The Effect of Big Data Adoption on Regional Bank Profitability: Simulated Data in the Financial Planning

Karona Cahya Susena[1*], Nenden Restu Hidayah[2], Sukrisno[3], Made Setini[4]

[1]*Department of Management, Faculty of Economics and Business, Universitas Dehasen Bengkulu; Bengkulu, Indonesia*

[2]*Department of Accounting, Faculty of Economics and Business, Universitas Dehasen Bengkulu; Bengkulu, Indonesia*

[3]*Department of Management, Sekolah Tinggi Ilmu Ekonomi Pariwisata Indonesia; Semarang, Indonesia*

[4]*Department of Management, Faculty of Economics and Business, Universitas Warmadewa; Denpasar, Indonesia*

*Corresponding Author E-Mail: karonacs@unived.ac.id

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ABSTRACT

Digital transformation, marked by the era of financial planning 5.0, presents both a challenge and an opportunity for regional banks. While large institutions rapidly adopt data-driven strategies, regional banks often lag due to resource constraints, potentially harming their profitability and competitiveness. This study examines the role of big data adoption within this modern framework to optimize the financial performance of regional banks. Using a quantitative approach with a multiple regression model, this research simulates data from ten regional banks to test the effects of big data adoption, operational efficiency, and risk management on two key profitability indicators: Return on assets and net interest margin. The analysis results show that big data adoption has a significant positive correlation with both profitability measures. In contrast, higher operational costs and increased non-performing loans negatively affect bank profitability. These findings demonstrate that strategic investment in data technology, when integrated with efforts to improve operational governance and human resource capabilities, can be a crucial lever for enhancing the financial performance and sustainability of regional banks in the digital age.

Keywords: *Bank Profitability, Big Data Adoption, Financial Planning 5.0, Operational Efficiency, Risk Management.*

INTRODUCTION

Digital transformation in the banking sector has moved beyond basic automation to intelligence-based decision-making in the financial planning 5.0 era, using AI, machine learning, and real-time data analytics to create predictive and personalized financial planning (Goyal & Joshi, 2021; Machireddy et al., 2023). Unlike traditional models that rely on historical data and manual analysis, this approach supports more dynamic and accurate projections. However, adoption is uneven: large national banks are advancing quickly, while regional banks struggle with limited budgets, outdated technology, and low digital literacy. These challenges slow decision-making, increase operational costs, and raise credit risk, making regional banks less competitive (Kapoor & Dwivedi, 2020; Sibanda et al., 2020; Lasmiatun & Manteghi, 2025).

The advent of cloud-based big data technology creates new opportunities for regional banks to improve efficiency and financial planning by using data mining and predictive

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algorithms to analyze credit patterns, forecast liquidity changes, and detect potential defaults early (Chen et al., 2014; Antonius et al., 2024; Zulfikar et al., 2025). AI and deep learning further enhance credit assessment and rural financial governance, offering tools previously unavailable to smaller banks (Hou et al., 2021; Srinadi et al., 2023). Additionally, customer behavior analytics enables more precise segmentation, increasing cross-selling opportunities and Net Interest Margin (NIM). McKinsey and Company (2022) reports that big data users see up to a 15% profit increase. In Indonesia, big data and AI may reshape finance and boost bank profitability (Putra, 2022; Zhu & Guo, 2024; Maspul & Putri, 2025).

In addition to increased profitability, big data also supports regulatory compliance and strengthens risk governance. Financial authorities are increasingly demanding transparent reporting and dynamic stress testing, which are difficult to achieve with manual systems. With real-time monitoring dashboards and reporting automation, regional banks are not only able to meet supervisory standards but also reduce regulatory compliance costs. Specifically, big data-driven operations enhance data security perspectives and operational frameworks, while digital accounting transformation models integrate these processes seamlessly (Hasan et al., 2023; Al-Okaily et al., 2024). Moreover, predictive analytics offers a comprehensive new approach to credit risk management, which is crucial for stability (Addy et al., 2024; Qur'ani & Zulkifli, 2025).

