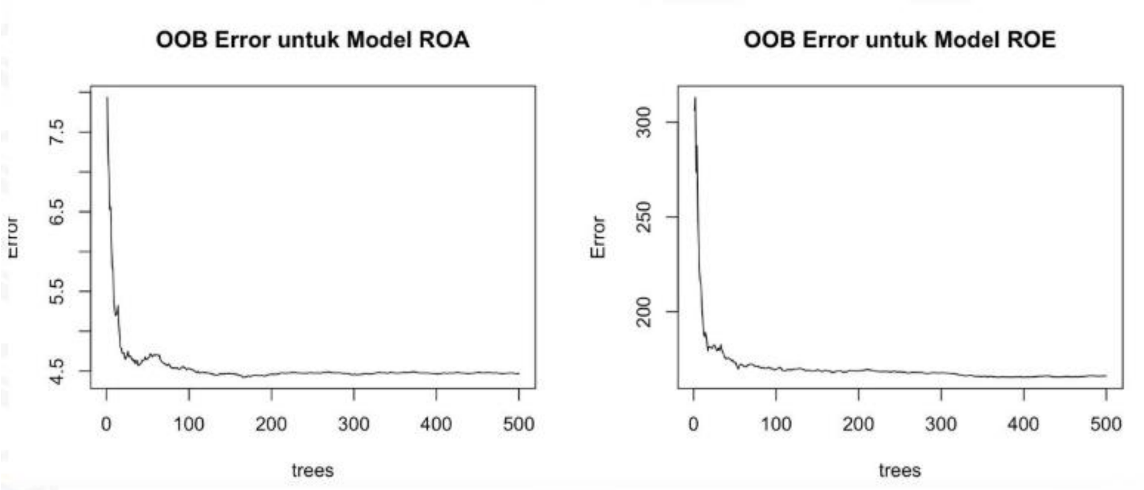
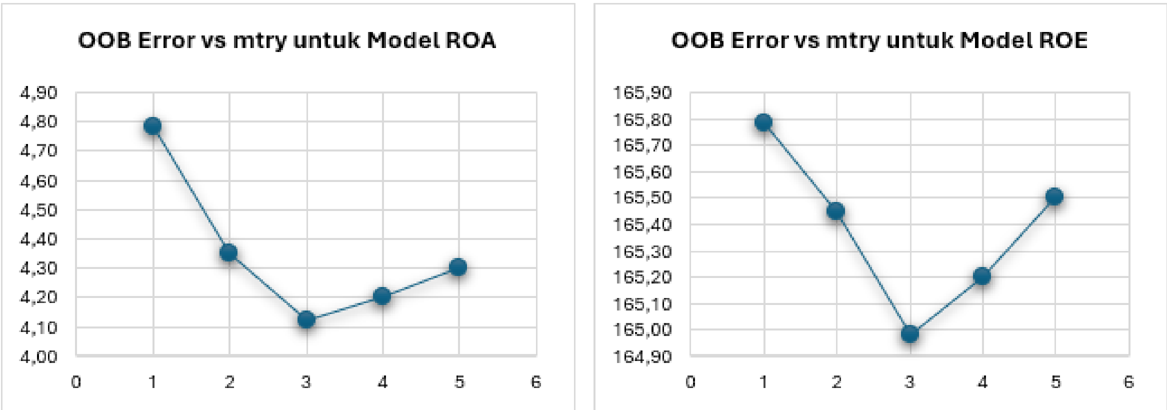
The initial step in applying Random Forests involved imputing missing values (NA) in the data using the Random Forest method. The number of iterations was set to 6, and the number of trees (ntree) was set to 500. As shown in the graph, increasing the number of trees reduces the Out-of-Bag (OOB) error, and after approximately 500 trees, the error rate stabilizes.

