

Digital Transformation and Banking Profitability: The Mediating Role of Operational Efficiency

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ABSTRACT

This study empirically examines how digital transformation influences bank profitability, with operational efficiency as a mediating variable, in commercial banks listed on the Indonesia Stock Exchange (IDX) during the 2020–2024 period. The rapid expansion of digital banking and increasing competition from fintech companies have encouraged banks to intensify technology investments, raising questions regarding whether digitalization improves profitability directly or through operational efficiency gains. Therefore, this study aims to analyze both the direct and indirect effects of digital transformation on bank profitability. Using purposive sampling, 31 banks were selected, resulting in 155 panel data observations across five years. The analysis employed panel data regression in EViews 13 while a cluster bootstrap approach with 5.000 replications was applied to evaluate the mediating effect. The findings indicate that digital transformation has a positive and significant direct effect on profitability (ROA). However, digital transformation does not significantly affect operational efficiency (BOPO), while BOPO negatively and significantly affects ROA. Furthermore, the bootstrap test confirms that operational efficiency does not mediate the relationship between digital transformation and profitability. These findings suggest that digitalization primarily enhances bank profitability through revenue expansion rather than cost efficiency.

Keywords: BOPO; Digital Transformation; Operational Efficiency; Profitability; ROA

INTRODUCTION

The global banking sector is transitioning from conventional, branch-based models toward an integrated digital ecosystem through the adoption of cutting-edge technologies such as mobile banking, AI, big data, and cloud computing (Gong & Ribiere, 2021). This transformation fundamentally restructures cost management, value creation, and the competitive landscape of the financial industry (Verhoef et al., 2021). In Indonesia, this shift accelerated sharply during the 2020–2024 period as IDX-listed banks responded to post-pandemic behavioral changes and market penetration by fintech firms (Berutu et al., 2026; Khairina, 2022). Given the broad nature of digital transformation, which is difficult to quantify through a single metric, empirical research commonly relies on observable financial proxies (Vial, 2019). Aligning with this approach, this study specifically focuses on the intensity of investments in technology-based intangible assets (such as software and digital licenses) to represent the banks' financial commitment to technology adoption, without claiming to encompass non-financial dimensions like cultural readiness or user adoption rates.

Evidence from global markets suggests that digital banking adoption improves operational efficiency, extends market reach, and strengthens financial performance through cost optimization and broader service accessibility (Citterio et al., 2024). Shen et al. (2025) found that digitalization significantly reduced cost inefficiency among Chinese commercial banks. Alam et al. (2025) similarly demonstrated that integrating digital technology into banking management can improve operational efficiency while enhancing the customer experience. In the Indonesian context, Daeli

& Wedari (2025) showed that digital transformation contributes positively to profitability, drawing on sentiment analysis of bank annual reports. Industry level data tell a more nuanced story. In 2021, early-stage technology investments and workforce adaptation costs drove inefficiency upward, with the BOPO ratio (operating expenses to operating revenue) reaching 83.53% and ROA stagnating at 1.84% (OJK, 2022). As digital infrastructure matured and branch networks were restructured, efficiency gradually recovered: by 2022–2023, BOPO had declined to 76.21% and ROA climbed to 2.74% (OJK, 2023). By early 2024, operational stability had become a primary factor in determining whether banks could convert digital capabilities into sustained profitability (Shen et al., 2025).

This trajectory can be understood through the productivity paradox, the well-documented lag between technology investment and measurable performance gains (Citterio et al., 2024). In the medium to long run, automation and resource optimization are expected to reduce the BOPO ratio and improve profitability (Alam et al., 2025; Herlanlam et al., 2026; Shen et al., 2025). However, in the short term, the burden of infrastructure costs, cybersecurity spending, and training expenses tends to offset efficiency benefits (Herlanlam et al., 2026). Pratiningsih & Wardhani (2025) found that digital transformation positively influences bank performance, largely through efficiency gains. Thakor (2020) similarly argued that while digitalization raises profitability, the size of this effect depends heavily on cost efficiency improvements. Other studies confirm that business process optimization and effective technology utilization eventually improve both efficiency and financial results (Xiang & Jiang, 2023).