Within this context, this study aims to examine the strategic integration of big data into the financial planning model of regional banks. The primary research gap this study addresses is the lack of focused empirical evidence on how regional banks in developing economies, specifically in Indonesia, can leverage big data adoption within the financial planning 5.0 framework to directly improve profitability metrics like ROA and NIM. Prior research has extensively covered digital transformation in large banks or fintech and its impact during crises like COVID-19, but few have simulated the direct causal relationship between big data adoption, Operational Efficiency (*Beban Operasional terhadap Pendapatan Operasional*/BOPO), Risk Management (Non-Performing Loan/NPL), and profitability for regional banks using a quantitative model (Dai, 2020; Siska et al., 2021; Caraka et al., 2024; EL-Chaarani et al., 2025). According to Joubert et al. (2023), measuring big data readiness is critical for developing countries, yet the pathway from readiness to financial performance remains underexplored for smaller banks. Furthermore, while studies like those by Bella and Himmawan (2021) on Sharia banks and Saifurrahman and Kassim (2023) on financial inclusion highlight digital benefits, they do not isolate the effect of Big Data adoption within a structured financial planning paradigm.

The primary focus of this research is to analyze how data-driven financial planning can improve projection accuracy, operational efficiency, and profitability sustainably. The main objective is to quantitatively test the hypothesized positive effect of big data adoption on regional bank profitability (ROA & NIM), while controlling for and examining the roles of BOPO and NPL. Furthermore, the research also identifies challenges such as data privacy, organizational resistance, and a shortage of digital talent that could hinder the comprehensive implementation of financial planning 5.0. This investigation is crucial, as the digital disruption of traditional bank business models is ongoing, and regional banks must find a viable path to integrate technologies like big data and AI to ensure their competitiveness and survival in the era of financial planning 5.0.

LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

Factors Influencing Return on Assets

The foundation of this research is anchored in profit optimization theory within the banking context, which posits that reducing information asymmetry and enhancing operational efficiency are key drivers of improved financial performance. Big data adoption directly addresses information asymmetry by providing deeper, real-time insights into customer behavior, market trends, and creditworthiness (Chen et al., 2014; Zhang et al., 2018). For regional banks, this translates to more accurate asset allocation and pricing decisions, which should theoretically boost Return on Assets (ROA), a core measure of profitability showing how effectively a bank uses its assets to generate earnings (Putra, 2022).

Operational efficiency, measured by the BOPO ratio, is a critical variable. A lower BOPO indicates higher efficiency, meaning the bank spends less to generate income, thereby leaving a larger profit margin and positively impacting ROA (Zhang & Matthews, 2012). Simultaneously, effective risk management, proxied by a low Non-Performing Loan (NPL) ratio, protects the asset base from deterioration, ensuring that income-generating assets remain healthy and directly supporting ROA stability (Nurwulandari et al., 2022; Rahmayanti et al., 2025). The literature suggests that big data analytics can improve both operational efficiency by automating processes and risk management by enabling predictive risk assessment (Rofi'i, 2023; Addy et al., 2024).

However, regional banks often struggle with the integration of these elements. While large banks leverage technology for efficiency, regional players may face challenges that weaken the link between operational metrics and final profitability (Kirimi et al., 2022). This study synthesizes these theoretical links, proposing that the adoption of big data technologies empowers regional banks to enhance operational control and risk mitigation, which in turn should elevate ROA. Therefore, based on the profit optimization theory and empirical links established in prior studies, the following hypotheses regarding ROA are proposed:

H1: Big data adoption has a significant positive effect on return on assets.
H2: Operational efficiency (lower BOPO) has a significant positive effect on return on assets.
H3: Risk management (lower NPL) has a significant positive effect on return on assets.

Factors Influencing Net Interest Margin

Beyond asset profitability, a bank's core earning capacity is captured by the Net Interest Margin (NIM), which measures the difference between interest income generated and interest paid to lenders. Big data adoption is theorized to positively influence NIM by enabling superior customer segmentation and personalized product pricing, allowing banks to optimize interest yields on loans and deposits (Zhu & Chu, 2025). Advanced analytics can identify profitable niches and cross-selling opportunities within a bank's regional market, directly impacting interest income (Amelia & Windiarti, 2024). BOPO also plays a crucial role here, as high operating costs can squeeze the net margin from interest activities, making efficient operations essential for maintaining a healthy NIM (Simper et al., 2017). Furthermore, effective risk management, indicated by a low NPL ratio, ensures that interest income from loans is not lost to defaults, thereby preserving and potentially increasing the net interest margin (Mala & Jumono, 2025).