Figure 1
Out of Bag Error



Based on Figure 1, the OOB error decreased sharply with the increase in the number of trees, stabilizing after 500 trees. For ROA, the error dropped from around 7 to approximately 4 after 100 trees and remained stable. Similarly, for ROE, the error dropped from 300 to around 200 after 100 trees and then stabilized, indicating that 500 trees are sufficient for optimal model performance. This stability suggests that adding more trees beyond 500 does not significantly improve accuracy, ensuring that the model remains computationally efficient.

Figure 2
Tuned Random Forest Mtry model ROA and ROE



Based on Figure 2, tuning the mtry parameter in the Random Forest model significantly influences the prediction accuracy for ROA and ROE. In the ROA model, an mtry value of 3 is optimal, yielding the lowest OOB error. Increasing mtry to 4 results in a higher OOB error, likely due to overfitting caused by the model's increased complexity. This highlights a

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decrease in prediction efficiency as the model struggles to generalize to unseen data. Similarly, in the ROE model, an mtry value of 3 produces the best performance, minimizing the OOB error. Deviations from this value, whether higher or lower, lead to suboptimal model performance due to an imbalance between bias and variance. These results emphasize the critical role of selecting an appropriate mtry value to achieve a balance between model accuracy, efficiency, and generalization capabilities.

Table 9
RMSE Model Random Forest

Random Forest	**ROA**	**ROE**
RMSE before tuning	1,9761	10,3236
RMSE after tuning	1,9990	10,3385

Table 9 shows the Root Mean Square Error (RMSE) for the Random Forest model in predicting ROA and ROE before and after tuning. Interestingly, post-tuning RMSE increased slightly for both metrics, with ROA moving from 1.9761 to 1.9990 and ROE from 10.3236 to 10.3385. This counterintuitive result suggests that while tuning parameters like mtry and ntree aimed to optimize the model, they may have inadvertently introduced sensitivity to less significant variables. This sensitivity could lead to minor overfitting, where the model performs better on training data but struggles to generalize on unseen data. The slight increase in RMSE post-tuning indicates that while tuning improved the theoretical model structure, it might not fully address issues related to noise and irrelevant variable interactions. This observation underscores the need for further refinements, such as evaluating additional hyperparameters, incorporating feature selection techniques, or adopting advanced cross-validation methods to enhance the model's predictive power. A thorough assessment is crucial to ensure that the model achieves robust performance, maintaining a balance between prediction accuracy and its ability to generalize effectively to test data.

Figure 3
Random Forest Variable Importance ROA and ROE

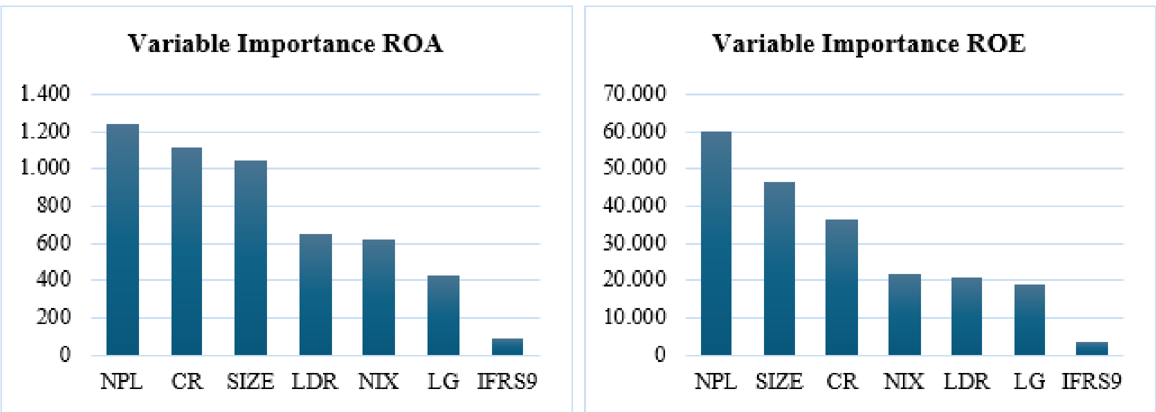

Figure 3 illustrates the importance of each variable in the Random Forest model for predicting ROA (Return on Assets) and ROE (Return on Equity). In the ROA model, Non-Performing Loans (NPL) emerge as the most critical variable, indicating its strong influence on asset efficiency. This is followed by the Capital Adequacy Ratio (CR), which reflects the bank's ability to manage financial risks, and bank size (SIZE), which suggests the role of

