International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 09 Issue 06 June 2026
DOI: 10.47191/ijcsrr/V9-i6-64, Impact Factor: 8.048
IJCSRR @ 2026
www.ijcsrr.org

Digital Transformation and Bank Profitability in Indonesia: The Role of Firm Size as a Moderating Variable

Silvyani Putri Sihotang
Fakultas Ekonomi dan Bisnis, Program Studi Magister Manajemen, Universitas Indonesia, Jakarta, Indonesia

ABSTRACT: This study investigates the effect of digital transformation on bank profitability in Indonesia, with firm size examined as a moderating variable. Specifically, it assesses whether digital transformation enhances financial performance and whether larger banks are better positioned to benefit from digital initiatives. Using a quantitative research design, the study analyzes panel data from 41 banks operating in Indonesia. A fixed-effects regression model is employed to estimate the direct effect of digital transformation on profitability, measured by return on assets (ROA) and return on equity (ROE), as well as the moderating effect of firm size. The results show that digital transformation has a positive and statistically significant effect on both ROA and ROE, indicating that investments in digital technologies improve banking performance. In addition, firm size positively moderates the relationship between digital transformation and profitability. Larger banks appear to derive greater benefits from digitalization due to their stronger technological infrastructure, greater financial capacity, and higher ability to invest in innovation and human capital. The study concludes that digital transformation is a key driver of bank profitability and that organizational scale enhances its effectiveness. These findings contribute to the literature on digital transformation and banking performance and offer practical implications for bank managers and regulators in formulating digital strategies that align with institutional size and capabilities.

KEYWORDS: bank profitability, digital transformation, firm size, ROA, ROE

INTRODUCTION

The banking sector plays a critical role in a country's financial system by functioning as an intermediary institution that channels funds from surplus units to parties in need of financing, while also supporting national economic growth. In recent years, the development of digital technology has become one of the main drivers of change in the banking industry. Digital transformation enables banks to improve operational efficiency, expand access to services, and develop business models that are more responsive to evolving customer needs. The adoption of technologies such as internet banking, mobile banking, big data analytics, and integration with financial technology (fintech) firms has transformed the way banks conduct operations and deliver services to the public (Xie & Wang, 2023).

In Indonesia, digital transformation in the banking sector has also been supported by various regulatory policies, particularly those introduced by Bank Indonesia (BI) and the Financial Services Authority (OJK), which aim to accelerate the digitalization of financial services while maintaining financial system stability. Regulations related to digital payment systems, open banking, digital banking services, customer data protection, and the development of the national payment ecosystem indicate that digitalization has become a strategic agenda in strengthening the national banking sector (Bank Indonesia and OJK, 2025). Accordingly, digital transformation is no longer viewed merely as a technological innovation but as a strategic necessity for enhancing the competitiveness of the banking industry amid an increasingly dynamic business environment.

However, implementing digital transformation is not without its challenges. The digitalization process requires substantial investment in technological infrastructure, system development, cybersecurity, and human capital development. In addition, banks face various operational risks and increasingly complex regulatory compliance requirements. As a result, digital transformation may produce different consequences for each bank, depending on its internal readiness, funding capacity, and implementation strategy (Nguyen-Thi-Huong et al., 2023). Therefore, although digitalization offers opportunities to improve efficiency and service innovation, its financial benefits may not be immediately visible in the short term.

A growing body of research suggests that digital transformation can improve bank profitability through cost efficiency, diversification of non-interest income (fee-based income), and improved service quality. Banks that are able to optimize the use of digital technology tend to have greater opportunities to reduce operational costs while increasing revenue from transaction-based

International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 09 Issue 06 June 2026
DOI: 10.47191/ijcsrr/V9-i6-64, Impact Factor: 8.048
IJCSRR @ 2026
www.ijcsrr.org

digital services (Ferli et al., 2022). However, other studies report inconsistent findings regarding the effect of digitalization on profitability. Xiang And Jiang (2023) explain that although investment in digital finance can reduce financial intermediation costs, it does not necessarily lead to significant improvements in profitability, as additional costs associated with adopting new technology, strengthening cybersecurity, and regulatory compliance offset these savings. Thus, the relationship between digital transformation and bank profitability still requires further empirical investigation.