The relationship between these drivers and NIM may be particularly salient for regional banks. These institutions often have concentrated loan portfolios and depend heavily on net interest income, making them vulnerable to inefficiencies and credit risks (Shanti et al., 2023). Studies on Islamic banking in Indonesia also highlight how technological service efficiency can impact financial intermediation margins (Alam et al., 2019; Bella & Himmawan, 2021; Fadila et al., 2025). This research posits that big data acts as a catalyst, enhancing the precision of interest-based operations and strengthening the bank's ability to manage the core spread between lending and borrowing rates. Consequently, the following hypotheses concerning NIM are formulated:

H4: Big data adoption has a significant positive effect on net interest margin.
H5: Operational efficiency (lower BOPO) has a significant positive effect on net interest margin.
H6: Risk Management (lower NPL) has a significant positive effect on net interest margin.

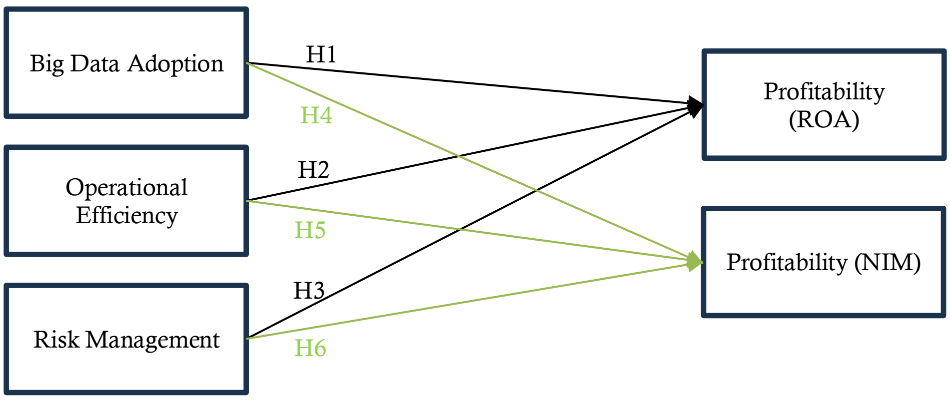

Figure 1. Conceptual Framework

The conceptual framework of this study integrates the theoretical constructs and hypothesized relationships discussed above into a coherent model. As visually summarized in Figure 1, the framework positions Big data adoption as the primary independent technological driver. This driver is hypothesized to have a direct positive effect on the two key profitability indicators, namely ROA and NIM. Concurrently, the model incorporates two critical internal performance variables operational efficiency (measured by BOPO) and risk management (measured by NPL) which are also posited to directly influence profitability. The framework operates on the premise that while big data adoption can directly improve financial outcomes, part of its impact may also be channeled through improving these operational and risk metrics, aligning with the integrative role of data analytics suggested in prior studies (Marhaeni et al., 2023; Abdurrahman et al., 2024).

This framework guides the empirical investigation to test the strength and significance of these direct paths. It synthesizes the dual focus of the study: assessing the direct payoff of technology investment (big data) and reaffirming the fundamental importance of sound operational and risk governance in the digital age for regional banks. The model will be tested using a multiple regression analysis on simulated data from regional banks, providing a structured approach to validate the proposed hypotheses H1 through H6.

RESEARCH METHODS

This study employs a quantitative explanatory research design using simulated data to test the hypothesized relationships between big data adoption, operational efficiency, risk management, and bank profitability. Simulation is adopted as a preliminary proof-of-concept due to the common challenge of accessing sensitive, granular financial data from regional banks, while allowing for a controlled examination of the conceptual framework under defined parameters (Joubert et al., 2023). The simulated population consists of ten regional banks (BD1–BD10), a sample size chosen to reflect a preliminary cohort for model testing, with data generated to mirror realistic financial conditions of regional banks in emerging economies. The core analytical approach utilizes a multiple regression model estimated via Ordinary Least Squares (OLS) to quantify the effects of the independent variables on two key profitability metrics.