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scale in operational performance. The Loan-to-Deposit Ratio (LDR) also contributes but to a lesser extent, with non-interest expenses (NIX), loan growth (LG), and IFRS9 having smaller effects on ROA. In the ROE model, NPL again proves to be the dominant factor, reinforcing its impact on equity returns through the management of credit risks. Bank size (SIZE) and CR follow as significant contributors, while non-interest expenses (NIX) play a moderately smaller role. Variables such as LDR, LG, and IFRS9 contribute less, suggesting a more marginal effect on equity profitability. These findings highlight the consistent significance of NPL, SIZE, and CR in shaping bank profitability across both models. Their influence underscores the importance of effective credit risk management, capital adequacy, and operational efficiency in maintaining financial performance. Conversely, variables like LDR, LG, and IFRS9, while relevant, provide more supplementary insights, emphasizing the need for a targeted approach to managing key drivers of profitability.

XGBoost

In this study, the XGBoost model was used to predict ROA (Return on Assets) and ROE (Return on Equity) by splitting the data into training and testing sets with an 80:20 ratio. The initial model was run with default parameters, including max_depth and 300 nrounds, to calculate the Root Mean Square Error (RMSE) for both training and testing data in each boosting iteration. Subsequently, tuning was performed through grid search on key parameters, such as max_depth, eta, and nrounds, to identify the optimal combination for improved model performance.