The literature on the digitalization-profitability nexus continues to expand, yet the resulting empirical conclusions still exhibit substantial variation. One strand of literature highlights a positive impact driven by market expansion and novel product development ((Citterio et al., 2024; Verhoef et al., 2021), whereas another group argues that heavy upfront outlays for technological infrastructure tend to minimize short-term financial returns (Gong & Ribiere, 2021; Shen et al., 2025). Within the Indonesian context, the inverse relationship between BOPO and ROA has been widely validated (Dari & Suarjaya (2025) and Fadhilah et al. (2025), yet empirical documentation regarding how operational efficiency mediates this relationship remains scarce and fragmented. This inquiry addresses this gap by evaluating operational efficiency as an intermediary transmission pathway across 31 commercial banks listed on the IDX. This study builds upon the integration of two complementary dimensions, methodological refinements and data-period contextualization to generate more reliable and comprehensive estimations of the structural mechanisms underlying technology adoption within the Indonesian banking ecosystem.

This study introduces three specific refinements to enhance estimation accuracy. First, it simultaneously incorporates SIZE, CAR, and NPL within a three-equation mediation framework to mitigate omitted variable bias. Second, the mediation effect is evaluated using a cluster bootstrap approach (5,000 replications) at the entity level, avoiding Sobel test errors on small-to-medium samples. Third, estimation employs Cross-Section Panel Corrected Standard Errors and the Pesaran CD Test to handle cross-sectional dependence inherent in this panel structure (N=31, T=5). These refinements are enriched by a 2020–2024 data window that captures Indonesia's post-pandemic digital acceleration. This tech-investment surge, driven by shifting customer behaviors and fintech competition, offers an ideal setup to examine whether digitalization benefits have materialized or remain stalled by the productivity paradox.

LITERATURE REVIEW

Resource-Based View Theory

The Resource-Based View (RBV) framework posits that sustainable market performance stems from a corporation's proficiency in deploying and harnessing proprietary internal capabilities. Barney (1991) asserted that strategic assets must adhere to the VRIN attributes: valuable, rare, imperfectly imitable, and non-substitutable. Willie (2024) extended this conceptualization to digital infrastructure, indicating that software architectures, digital platforms, and consumer data profiles meet these VRIN benchmarks due to the extensive capital and temporal commitment required for development, which effectively impedes competitor replication.

Under the RBV lens, digital transformation serves as a core competence that allows banking

institutions to cultivate enduring market leadership by enhancing organizational capacities. This mechanism entails re-engineering business workflows through information infrastructure, data frameworks, and computational analytics (Daeli & Wedari, 2025). Conceptually, these technological deployments empower financial firms to automate routines, mitigate reliance on brick-and-mortar facilities, and augment operational efficiency, thereby minimizing transactional expenditures (Citterio et al., 2024).

Importantly, the financial effects of digital transformation are not always direct. When supported by adequate organizational capabilities, digitalization tends to improve financial performance through changes in cost structure rather than through immediate revenue gains. More efficient service processes and better data management create operational efficiencies that serve as a transmission mechanism for profitability. A systematic digital transformation strategy therefore functions as a strategic asset that strengthens a bank's competitive position in an increasingly platform-driven financial industry (Pratiningsih & Wardhani, 2025; Shen et al., 2025).

Digital Transformation, Bank Profitability, and Operational Efficiency

Digital transformation involves integrating computational technologies into corporate operations to optimize organizational productivity and financial returns. Within the banking realm, this paradigm includes deploying electronic services, automating operational workflows, leveraging big data analytics and AI, and migrating toward platform-centric architectures (Gong & Ribiere, 2021; Verhoef et al., 2021). In this paper, digital transformation is measured by evaluating the share of digital intangible assets relative to total intangible assets a proxy indicating a financial firm's capital allocation toward technology-driven investments, including proprietary software, digital permits, and structural platforms.