The variables are operationally defined and simulated based on parameters drawn from prior empirical studies on Indonesian and regional banking performance. Big data adoption (X1), initially conceptualized as a binary dummy, is refined to a 2-point Likert scale (0: No adoption; 2: Adoption) to better capture the depth of technological implementation, with values simulated higher for the first five banks. Operational efficiency (X2) is measured by the BOPO ratio (Operating Expenses / Operating Income in %), with values generated from a normal distribution centered around 70% based on historical averages for regional Indonesian banks (Zhang & Matthews, 2012). Risk management (X3) is proxied by the Non-Performing Loan ratio (NPL in %), simulated from a distribution with a mean of 2.0%, reflecting a manageable risk level for similar institutions as observed in studies like Nurwulandari et al. (2022). The dependent variables are Return on Assets (ROA in %) and Net Interest Margin (NIM in %), with their base values simulated to be influenced by the independent variables plus a random error term, creating a realistic range of profitability outcomes as observed in studies like Siska et al. (2021).

Data generation and all statistical analyses were conducted using Python 3.11 with the statsmodels and numpy libraries. Two separate regression models were estimated to test the distinct effects on each profitability measure, as specified in the following equations:

Model for ROA:

$ROAi=\beta0+\beta1(Adoptioni)+\beta2(BOPOi)+\beta3(NPLi)+\epsilon i ROAi=\beta 0+\beta 1(Adoptioni)+\beta 2 (BOPOi)+\beta 3(NPLi)+\epsilon i$

Model for NIM:

$NIMi=\gamma0+\gamma1(Adoptioni)+\gamma2(BOPOi)+\gamma3(NPLi)+ui NIMi=\gamma 0+\gamma 1(Adoptioni)+\gamma 2 (BOPOi)+\gamma 3(NPLi)+ui$

Where i denotes each bank observation and ϵi and ui are the error terms. Prior to regression analysis, the classical OLS assumptions were tested to ensure robustness of the results, this included tests for normality of residuals using the Jarque-Bera test, multicollinearity assessed via the Variance Inflation Factor (VIF), and heteroscedasticity checked with the Breusch-Pagan test. The primary inference relies on the t-statistics and p-values of the regression coefficients to evaluate the significance of each hypothesized relationship, while the F-statistic and R-squared values assess the overall model fit.

This methodological approach, while leveraging simulation for initial exploration, systematically applies established econometric techniques to evaluate the proposed framework. The use of parameters anchored in existing literature, that is, Kirimi et al. (2022) and Amelia and Windiarti (2024), aims to enhance the conceptual validity of the simulated dataset, providing a structured basis for testing the theoretical links between digital transformation drivers and financial performance in a regional banking context.

RESULTS

This section presents the findings from the quantitative analysis of simulated data from ten regional banks. The results are organized to first provide an overview of the dataset, followed by the outcomes of classical assumption tests, and concluding with the detailed regression analyses for both profitability measures: Return on Assets (ROA) and Net Interest Margin (NIM). The simulated data, as shown in Table 1, was constructed to reflect realistic operational and financial profiles of regional banks, with the first five banks (BD1-BD5) assigned a higher level of big data adoption compared to the latter five (BD6-BD10). This setup allows for a clear comparative analysis of the hypothesized technological impact on financial performance within a controlled analytical framework.