Moreover, the impact of digital transformation is expected to vary across banks due to heterogeneity in firm characteristics, particularly bank size. Large banks generally possess stronger financial resources, infrastructure, and organizational capacity to undertake sustained digital investment. In contrast, small and medium-sized banks tend to face greater constraints in funding and technological capabilities, although in some cases they may exhibit greater flexibility in adopting innovations. Do et al. (2022) show that large banks tend to have more stable digital transformation structures, whereas smaller banks are more flexible in adopting technology but are also more vulnerable to security risks and technological volatility. These findings suggest that bank size may be an important factor influencing the strength of the relationship between digital transformation and profitability.

Although research on banking digitalization continues to expand, important gaps remain, particularly in the Indonesian context. Most previous studies have examined the effects of digitalization in general terms without explicitly considering differences in bank characteristics, including size, business model, and level of technological readiness. In addition, much of the existing literature focuses on developed countries, while empirical evidence on the impact of digital transformation on bank profitability in developing countries such as Indonesia remains relatively limited (Anabel & Hidayat, 2025). At the same time, Indonesia has distinct characteristics in its digital transformation process, including unequal technological infrastructure across regions, regulatory challenges, and ongoing concerns regarding data security and privacy (Bousrih, 2023). These conditions underscore the importance of research that specifically examines the effect of digital transformation within the Indonesian banking industry.

Based on this background, this study aims to analyze the effect of digital transformation on bank profitability in Indonesia by considering firm size as a moderating variable. Specifically, the study has two objectives: (1) to examine and analyze the effect of digital transformation on bank profitability in Indonesia, and (2) to examine and analyze whether bank size moderates the relationship between digital transformation and bank profitability. This inquiry is relevant because previous research indicates that firm size may either strengthen or weaken the effect of digital transformation on financial performance (Lantip & Daljono, 2023). By employing a panel data regression approach, this study is expected to make an academic contribution by enriching the literature on digital transformation in the banking sector, while also offering practical value for bank management and regulators in formulating more effective and sustainable digitalization strategies (Uli et al., 2024).

In line with these objectives, the hypotheses proposed in this study are as follows: H1: Digital transformation has a positive effect on bank profitability in Indonesia. H2: Bank size moderates the relationship between digital transformation and bank profitability in Indonesia. Accordingly, this study is expected to provide a more comprehensive understanding of how digital transformation affects banking performance and to clarify the role of bank size in determining the success of digitalization initiatives amid the continuing evolution of the digital economy (Lantip & Daljono, 2023; Uli et al., 2024).

MATERIALS AND METHODS

This study employed a quantitative approach with a descriptive-causal design. The quantitative approach was chosen because the study examines relationships among numerically measurable variables, particularly the relationship between digital transformation and bank profitability in Indonesia, with bank size as a moderating variable (Sugiyono, 2020). The descriptive aspect was used to portray the condition of digital transformation in the banking industry, while the causal aspect was intended to test its effect on bank profitability.

The study focused on conventional banks listed on the Indonesia Stock Exchange (IDX) during 2018–2023. Indonesia was selected because of the rapid digitalization of its financial sector, supported by regulatory policies, as well as variations in digital readiness across banks that may lead to differences in the profitability effects of digital transformation (Xie & Wang, 2023; Anabel & Hidayat, 2025).

Population, Sample, and Data Sources

The population consisted of all banks listed on the Indonesia Stock Exchange (IDX) during the observation period. The sample was selected using purposive sampling based on the following criteria: (1) conventional banks listed on the IDX during 2018–2023; (2)

banks with complete and accessible annual financial statements; (3) banks actively undertaking digital transformation, as indicated in their annual reports; (4) banks not involved in mergers or acquisitions during the study period; and (5) Islamic banks were excluded to maintain homogeneity in model characteristics and regulatory conditions.

This study used secondary data obtained from: (1) annual reports and financial statements published by the banks and the Indonesia Stock Exchange; (2) publications from Bank Indonesia (BI) and the Financial Services Authority (OJK) related to banking and digitalization; and (3) macroeconomic data from Statistics Indonesia (BPS) and other official publications. Secondary data were used because they are generally reliable, verified, and widely applied in panel-data studies in banking research (Lantip & Daljono, 2023; Do et al., 2022).

Variable Operationalization and Measurement

Dependent Variables

Bank profitability was measured using Return on Assets (ROA) and Return on Equity (ROE). ROA reflects a bank's ability to generate profit from total assets, while ROE reflects its ability to generate returns for shareholders through equity (Bakkara & Sihotang, 2024; Anabel & Hidayat, 2025). The formulas are:

ROA = Net Income After Tax / Total Assets × 100%

ROE = Net Income After Tax / Total Equity × 100%

Using both indicators allows profitability to be assessed more comprehensively from the perspectives of asset efficiency and equity returns.