Extensive empirical evidence confirms a positive relationship between digital transformation and bank profitability. Citterio et al. (2024) observed this favorable impact in European commercial banking, while Daeli & Wedari (2025) confirmed it within the Indonesian environment via textual analysis of annual performance reports. Similarly, Pratiningsih & Wardhani (2025) reported comparable positive metrics regarding aggregate banking performance. Khattak et al. (2023) demonstrated that diversifying digital banking offerings reinforces structural stability and corporate returns. Relying on these empirical insights, the initial hypothesis is formulated as follows:

H1: Digital transformation has a positive effect on bank profitability

Digital transformation plays a vital role in curbing bank operational expenditures. Prior studies indicate that technological advancement significantly influences cost efficiency optimization in commercial banks (Shen et al., 2025). Integrating digital applications into banking management workflows further enables corporations to streamline processes and maximize structural resources Alam et al. (2025). Moreover, the operational efficiency pathway has been validated as a key intermediary channel transmitting the effects of technological shifts onto financial outcomes (Herlanlam et al., 2026). Within the Indonesian environment, a reduction in the BOPO metric among major financial institutions is heavily driven by the widening footprint of digital banking applications (Novianti & Apriadi, 2026). Since BOPO operates as an inverse reflection of cost control where lower values signal enhanced efficiency digital adoption is anticipated to yield a negative relationship with this ratio. Building upon this theoretical background, the subsequent hypothesis is proposed:

H2: Digital transformation has a negative effect on BOPO

Operational efficiency, proxied by BOPO, is widely recognized as a primary determinant of banking returns. This ratio measures a financial institution's proficiency in minimizing operating expenses relative to its generated revenue, where diminished BOPO values signify superior cost control. Prudent expenditure management enables banking institutions to maximize internal resources, augment productivity, and optimize financial gains. On the contrary, inflated operating costs constrain net profit margins and compress overall corporate performance. Extensive empirical evidence supports the inverse link between BOPO and profitability. Within the Indonesian banking context, Irawan et al. (2025) identified a significant adverse impact of BOPO on ROA across commercial banks. Dari & Suarjaya (2025) demonstrated that operational inefficiencies directly erode earnings structure. This inverse BOPO–ROA relationship was further validated by Fadhilah

et al. (2025) for IDX-listed banks over the 2018–2023 period, while Azzahra & Aisyah (2025) documented that structural efficiency enhancements at BCA Syariah driven stronger financial outcomes during 2023–2024. Consequently, the third hypothesis is stated as follows:

H3: BOPO has a negative effect on ROA

Digital transformation is expected to improve profitability by reducing operational costs and increasing organizational efficiency. Lower operating expenses allow banks to optimize profit margins, which ultimately contributes to higher ROA. Herlanlam et al. (2026) explain that operational cost reduction serves as an important mechanism linking digital transformation to financial performance. Similar findings are reported by Kurniawan et al. (2021) in Regional Development Banks in Indonesia, while Nguyen-thi-huong et al. (2023) demonstrate that digital capabilities can enhance bank performance through efficiency improvements. From the RBV perspective, digital resources function as strategic assets that strengthen operational efficiency and subsequently improve overall financial performance. Therefore, the following hypothesis is proposed:

H4: Operational efficiency mediates the effect of digital transformation on bank profitability

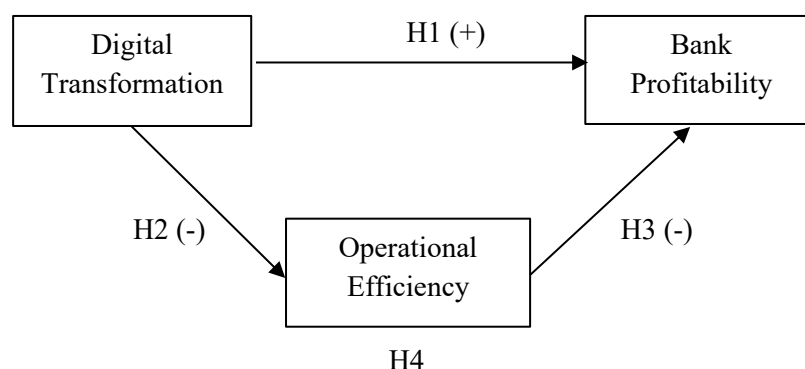


Figure 1: Research Model
Source: Processed data (2026)