Figure 4

Iterations for ROA and ROE

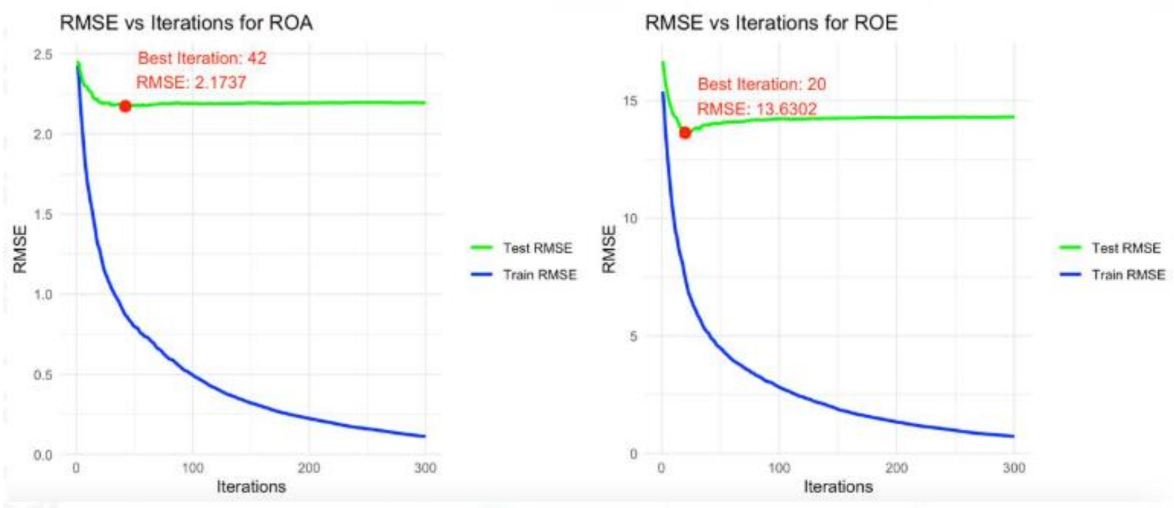

Figure 4 presents the RMSE values across iterations for ROA and ROE during the XGBoost tuning process. For ROA, the lowest RMSE of 2.1737 was achieved at iteration 42, indicating the point where the model balanced complexity and predictive accuracy for asset efficiency. Similarly, for ROE, the model reached its optimal RMSE of 13.6302 at iteration 20, highlighting the iteration at which it maximized accuracy in predicting equity profitability. These results demonstrate the model's ability to fine-tune parameters such as max_depth, eta, and nrounds to minimize prediction errors while avoiding overfitting

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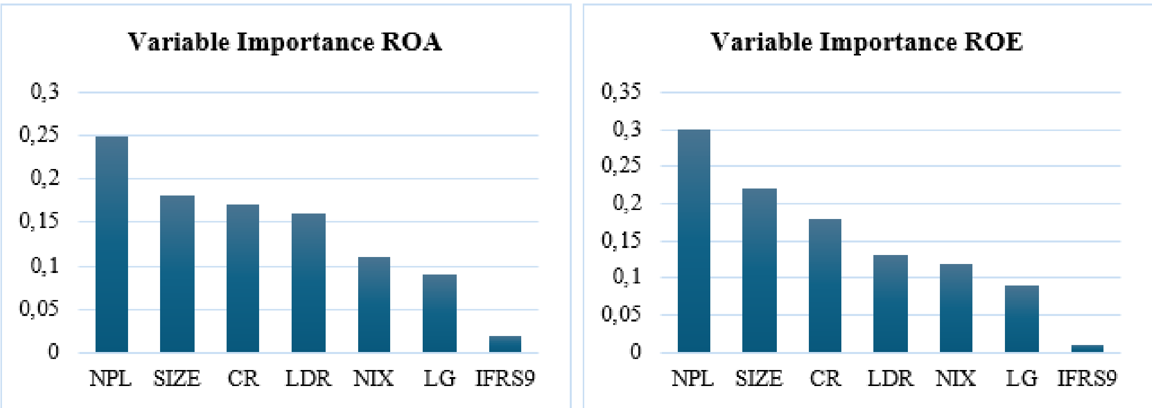
Table 10
XGBoost RMSE

XGBoost	ROA	ROE
RMSE before tuning	2,2100	13,8721
RMSE after tuning	2,1737	13,6302

Table 10 highlights the improvement in RMSE values for ROA and ROE following the tuning of the XGBoost model. Before tuning, the RMSE for ROA was 2.2100, while for ROE, it stood at 13.8721. After optimizing key parameters such as max_depth and eta, the RMSE values dropped to 2.1737 for ROA and 13.6302 for ROE. This reduction reflects the tuning process's success in refining the model to achieve better prediction accuracy. The decrease in RMSE signifies an enhanced balance between bias and variance, ensuring the model is less prone to overfitting while maintaining robustness in handling unseen data. By iteratively testing parameter combinations, the tuning process allowed the model to identify the optimal number of boosting rounds (nrounds) and tree depth, ensuring maximum accuracy without excessive computational complexity. This improvement is particularly important in the context of bank profitability analysis, where accurate predictions of metrics like ROA and ROE are crucial for understanding the impact of financial variables on performance. The refined XGBoost model demonstrates its capability to generalize effectively, providing reliable insights into the relationship between critical financial factors and profitability.