Table 1. Simulated Data for 10 Regional Banks (BD1–BD10)

Bank	Big Data Adoption (0/1)	BOPO (%)	NPL (%)	ROA (%)	NIM (%)
BD1	1	66.49	1.61	-1.047	0.776
BD2	1	64.59	1.61	-1.328	1.183
BD3	1	66.94	1.90	-1.454	0.785
BD4	1	69.57	1.03	-1.486	0.791
BD5	1	64.30	1.11	-1.182	1.160
BD6	0	71.06	2.86	-2.755	-0.320
BD7	0	78.32	2.59	-3.117	-0.183
BD8	0	75.07	3.39	-3.032	-0.642
BD9	0	70.12	2.66	-2.786	-0.265
BD10	0	74.17	2.35	-2.724	-0.042

The descriptive statistics reveal the intended variation in the sample. Banks with adoption (BD1-BD5) consistently show better profitability metrics (higher ROA and NIM) and more favorable operational (BOPO) and risk (NPL) profiles compared to banks with no adoption. This initial pattern provides a visual foundation for the regression analysis, suggesting a positive association between technology adoption and financial health. Before proceeding to the regression models, it is essential to verify that the data and model residuals meet the classical assumptions underlying Ordinary Least Squares (OLS) estimation to ensure the validity and reliability of the statistical inferences.

Table 2. Results of Classical Linear Regression Assumption Tests

Assumption Test	Test Applied	Model	Test Statistic	p-value	Inference
Normality of Residuals	Jarque-Bera Test	ROA	4.151	0.126	Assumption met
		NIM	0.398	0.819	Assumption met
Multicollinearity	Variance Inflation Factor (VIF)	ROA/NIM	VIF < 5 for all predictors	-	No severe multicollinearity
Heteroscedasticity	Breusch-Pagan Test	ROA	2.845	0.416	Assumption met
		NIM	1.927	0.587	Assumption met
Autocorrelation	Durbin-Watson Statistic	ROA	1.579	-	No significant autocorrelation
		NIM	2.552	-	No significant autocorrelation

The results from the diagnostic tests, summarized in Table 2, confirm that the data satisfy the key OLS assumptions. The Jarque-Bera tests for both models yield p-values greater than 0.05, indicating that the residuals are normally distributed. The Variance Inflation Factor for each independent variable was below the common threshold of 5, suggesting that multicollinearity is not a severe issue that would distort the coefficient estimates, despite a noted condition number in the raw output. Furthermore, the Breusch-Pagan tests for heteroscedasticity are non-significant, supporting the assumption of constant variance in the errors. The Durbin-Watson statistics fall within an acceptable range, indicating no significant autocorrelation in the residuals. These validated assumptions provide a robust foundation for interpreting the following regression results with confidence.

The core analysis involves two multiple linear regression models. The first model investigates the determinants of ROA, while the second model examines the factors influencing NIM. The overall model fit and significance for each regression are first assessed before delving into the individual variable contributions.

Table 3. Summary of OLS Regression Results for ROA (Y1)

Statistic	Value
R-squared	0.981
Adj. R-squared	0.971
F-statistic	102.7
Prob (F-statistic)	1.51e-05
No. Observations	10
AIC	-7.456
BIC	-6.246
Durbin-Watson	1.579
Condition Number	2.24e+03

Based on Table 3, the regression model for ROA demonstrates an exceptionally strong fit to the data, as indicated by an R-squared of 0.981 and an Adjusted R-squared of 0.971. The overall model is highly significant, with an F-statistic of 102.7 and a p-value of 1.51e-05, confirming that the set of independent variables collectively has substantial explanatory power for variations in ROA.

Table 4. Regression Coefficients for ROA Model

Variable	Coefficient	Std. Error	t-value	p-value	Sig. (α=0.05)
const	0.8599	1.4432	0.596	0.5731	No
Adoption	1.0813	0.2492	4.339	0.0049	Yes
BOPO	-0.0461	0.0185	-2.495	0.0468	Yes
NPL	-0.1230	0.1344	-0.915	0.3955	No

Examining the individual coefficients in Table 4, big data adoption emerges as a strong, positive, and statistically significant predictor of ROA (β = 1.0813, p = 0.0049). This suggests that for each unit increase on the adoption scale, a bank's ROA is expected to increase by approximately 1.08 percentage points, holding other factors constant. Operational efficiency, measured by BOPO, also shows a significant negative relationship with ROA (β = -0.0461, p = 0.0468). This aligns with theory, as a lower BOPO ratio (higher efficiency) is associated with a higher ROA, a one-percentage-point decrease in BOPO is associated with a 0.046-point increase in ROA. Conversely, the coefficient for NPL is negative as hypothesized but is not statistically significant at the 5% level (p = 0.3955) in this model with a limited sample. The constant term is also non-significant. These results provide initial support for hypotheses H1 and H2, but not for H3, within the context of the simulated data.