METHOD

This inquiry employs a quantitative design via panel data regression to evaluate how digital transformation dictates bank profitability, incorporating operational efficiency as a mediator. The population encompasses all commercial banks listed on the IDX. A purposive sampling technique was applied based on three benchmarks: (1) uninterrupted listing status on the IDX from 2020 to 2024; (2) continuous availability of complete annual reports and financial statements; and (3) full disclosure of all data metrics required for the operationalized variables. Accordingly, 31 banks met these parameters, establishing 155 observations (31 banks x 5 years). The 2020–2024 timeframe was selected to capture Indonesia's post-pandemic digital acceleration, an era marked by shifting consumer behavior and intense fintech competition. This study utilizes three variables, where the primary independent construct is digital transformation (DT), quantified by:

$$DT = \frac{\text{Digital Intangible Assets}}{\text{Intangible Assets}}$$

This ratio reflects a bank's investment in technology-based intangible assets software, licenses, management systems, and digital platforms and serves as a proxy for its commitment to digital adoption (Daeli & Wedari, 2025; Kurniawan et al., 2021; Shen et al., 2025). The dependent variable is profitability, proxied by Return on Assets (ROA):

$$ROA = \frac{\text{Net Profit}}{\text{Total Assets}}$$

ROA captures managerial effectiveness in generating profit from total assets (Citterio et al.,

2024; Khattak et al., 2023). The mediating variable is operational efficiency, proxied by BOPO (operating expenses to operating revenue):

$$\text{BOPO} = \frac{\text{Total Operating Expenses}}{\text{Total Operating Revenue}}$$

As a standard efficiency metric utilized by Bank Indonesia and OJK, this ratio measures how effectively a bank controls operational expenditures against its operating revenue (Herlanlam et al., 2026; Novianti & Apriadi, 2026). Empirical estimation was performed via panel data regression using EViews 13. This method was selected for its capacity to concurrently capture cross-sectional and time-series variations, offering superior efficiency over pooled OLS (Baltagi, 2021). Optimal model selection was determined using three successive diagnostic checks: the Chow Test (Common vs. Fixed Effects), the Hausman Test (Fixed vs. Random Effects), and the Lagrange Multiplier Test (Common vs. Random Effects). The empirical model includes three control variables that are theoretically relevant to bank profitability. Bank size (SIZE), measured by the natural logarithm of total assets; the capital adequacy ratio (CAR), which reflects a bank's capital capacity to absorb risk; and the nonperforming loan ratio (NPL), which reflects a bank's asset quality and credit risk. The operational regression models are specified as follows:

$$\begin{aligned} \text{ROA}_{it} &= \alpha + \beta_1 \text{DT}_{it} + \beta_2 \text{SIZE}_{it} + \beta_3 \text{CAR}_{it} + \beta_4 \text{NPL}_{it} + \varepsilon_{it} \\ \text{BOPO}_{it} &= \alpha + \beta_5 \text{DT}_{it} + \beta_6 \text{SIZE}_{it} + \beta_7 \text{CAR}_{it} + \beta_8 \text{NPL}_{it} + \varepsilon_{it} \\ \text{ROA}_{it} &= \alpha + \beta_9 \text{DT}_{it} + \beta_{10} \text{BOPO}_{it} + \beta_{11} \text{SIZE}_{it} + \beta_{12} \text{CAR}_{it} + \beta_{12} \text{NPL}_{it} + \varepsilon_{it} \end{aligned}$$

Description:

α	= Constant
β	= Coefficient
ROA_{it}	= <i>Return on Assets</i> for firm <i>i</i> in year <i>t</i>
DT_{it}	= <i>Digital Transformation</i> for firm <i>i</i> in year <i>t</i>
BOPO_{it}	= <i>perating Expenses / Operating Revenue</i> for firm <i>i</i> in year <i>t</i>
$\text{SIZE}_{it}, \text{CAR}_{it}, \text{NPL}_{it}$	= bank <i>i</i> control variables in year <i>t</i>
ε	= <i>error term</i>