Independent Variable

The independent variable was digital transformation (DT). Following Lantip and Daljono (2023), DT was measured as the ratio of digital intangible assets to total intangible assets:

DT = Digital Intangible Assets / Intangible Assets

This measure represents the intensity of a bank's digital transformation through intangible assets associated with digitalization. Conceptually, digital transformation encompasses digital strategy, digital business transformation, and digital management transformation, which support efficiency, service innovation, and competitiveness (Xie & Wang, 2023; Lantip & Daljono, 2023).

Moderating Variable

The moderating variable was bank size (Size), measured by the natural logarithm of total assets:

Size = ln (Total Assets)

Bank size was included because organizational scale may strengthen or weaken the effect of digital transformation on profitability. Larger banks generally have greater technological resources but also face higher organizational complexity, whereas smaller banks tend to be more flexible but more resource-constrained (Dang et al., 2018; Do et al., 2022; Xiang & Jiang, 2023)

Control Variables

To reduce estimation bias, the study included several control variables: Total Deposits, Total Profit, Capital Adequacy Ratio (CAR), Non-Performing Loan Ratio (NPLR), Cost to Income Ratio (CIR), Money Supply (M2), Gross Domestic Product (GDP) Growth, and a COVID-19 dummy variable coded 1 for pandemic years and 0 otherwise. These variables were selected because bank profitability is influenced not only by firm-specific characteristics but also by macroeconomic conditions and operational efficiency (Do et al., 2022; Athanasoglou, Brissimis, & Delis, 2008).

Data Collection Procedure

Data were collected using documentation techniques by identifying, downloading, and processing annual reports, financial statements, and official publications from regulators and statistical agencies. Information on profitability, total assets, total equity, total deposits, profit, and intangible assets was obtained from bank reports, while macroeconomic variables such as economic growth and money supply were obtained from BI, OJK, and BPS.

The data were organized as panel data, combining time-series data for 2018–2023 and cross-sectional data across banks. This structure enabled the study to capture both interbank variation and temporal change, making it appropriate for examining the effect of digital transformation on bank profitability (Xie & Wang, 2023; Winarno, 2023).

International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 09 Issue 06 June 2026
DOI: 10.47191/ijcsrr/V9-i6-64, Impact Factor: 8.048
IJCSRR @ 2026
www.ijcsrr.org

Research Model

Two panel-data regression models were used, with ROA and ROE serving as alternative profitability measures. The interaction between digital transformation and bank size was included to test the moderating effect.

Model 1

$$ROA_{it} = \beta 0_{it} + \beta 1DT_{it} + \beta 2Size_{it} + \beta 3DT * Size_{it} + \beta 4Deposito_{it} + \beta 5Laba_{it} + \beta 6CAR_{it} + \beta 6NPL_{it} + \beta 7CIR_{it} + \beta 8M2_{it} + \beta 9GDP_{it} + e_{it}$$

Model 2

$$ROE_{it} = \beta 0_{it} + \beta 1DT_{it} + \beta 2Size_{it} + \beta 3DT * Size_{it} + \beta 4Deposito_{it} + \beta 5Laba_{it} + \beta 6CAR_{it} + \beta 6NPL_{it} + \beta 7CIR_{it} + \beta 8M2_{it} + \beta 9GDP_{it} + e_{it}$$

Where ROA_$_{it}$ and ROE_$_{it}$ represent the profitability of bank i in period t; DT_it is digital transformation; Size_$_{it}$ is bank size; DT_$_{it}$ × Size_$_{it}$ is the interaction term; Deposito_$_{it}$, Laba_$_{it}$, CAR_$_{it}$, NPL_$_{it}$, CIR_$_{it}$, M2_it, GDP_$_{it}$, and COVID_$_{it}$ are the control variables; and e_$_{it}$ is the error term. The interaction model was used because prior studies suggest that the effect of digital transformation may vary across banks of different organizational scales (Do et al., 2022; Xiang & Jiang, 2023; Lantip & Daljono, 2023).

Data Analysis

The analysis was conducted in four stages. First, descriptive statistics were used to summarize the characteristics of each variable through the mean, median, maximum, minimum, and standard deviation (Winarno, 2023).

Second, panel-data regression was performed using three alternative estimation models: the Common Effect Model (CEM), the Fixed Effect Model (FEM), and the Random Effect Model (REM). Model selection was based on the Chow, Hausman, and Lagrange Multiplier tests (Winarno, 2023).