Figure 5
XGBoost Variable Importance ROA dan ROE



Based on Figure 5, the XGBoost model reveals distinct levels of variable importance in predicting ROA (Return on Assets) and ROE (Return on Equity). Non-Performing Loans (NPL) emerge as the most critical variable for both metrics, underscoring its dominant role in influencing bank profitability. For ROA, NPL is followed by bank size (SIZE) and Capital Ratio (CR), which also have a substantial impact, indicating their significant contributions to asset efficiency. Other variables, including Loan-to-Deposit Ratio (LDR), non-interest expenses (NIX), loan growth (LG), and IFRS9, have a smaller influence on ROA predictions, suggesting a more supplementary role. Similarly, for ROE, NPL maintains its position as the most influential variable, again highlighting the critical importance of credit risk management in maximizing equity returns. Bank size (SIZE) and Capital Ratio (CR) are the next most important factors, reinforcing their relevance in equity profitability. Meanwhile,

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LDR, NIX, LG, and IFRS9 play less prominent roles, indicating that their direct impact on ROE is comparatively minimal. These findings underscore the consistent and substantial effect of variables like NPL, SIZE, and CR on financial performance metrics. They highlight the need for banks to focus on managing credit risk, optimizing capital structures, and scaling operations efficiently to improve profitability. The smaller contributions of LDR, LG, and IFRS9 suggest that while they are relevant, their roles are secondary and may serve as complementary factors in the broader context of financial performance analysis.

Improving Model Performance

Based on the panel regression analysis using the fixed effects model and machine learning evaluation, model optimization was undertaken to enhance the prediction efficiency of bank profitability. In the ROA model, the variable Loan Growth (LG) was removed due to its low contribution to asset efficiency variance, while in the ROE model, the Non-Interest Expenses (NIX) variable was excluded because of its minimal impact on equity profitability. Removing these variables simplifies the models without losing critical information, thereby improving their accuracy and predictive performance.

Model Equations Before Variable Removal

$$ROA_{it} = \alpha_0 + \beta_1 IFRS9 + \beta_2 LDR_{it} + \beta_3 NPL_{it} + \beta_4 CR_{it} + \gamma_1 Size_{it} + \gamma_2 LG_{it} + \gamma_3 NIX_{it} + \varepsilon_{it}$$
$$ROE_{it} = \alpha_0 + \beta_1 IFRS9 + \beta_2 LDR_{it} + \beta_3 NPL_{it} + \beta_4 CR_{it} + \gamma_1 Size_{it} + \gamma_2 LG_{it} + \gamma_3 NIX_{it} + \varepsilon_{it}$$

Model Equations After Variable Removal

$$ROA_{it} = \alpha_0 + \beta_1 IFRS9 + \beta_2 NPL_{it} + \beta_3 CR_{it} + \gamma_1 LG_{it} + \gamma_2 NIX_{it} + \varepsilon_{it}$$
$$ROE_{it} = \alpha_0 + \beta_1 IFRS9 + \beta_2 NPL_{it} + \beta_3 CR_{it} + \gamma_1 LG_{it} + \gamma_2 NIX_{it} + \varepsilon_{it}$$

After removing the variables LDR and SIZE from the ROA and ROE models, an evaluation was conducted to measure the improvement in model performance.

Table 11
Comparison of Adjusted R-Squared

Model	Adjusted R-Squared Before	Adjusted R-Squared After
ROA	0,0769	0,0776
ROE	0,0822	0,0826

Based on Table 11, the Adjusted R-Squared for the Return on Assets (ROA) model increased slightly from 0.0769 to 0.0776 after the exclusion of the Loan to Deposit Ratio (LDR) and bank size (SIZE) variables. This improvement suggests that removing these less impactful variables enhanced the model's explanatory power by focusing on factors more closely linked to bank asset efficiency, such as credit risk (NPL) and capital adequacy (CAR). Similarly, for the Return on Equity (ROE) model, the Adjusted R-Squared rose from 0.0822 to 0.0826, reflecting a marginally improved capacity to explain equity profitability. These adjustments demonstrate the importance of a streamlined model that prioritizes variables with significant explanatory relevance, consistent with econometric theories on parsimony and model efficiency. By refining the model, the analysis yields more accurate insights into how key financial metrics drive profitability under PSAK 71.