This study evaluates the significance of the indirect effect of DT on ROA through BOPO using a cluster bootstrap mediation test. The bootstrap method was chosen because it yields more valid inferences for small-to-medium-sized samples without requiring the assumption of a normal distribution for the indirect effect ($a \times b$) (Preacher & Hayes, 2004). The procedure was carried out by resampling panel data at the bank level 5.000 times to form an empirical distribution of the re-estimated path *a* (DT → BOPO) and path *b* (BOPO → ROA).

RESULTS

Based on 155 panel observations, the descriptive statistics reveal varied data characteristics. The DT variable recorded a mean of 0.427058 with a standard deviation (std. dev.) of 0.311741, indicating that the data distribution tends to be even within the sample. The ROA variable yielded a mean of 0.025156 with a higher std. dev. of 0.149743, indicating significant volatility in profitability across companies. Meanwhile, the BOPO variable shows a mean of 2.731307 and a std. dev. of 0.436681, reflecting moderate fluctuations in the level of operational cost efficiency. Furthermore, the control variables SIZE and the NPL ratio exhibit high stability, with std. dev. well below their mean values, in contrast to the CAR ratio, which recorded a standard deviation of 0.524080, indicating dynamic variations in capital adequacy. In short, these descriptive metrics confirm sufficient data variability, thereby supporting further econometric estimation.

Table 1. Results of Descriptive Statistical Tests

	DT	ROA	BOPO	SIZE	CAR	NPL
Mean	0.427058	0.025156	2.731307	31.06145	0.487308	0.035995
Median	0.332998	0.005700	2.795392	30.60991	0.299200	0.029000
Maximum	1.000000	1.155000	4.284000	35.42552	3.905000	0.224700
Minimum	0.001397	-0.135700	0.831000	27.30446	0.115900	0.000000
Std. Dev.	0.311741	0.149743	0.436681	1.707220	0.524080	0.033305
Skewness	0.712893	6.247321	-2.069988	0.697875	3.854562	2.978312
Kurtosis	2.310918	43.49371	11.49921	2.864929	21.08646	15.25233
Jarque-Bera	16.19556	11598.24	577.2198	12.69.941	2496.472	1198.672
Probability	0.000304	0.000000	0.000000	0.001747	0.000000	0.000000
Sum	66.19405	3.899111	423.3525	4814.525	75.53270	5.579300
Sum Sq. Dev.	14.96606	3.453145	29.36625	4488.482	42.29761	0.170823
Observations	155	155	155	155	155	155

Source: Processed data (2026)

The selection of the panel data regression model was determined through three diagnostic tests. First, the Chow test yielded p-values for all < 0.05 (specifically: 0.0003; 0.0230; 0.0083; and 0.0003), so the Common Effects Model (CEM) was rejected in favor of the Fixed Effects Model (FEM). Second, the Hausman test showed that all equations had p-values > 0.05 (as follows: 0.1725; 0.6690; 0.9369; and 0.1853), meaning that the FEM was rejected and the Random Effects Model (REM) was more appropriate. Finally, the Lagrange Multiplier (LM) test was conducted as a final confirmation; the first (0.0222) and fourth (0.0332) equations had p-values < 0.05, leading to the conclusion that the REM should be used. Conversely, the second (0.2745) and third (0.0785) equations had p-values > 0.05, so the CEM was selected as the best model. Comprehensive results for these diagnostics are displayed in Table 2:

Table 2. Results of the Chow Test, Hausman Test, and Lagrange Multiplier Test

Equation	Chow Test	Hausman Test	LM Test	Results
ROA = f(DT, SIZE, CAR, NPL)	0.0003	0,1725	0.0222	REM
BOPO = f(DT, SIZE, CAR, NPL)	0,0230	0,6690	0.2745	CEM
ROA = f(BOPO, SIZE, CAR, NPL)	0,0083	0,9369	0.0785	CEM
ROA = f(DT, BOPO, SIZE, CAR, NPL)	0,0003	0,1853	0.0332	REM

Source: Processed data (2026)

Following the comprehensive diagnostic screening, the Random Effect Model (REM) was selected for the first and fourth equations, whereas the Common Effects Model (CEM) was deemed optimal for the second and third equations.