Third, classical assumption tests were conducted, including tests of normality, multicollinearity, heteroskedasticity, and autocorrelation, to ensure that the regression model satisfied the required statistical assumptions (Gujarati et al., 2010; Winarno, 2023).

Fourth, hypothesis testing was conducted using the coefficient of determination (R^2), the F-test, and the t-test. The significance level used in this study was 5% (Winarno, 2023).

Software

Data processing and analysis were conducted using panel-data statistical software, such as EViews, Stata, or similar programs that support panel estimation, model selection, and classical assumption testing. The use of statistical software ensured accurate data processing and model estimation.

RESULTS

Study Sample

This study used panel data from conventional banks listed on the Indonesia Stock Exchange (IDX) over the 2018–2023 period. After screening for the completeness of financial reports and compliance with the sample criteria, 41 banks were retained for analysis. The distribution of the sample by BUKU classification is presented in Figure 1.

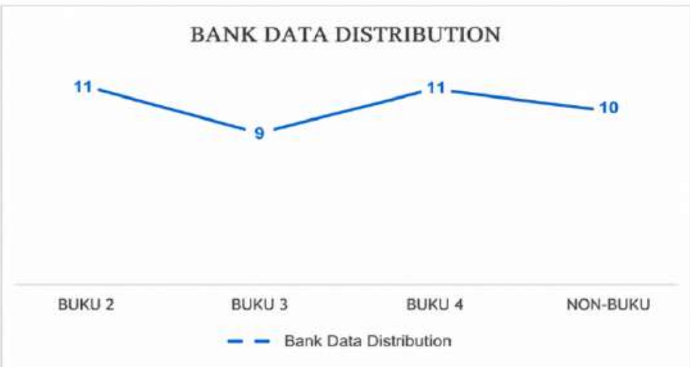

Fig 1. Bank Data Distribution

International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 09 Issue 06 June 2026
DOI: 10.47191/ijcsrr/V9-i6-64, Impact Factor: 8.048
IJCSRR @ 2026
www.ijcsrr.org

As shown in Figure 1, the sample consisted of 11 banks in BUKU 2, 9 in BUKU 3, 11 in BUKU 4, and 10 banks not classified within BUKU 1–4 in the dataset used. This distribution indicates that the sample includes banks with diverse business scales, thereby allowing the moderating role of bank size to be examined.

The final sample included 240 observations for the ROA model and 235 observations for the ROE model. The difference in the number of observations resulted from data cleaning, particularly the removal of outliers that could substantially influence model estimation.

Descriptive Statistics

Descriptive statistical analysis was conducted to provide an overview of the data through measures of central tendency and dispersion, including the mean, maximum, minimum, and standard deviation (Winarno, 2023). The results for the ROA and ROE models are presented in Tables 1 and 2, respectively.

Table 1. Descriptive Statistics of Model 1

	Mean	Maximum	Minimum	Std. Dev.	Observasi
ROA (%)	0.62643	4.9388	-8.6962	1.7102	240
DT (Rasio)	0.94083	1.0000	0.0400	0.1741	240
SIZE (Ln)	17.6230	21.4999	13.4071	1.7928	240
DEPOSITO (Rp Triliun)	51.6837	484.0000	0.2000	85.3806	240
LABA (Rp Triliun)	3.6623	60.4250	-6.0557	10.0331	240
CAR (%)	0.3130	2.0157	0.0901	0.2350	240
NPL (%)	3.3776	22.2700	0.0700	2.5383	240
CIR (%)	0.5622	4.2618	0.0003	0.3881	240
M2 (Rp Kuadraliun)	6.6583	8.0000	5.0000	1.1128	240
GDP	0.0437	0.0531	0.0207	0.0117	240
COVID (Dummy)	0.6666	1.0000	0.0000	0.4723	240

Based on Table 1, ROA had a mean of 0.6264%, a maximum of 4.9388%, a minimum of -8.6962%, and a standard deviation of 1.7102. The mean DT value was 0.9408, indicating that the level of digital transformation among the sample banks was generally high. The mean of SIZE was 17.6230, with a standard deviation of 1.7928, suggesting variation in bank size across the sample. The control variables—Deposits, Profit, CAR, NPL, CIR, M2, GDP, and COVID—also showed sufficient variation to support further regression analysis.