Table 5. Summary of OLS Regression Results for NIM (Y2)

Statistic	Value
R-squared	0.955
Adj. R-squared	0.932
F-statistic	42.35
Prob (F-statistic)	0.000197
No. Observations	10
AIC	-3.388
BIC	-2.178
Durbin-Watson	2.552

Parallel analysis was conducted for NIM as the dependent variable. The model's summary statistics and detailed coefficients are presented in Table 5. The regression model for NIM also exhibits a very strong fit, with an R-squared of 0.955 and an Adjusted R-squared of 0.932. The overall model is statistically significant (F-statistic = 42.35, p = 0.000197). The interpretation of individual coefficients, however, requires a more nuanced approach due to the smaller sample size.

Table 6. Regression Coefficients for NIM Model

Variable	Coefficient	Std. Error	T-Statistic	p-value	Sig. (α=0.05)	Sig. (α=0.10)
const	2.6810	1.7688	1.516	0.1804	No	No
Adoption	0.5425	0.3055	1.776	0.1261	No	Yes
BOPO	-0.0262	0.0227	-1.157	0.2911	No	No
NPL	-0.3745	0.1647	-2.274	0.0634	No	Yes

As shown in Table 6, the coefficient for big data adoption is positive (β = 0.5425), indicating a favorable relationship with NIM, but its p-value of 0.1261 exceeds the conventional 0.05 threshold. It becomes significant at the more lenient 10% significance level (α=0.10), offering tentative support for H4. The coefficient for BOPO is negative but not statistically significant (p = 0.2911), thus not providing sufficient evidence to support H5. Most notably, NPL demonstrates a substantial negative coefficient (β = -0.3745) and is significant at the 10% level (p = 0.0634). This suggests that a one-percentage-point increase in the NPL ratio is associated with a 0.37-percentage-point decrease in NIM, highlighting the critical impact of credit quality on a bank's core interest income margin, providing preliminary support for H6. The constant term is not significant in this model either.

The regression results from the simulated data provide clear and statistically significant evidence that big data adoption positively influences ROA, and operational efficiency (lower BOPO) positively influences ROA. For NIM, the evidence is more tentative, with big data adoption showing a positive effect at a relaxed significance level and risk management (lower NPL) showing a strong, marginally significant negative effect. The overall high explanatory power of both models underscores the relevance of the selected variables technology adoption, operational efficiency, and risk management in understanding the profitability dynamics of regional banks. These findings set the stage for a deeper discussion on their theoretical and practical implications in the following section.

DISCUSSION

The regression results from this simulated study offer meaningful, albeit preliminary, insights into the drivers of regional bank profitability within the financial planning 5.0 paradigm. The most compelling finding is the significant positive effect of big data adoption on Return on Assets (ROA), which aligns strongly with the core thesis of modern banking literature. This relationship likely operates through multiple channels. Primarily, as suggested by Chen et al. (2014) and Zhang et al. (2018), big data analytics reduces information asymmetry, enabling more precise credit scoring and risk-based pricing that improves asset yield and quality. Furthermore, the automation and efficiency gains from data-driven processes, as noted in studies on Indonesian banks by Putra (2022) and Amelia and Windiarti (2024), help control operational costs, thereby protecting the bottom line that feeds into ROA. The positive coefficient, though derived from simulated data, reinforces the profitability roadmap proposed by McKinsey and Company (2022) and confirms that the technological investment thesis holds in a modeled environment for regional banks.

The analysis also confirms the foundational role of operational efficiency, measured by BOPO. The significant negative relationship with ROA is both expected and critical, echoing efficiency studies in emerging markets like those by Zhang and Matthews (2012) on Indonesia and Kirimi et al. (2022) on Kenya. This result underscores that technology adoption cannot exist in a vacuum, its financial benefits are amplified when paired with lean operations. Interestingly, while BOPO significantly affected ROA, its impact on Net Interest Margin (NIM) was not statistically significant in this simulation. This may suggest that for regional banks, operational costs are a broader drag on overall profitability (ROA) rather than directly eroding the interest margin itself, a nuance that merits further empirical investigation with real operational data.