Table 3. Results of the Multicollinearity Test

	DT	ROA	BOPO	SIZE	CAR	NPL
DT	1,000000					
ROA	0.197632	1,000000				
BOPO	-0.119639	-0,673570	1,000000			
SIZE	0.045136	0.171594	-0.249371	1,000000		
CAR	-0.061383	-0.058363	0.201029	-0.485127	1,000000	
NPL	-0.085207	-0.098831	0.094378	-0.210612	-0.015682	1,000000

Source: Processed data (2026)

The diagnostic assessment of multicollinearity in Table 3 shows that the highest correlation coefficient among the independent variables is found in the relationship between BOPO and ROA, at -0.673570, followed by the relationship between SIZE and CAR, at -0.485127. In econometric modeling, multicollinearity poses a severe threat if the correlation between independent constructs exceeds the 0.80 threshold (Ghozali, 2018). Consequently, the empirical framework is confirmed to be free from multicollinearity distortions, establishing its suitability for subsequent hypothesis estimation.

Table 4. Results of the Panel Data Regression Test

Component	Equation 1 (ROA)	Equation 2 (BOPO)	Equation 3 (ROA)	Equation 4 (ROA)
Constant	-0.463356 (-1.294898)	3.863334 (11.40195)	0.410501 (6.015631)	0.449895 (1.802644)
Prob.	0.1973	0.0000	0.0000	0.0735
DT	0.121837 (2.346791)	-0.088225 (-1.590395)	-	0.084248 (2.270159)
Prob.	0.0202	0.1139	-	0.0246
BOPO	-	-	-0.138310 (-9.587117)	-0.224352 (-4.587301)
Prob.	-	-	0.0000	0.0000
SIZE	0.014188 (1.210945)	-0.034659 (-3.367350)	-0.000487 (-0.419808)	0.004520 (0.682486)
Prob.	0.2278	0.0010	0.6752	0.4960
CAR	0.010830 (1.195129)	-0.014445 (-0.264624)	0.008967 (2.235668)	0.028407 (1.532164)
Prob.	0.2339	0.7917	0.0269	0.1276
NPL	-0.263723 (-1.402464)	0.973810 (1.270529)	-0.068908 (-0.677792)	-0.060292 (-0.201233)
Prob.	0.1628	0.2059	0.4989	0.8408
Weighted Statistic				
R-squared (R²)	0.066530	0.179725	0.580492	0.473583
Adjusted R²	0.041637	0.157851	0.569305	0.455918
F-statistic	2.672676	8.216358	51.89046	26.80907
Prob (F-statistic)	0.034272	0.000005	0.000000	0.000000

Note: The numbers in parentheses () are the t-statistic values.

Source: Processed data (2026)

Before the final estimation, diagnostic tests were conducted first. The results of the Pesaran Cross-sectional Dependence (CD) test showed a probability of 0.7598 ($p > 0.05$), confirming the absence of residual dependence among cross-sectional units. Furthermore, the Durbin-Watson value of 1.959959, which is close to 2, indicates that the model is free from serious autocorrelation issues. The panel data regression estimates in this model were calculated using the Cross-Section (Panel Corrected Standard Errors) method to obtain standard errors that are more robust to potential heteroscedasticity and correlations among cross-sectional units. This approach yields more reliable parameter estimates, thereby making statistical significance tests more accurate. Based on the estimation results in Equation 4 using the Random Effects Model (REM), the regression coefficient for DT is positive at 0.084248, meaning that a one-unit increase in DT will increase ROA by 0.084248. Conversely, the coefficients for BOPO (-0.224352) and NPL (-0.060292) are negative, indicating that a one-unit increase in these two ratios will reduce ROA by 0.224352 and 0.060292, respectively. Meanwhile, the SIZE variable has a positive coefficient of 0.004520 and the CAR has a coefficient of 0.028407, both of which are positively correlated with an increase in ROA.