Table 2. Descriptive Statistics of Model 2

	Mean	Maximum	Minimum	Std. Dev.	Observasi
ROE (%)	0.5987	4.8888	-8.7462	1.6345	235
DT (Rasio)	0.9415	1.0000	0.0400	0.1737	235
SIZE (Ln)	17.6491	21.4999	13.4071	1.7961	235
DEPOSITO (Rp Triliun)	52.5600	484.0000	0.2000	86.0545	235
LABA (Rp Triliun)	3.7645	60.4250	-5.0325	10.1085	235
CAR (%)	0.3097	2.0157	0.0901	0.2301	235
NPL (%)	3.3465	22.2700	0.0700	2.5017	235
CIR (%)	0.5653	4.2618	0.0003	0.3914	235
M2 (Rp Kuadraliun)	6.6425	8.0000	5.0000	1.1131	235
GDP	0.0436	0.0531	0.0207	0.0118	235
COVID (Dummy)	0.5987	4.8888	-8.7462	1.6345	235

As reported in Table 2, ROE had a mean of 0.5987%, a maximum of 4.8888%, a minimum of -8.7462%, and a standard deviation of 1.6345. The mean values of DT and SIZE were 0.9415 and 17.6491, respectively. Overall, the distributional patterns of the control variables in the ROE model were similar to those in the ROA model. Together, these descriptive statistics indicate adequate variability in the dataset used in this study (Winarno, 2023).

Panel Data Model Selection

This study considered three panel-data estimation approaches: the common-effects model, fixed-effects model, and random-effects model. Model selection was based on the Chow, Hausman, and Lagrange Multiplier tests (Winarno, 2023). The results are presented in Tables 3, 4, and 5.

Table 3. Chow Test

Model 1			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	5.4421	(40,194)	0.0000
Cross-section Chi-square	185.0901	40	0.0000
Model 2			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	5.4421	(40,194)	0.0000
Cross-section Chi-square	185.0901	40	0.0000

As shown in Table 3, the Chow test yielded probability values of 0.0000 for both the cross-section F and cross-section Chi-square statistics in Model 1 and Model 2, indicating that the fixed effect model was preferred over the common effect model.

Table 4. Hausman Test

Model 1			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	0.000000	11	1.0000
Model 2			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	0.000000	11	1.0000

However, Table 4 shows that the Hausman test yielded a probability value of 1.0000 for both models, indicating that the random-effects model was more appropriate than the fixed-effects model.

Table 5. Lagrange Multiplier Test

Model 1	
	Prob.
Cross-section Breusch-Pagan	0.00000
Model 2	
	Prob.
Cross-section Breusch-Pagan	0.00000

Table 5 further indicates that the Breusch-Pagan probabilities from the Lagrange Multiplier test were 0.0000 for both models, supporting the use of the random-effects model over the common-effects model. Taken together, these results indicate that the random effect model was the most appropriate specification for this study (Winarno, 2023).

Classical Assumption Tests

International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 09 Issue 06 June 2026
DOI: 10.47191/ijcsrr/V9-i6-64, Impact Factor: 8.048
IJCSRR @ 2026
www.ijcsrr.org

Classical assumption tests were conducted to assess the adequacy of the regression model prior to hypothesis testing. These included tests of normality, multicollinearity, heteroskedasticity, and autocorrelation (Ghozali, 2018; Winarno, 2023).

Normality Test

Normality was assessed using the Jarque–Bera statistic to determine whether the residuals were normally distributed (Ghozali, 2018). The results for the ROA and ROE models are presented in Figures 2 and 3.

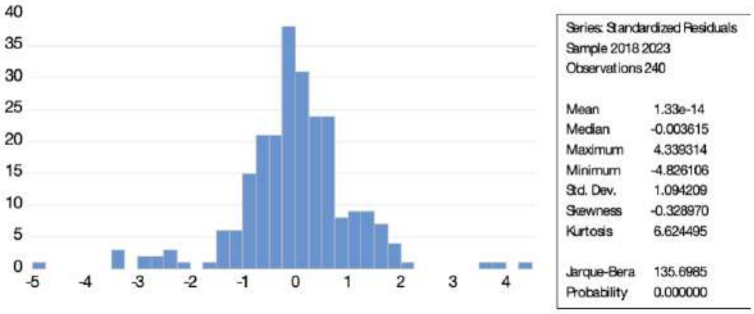

Fig 3. Normality Test for Model 1 (ROA)