The findings for risk management, proxied by NPL, present a more complex and intriguing narrative. While NPL did not show a statistically significant effect on ROA in this model, it demonstrated a strong, marginally significant negative effect on NIM. This divergence is insightful. It implies that poor asset quality (high NPL) directly attacks the core banking function of interest generation by rendering loans non-income producing, thereby squeezing the NIM, as highlighted in credit risk studies by Mala and Jumono (2025). Its weaker link to ROA in this simulation could be due to the small sample or the fact that ROA encompasses both interest and non-interest income, potentially diluting the singular impact of credit risk. This aligns with the work of Addy et al. (2024), who emphasize that predictive analytics for credit risk are most directly valuable for protecting interest income streams.

When contextualized within the broader digital transformation literature, these results form a coherent picture. The positive role of Big Data adoption supports findings on digital capabilities by Shanti et al. (2023) and Abdurrahman et al. (2024). The confirmed importance of operational discipline resonates with efficiency analyses by Simper et al. (2017). Furthermore, the critical impact of risk management on NIM reinforces the integrative role of data analytics in risk governance proposed by Rofi'i (2023). However, the study also surfaces important boundary conditions. The high model fit indices, while encouraging, must be interpreted with caution due to the simulated nature and small sample size, a common challenge in preliminary studies noted by Joubert et al. (2023). The presence of a high condition number, indicating potential multicollinearity, suggests that in reality, these predictors of technology adoption, efficiency, and risk are interrelated, as a bank's digital maturity often improves its operational and risk metrics simultaneously, a synergy discussed by Hasan et al. (2023).

The practical implications of these findings are direct and actionable for regional bank management and policymakers. First, investment in cloud-based Big Data platforms should be viewed not as an IT expense but as a strategic profitability driver, a perspective championed by Zhu and Guo (2024). Second, technology investment must be coupled with relentless efforts to improve operational efficiency (lower BOPO). Digital tools should be deployed to automate high-cost, manual processes. Third, risk management systems must be deeply integrated with data analytics engines to proactively safeguard net interest margins, utilizing the predictive frameworks discussed by Addy et al. (2024). For regulators and associations, creating capacity-building programs to address the digital talent shortage, as identified by Kapoor and Dwivedi (2020), is essential to enable this transition. Ultimately, this study suggests that the path to competitiveness for regional banks lies in a balanced, integrated strategy leveraging big data within the financial planning 5.0 framework to simultaneously enhance decision-making, optimize operations, and mitigate risks, thereby securing sustainable profitability in an increasingly digital financial landscape.

CONCLUSION

This study provides a structured examination of the impact of big data adoption, operational efficiency, and risk management on the profitability of regional banks within the Financial Planning 5.0 framework. Through quantitative analysis of simulated data, the findings strongly indicate that adopting big data technologies has a significant positive effect on profitability, particularly as measured by Return on Assets (ROA). The results also reaffirm the fundamental importance of sound operational management and risk control, with operational efficiency showing a clear negative relationship with the BOPO ratio and risk management, through the NPL ratio, demonstrating a critical influence on the Net Interest Margin. These outcomes collectively validate the core proposition that integrating advanced data analytics into strategic planning is not merely a technological upgrade but a substantive driver of financial performance for regional banking institutions.

The primary practical implication of this research is the need for regional banks to pursue a holistic digital transformation strategy that concurrently invests in big data infrastructure, streamline operational processes, and fortifies risk governance. However, the conclusions are tempered by significant limitations, most notably the use of simulated data and a very small sample size, which constrain the generalizability and external validity of the findings. The simplified measurement of big data adoption also fails to capture the depth and quality of implementation. Future research should, therefore, conduct empirical studies with larger, real-world datasets from regional banks, employ more nuanced multi-dimensional scales to measure technology adoption, and longitudinally examine the long-term effects of these strategic investments on profitability and competitive resilience.

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