The validity of this model is supported by a Weighted R-squared value of 0.473583, which confirms that the combination of all independent variables explains 47.36% of the variation in profitability, as further supported by an Adjusted R^2 value of 0.455918. Based on the partial hypothesis test (t-test), the DT variable was found to have a positive and significant effect on ROA with a t-statistic of 2.270159 and a probability of 0.0246 ($p < 0.05$). Similarly, BOPO showed a highly significant negative effect on ROA, with a t-statistic of -4.587301 and a probability of 0.0000 ($p < 0.05$). On the other hand, the control variables SIZE ($p = 0.4960$), CAR ($p = 0.1276$), and NPL ($p = 0.8408$) were found to have no significant effect on ROA because their probability values were above the 0.05 threshold. These results reinforce the empirical evidence that the acceleration of digital transformation and the reduction of operating costs (decrease in BOPO) are the main drivers in optimizing profits.

Table 5. Results of the Bootstrap Mediation Test (5.000 Replications)

Component	Value	Details
Path a (BOPO = f(DT))	-0.140989	$p = 0.299$
Path b (ROA = f(DT, BOPO))	-0.228759	$p = 0.003$
Path c' (direct ROA = f(DT))	0.058123	$p = 0.050$
Path c (total ROA = f(DT))	0.090375	$p = 0.016$
Indirect effect ($a \times b$)	0.032252	$p = 0.396$
Bootstrap std. err.	0.038037	-
95% Bootstrap CI	[-0.042298; 0.106803]	Includes zero
Proportion Mediated	35.69%	Not significant

Source: Processed data (2026)

Based on the bootstrap test, the indirect effect of DT on ROA through BOPO was found to be 0.032252 (standard error = 0.038037). This effect is not statistically significant because the p-value is 0.396 ($p > 0.05$) and the 95% confidence interval (-0.042298 to 0.106803) still includes zero. Thus, the mediation hypothesis is rejected, meaning that BOPO was not found to mediate the effect of digital transformation on ROA. Although this indirect effect accounts for 35.69% of the total effect, this figure lacks sufficient statistical power to be declared a significant mediation path. This outcome indicates that capital investments in digital infrastructure yield a more pronounced direct footprint on earnings, rather than being channeled optimally through cost-efficiency mechanisms to compress operating expenditures during the observation period.

DISCUSSION

Empirical evidence demonstrates that digital transformation (DT) exerts a positive and statistically significant impact on ROA, given the probability value of 0.0202 ($p < 0.05$), thereby supporting the first hypothesis (H1). This outcome validates the Resource-Based View (RBV)

premise, illustrating that strategic capital allocation in digital assets supplies firms with VRIN-compliant resources essential for sustaining competitive advantages (Barney, 1991; Willie, 2024). Mechanistically, such earnings optimization is propelled by deploying specialized mobile trading platforms alongside automated customer touchpoints. This trend corroborates prior research within the Indonesian banking sector, which highlights that precision-targeted IT spending directly fortifies core corporate profitability (Chaniago et al., 2024; Citterio et al., 2024; Daeli & Wedari, 2025). Contrarily, estimates from the second empirical model reveal that the DT parameter lacks statistical significance regarding BOPO ($p = 0.1139 > 0.05$), leading to the rejection of the second hypothesis (H2). Data from IDX-listed banks spanning 2020–2024 indicates that technological integration serves primarily as a vehicle for service differentiation and market penetration rather than a mechanism for operational cost reduction. This discrepancy typifies the productivity paradox, wherein expected cost efficiencies face latency due to substantial upfront outlays for digital infrastructure and cybersecurity frameworks (Akbari et al., 2025; Papathomas & Konteos, 2024). Consequently, these contemporary expenditures appear to operate concurrently with legacy systems, preventing an instantaneous contraction of the BOPO ratio. In line with this, Shen et al. (2025) assert that successful operational cost reduction necessitates a comprehensive integration of systems across all management echelons, a condition that may not yet be fully realized within the sample period.