The decision to retain the IFRS9 variable, despite its lower direct significance in the models, underscores its systemic importance in the regulatory framework of PSAK 71. IFRS9 represents a paradigm shift from incurred-loss to expected-loss models in credit provisioning, emphasizing proactive risk management and financial transparency. Its

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inclusion ensures the model captures the broader regulatory context, particularly its influence on credit provisioning, financial stability, and operational strategies. This finding aligns with prior literature, such as Rodrigues Boscia et al. (2022), which highlights IFRS9's critical role in transforming banking practices globally. The retained variable reflects how compliance with PSAK 71 indirectly affects profitability by reshaping risk management frameworks, even when its direct statistical influence on metrics like NPL and CR is less pronounced.

These findings offer actionable recommendations for stakeholders. Policymakers should leverage the insights from PSAK 71's systemic impact to further strengthen risk management standards, encourage compliance, and promote innovations in predictive analytics to refine credit risk assessments. For practitioners, the results emphasize the need to focus on operational efficiency and strategic capital allocation to balance compliance costs with profitability objectives. Banks should adopt technology-driven solutions to streamline processes and reduce non-interest expenses, which directly influence profitability. Additionally, the findings highlight the necessity of addressing credit risk proactively, particularly by improving loan quality and recovery strategies. By aligning strategic initiatives with the regulatory framework of PSAK 71, stakeholders can achieve enhanced resilience, sustain profitability, and navigate an evolving financial environment effectively.

4. Conclusion

This study explores the influence of key financial variables on bank profitability in Indonesia, emphasizing the implications of PSAK 71, which aligns with IFRS 9. This regulatory standard mandates the early recognition of potential credit losses and the establishment of larger credit reserves, introducing operational challenges that impact profitability. The research examines factors such as credit risk, liquidity, capital adequacy, bank size, loan growth, and non-interest expenses to determine their effects on profitability, measured through Return on Assets (ROA) and Return on Equity (ROE). By addressing these dimensions, the study provides insights into how regulatory and operational elements intersect with financial performance in the banking sector.

The findings highlight that the implementation of IFRS 9 negatively affects bank profitability by raising operational costs and diminishing both asset efficiency (ROA) and equity returns (ROE). Among the variables, Non-Performing Loans (NPL) emerge as a major detractor from profitability, as banks must allocate additional resources to manage credit losses, thereby straining financial stability. The Capital Adequacy Ratio (CR), on the other hand, enhances asset efficiency by ensuring sufficient capital buffers but has a limited effect on equity returns due to its allocation to risk reserves. Loan growth (LG) displays a dual impact, reducing asset efficiency because of heightened credit risk while supporting equity returns through increased interest income. Meanwhile, bank size (SIZE) and the Loan-to-Deposit Ratio (LDR) show no significant impact on profitability, as operational complexities and liquidity buffers offset their potential benefits. Non-interest expenses (NIX) affect asset efficiency but do not significantly influence equity returns, with profitability more reliant on capital allocation strategies.

To enhance profitability and competitiveness, the study recommends strategic actions focusing on credit risk management, including stricter loan selection processes and proactive portfolio restructuring to minimize NPL. Banks are encouraged to adopt advanced predictive models to estimate credit losses accurately and streamline credit growth toward productive and low-risk sectors. Allocating capital to profitable investments can amplify returns, while

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improving operational efficiency through investments in digital technologies and human resource development can strengthen both short-term financial performance and long-term market positioning. These strategies collectively aim to balance regulatory compliance with operational and financial efficiency, fostering sustainable growth in a competitive banking environment.

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Declarations

Author Contribution : Author 1: Conceptualization, Writing - Original Draft, Editing and Visualization; Author 2: Writing - Review & Editing, Formal analysis, and Methodology; Author 3: Validation and Supervision (https://www.elsevier.com/authors/policies-and-guidelines/credit-author-statement).

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