Strong empirical evidence for H3 demonstrates that BOPO exerts a significant negative effect on ROA, with a coefficient of -0.138310 ($p = 0.0000$; $p < 0.05$). Through the lens of the RBV, this confirms that cost management is an independent capability of strategic value for generating competitive advantage, irrespective of digital investment, aligning with the consistently documented negative BOPO-ROA nexus in Indonesian banking (Dari & Suarjaya, 2025; Fadhilah et al., 2025; Irawan et al., 2025). Control variable analysis further reveals asymmetric resource conversion. SIZE significantly affects only BOPO ($p = 0.0010$) rather than ROA directly, indicating that bank scale serves as a complementary resource prerequisite for optimizing efficiency capacity (Lestari & Sasmi, 2025). Meanwhile, CAR significantly influences ROA ($p = 0.0269$), reinforcing previous research (Ananda et al., 2025; Cahyani & Amirudin, 2024). Signifying that capital adequacy acts as a strategic buffer to generate earnings while functionally complementing technological investment capacity. Lastly, all estimated models indicate that NPLs are statistically insignificant. This suggests that credit risk is not a sufficiently strong variable to differentiate characteristics among the sampled banks.

The failure of H4 to satisfy the mediation criteria due to an insignificant indirect effect ($p = 0.396 > 0.05$) (Preacher & Hayes, 2004). This indicates that digital transformation (DT) has not tangibly altered BOPO, thereby disrupting the transmission of value substance toward ROA. This implies that banking technology investments on the IDX during the 2020–2024 period primarily bolster profitability via direct revenue-generating pathways rather than through cost-reduction channels. This phenomenon reflects an investment adaptation phase, wherein heavy initial outlays for system procurement and cybersecurity infrastructure maintenance temporarily offset anticipated operational savings. Framed within the Resource-Based View (RBV), this finding reinforces that digital instruments and cost-efficiency capabilities develop as two independent strategic routes rather than a linear, sequential process where technology must contract operational expenditures before yields in profitability are realized. This reality aligns with Hasani (2026), Hutabarat & Siallagan (2026), and Shanti et al. (2024), who assert that the financial outcomes of technological integration are non-linear; while IT infrastructure expenditures can immediately stimulate top-line revenues, achieving structural cost efficiencies demands a more extended time horizon and rigorous asset management to stabilize long-term profit margins.

CONCLUSION

This study demonstrates that digital transformation (DT) on the IDX (2020–2024) contributes positively and significantly to directly bolstering profitability (ROA), even after controlling for bank size, capital adequacy, and credit risk. Conversely, DT fails to reduce the BOPO ratio as banks remain embedded in an investment adaptation phase, where heavy system maintenance expenditures temporarily offset potential operational savings. Meanwhile, BOPO remains a critical

independent predictor, showing a robust and consistent negative nexus with ROA. Among the control variables, only bank size and capital adequacy display relevant roles across different models, while credit risk is statistically insignificant. Crucially, the non-functioning of BOPO as a mediator confirms that the financial gains from digital investments during this period are optimized purely through direct revenue-generating pathways rather than operational cost-cutting channels.

From a managerial perspective, bank executives must prioritize technology cost governance to prevent digital expenditures from overly burdening operational profits, while regulators can support the industry by easing the adaptation burdens associated with digital compliance. Furthermore, the mediation failure of BOPO opens four strategic avenues for future research. First, the DT proxy should be expanded into a multidimensional composite index that captures operational dimensions like big data and artificial intelligence. Second, the observation window (2020–2024) needs extension to capture long-term efficiency cycles as predicted by the productivity paradox. Third, future studies should test alternative mediating variables such as the fee-based income ratio, NIM, or digital customer acquisition rates. Finally, exploring a threshold effect is highly recommended to ascertain whether the impact of DT on BOPO only activates after crossing a specific digital investment baseline.

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