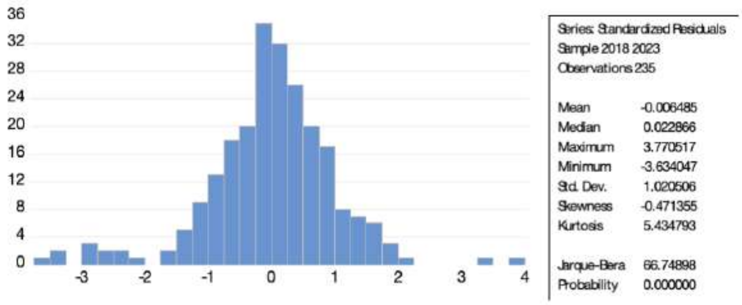

Fig 3. Normality Test for Model 2 (ROE)

Based on Figure 2 and Figure 3, the Jarque–Bera probability values for both models were below 0.05, indicating that the residuals were not perfectly normally distributed. Nevertheless, the sample sizes were relatively large, with 240 observations for the ROA model and 235 for the ROE model. Under these conditions, the Central Limit Theorem supports continued estimation of the model despite deviations from normality (Gujarati, 2015).

Multicollinearity Test

Multicollinearity was assessed using the correlation matrix among the independent variables. A regression model is generally considered free from serious multicollinearity when the correlation coefficients among independent variables are below 0.90 (Gujarati et al., 2010; Winarno, 2023). The results for the ROA and ROE models are presented in Tables 6 and 7.

Table 6. Multicollinearity Test for Model 1 (ROA)

	DT	SIZE	DT*SIZE	DEPOSITO	LABA	CAR	NPL	CIR	M2	GDP	COVID
DT	1.0000	-0.1544	0.8624	-0.0721	-0.1189	-0.0197	0.1149	-0.1526	-0.0177	0.0754	-0.0657
SIZE	-0.1544	1.0000	0.3596	0.7738	0.6343	-0.4033	-0.2705	-0.1898	0.1173	0.0149	0.0917
DT*SIZE	0.8624	0.3596	1.0000	0.3231	0.1933	-0.2135	-0.0313	-0.2010	0.04134	0.0721	-0.0122
DEPOSITO	-0.0721	0.7738	0.3231	1.0000	0.8291	-0.2165	-0.1558	-0.1517	0.0676	-0.0133	0.0696
LABA	-0.1189	0.6343	0.1933	0.8291	1.0000	-0.1251	-0.1723	-0.0986	0.0873	0.0791	0.0280
CAR	-0.0197	-0.4033	-0.2135	-0.2165	-0.1251	1.0000	0.01788	0.1342	0.2265	-0.0176	0.2287
NPL	0.1149	-0.2705	-0.0313	-0.1558	-0.1723	0.0178	1.0000	0.2233	-0.1146	-0.0929	-0.0450

CIR	-0.1526	-0.1898	-0.2010	-0.1517	-0.0986	0.1342	0.2233	1.0000	0.0034	-0.0688	0.0560
M2	-0.0177	0.1173	0.04134	0.0676	0.0873	0.2265	-0.1146	0.0034	1.0000	0.2199	0.7455
GDP	0.0754	0.0149	0.0721	-0.0133	0.0791	-0.0176	-0.0929	-0.0688	0.2199	1.0000	-0.4320
COVID	-0.0657	0.0917	-0.0122	0.0696	0.0280	0.2287	-0.0450	0.0560	0.7455	-0.4320	1.0000

Table 7. Multicollinearity Test for Model 2 (ROE)

	DT	SIZE	DT*SIZE	DEPOSITO	LABA	CAR	NPL	CIR	M2	GDP	COVID
DT	1.0000	-0.1488	0.8621	-0.0722	-0.1285	-0.0271	0.1417	-0.1551	-0.0090	0.0805	0.0771
SIZE	-0.1488	1.0000	0.3653	0.7738	0.6375	-0.3982	-0.2751	-0.1965	0.1255	0.0208	-0.0156
DT*SIZE	0.8621	0.3653	1.0000	0.3234	0.1861	-0.2170	-0.0087	-0.2060	0.0540	0.0797	0.0577
DEPOSITO	-0.0722	0.7738	0.3234	1.0000	0.8297	-0.2149	-0.1558	-0.1562	0.0746	-0.0096	-0.0075
LABA	-0.1285	0.6375	0.1861	0.8297	1.0000	-0.1249	-0.1668	-0.1025	0.0967	0.0840	0.0263
CAR	-0.0271	-0.3982	-0.2170	-0.2149	-0.1249	1.0000	-0.0198	0.1398	0.2191	-0.0302	-0.0886
NPL	0.1417	-0.2751	-0.0087	-0.1558	-0.1668	-0.0198	1.0000	0.2297	-0.1378	-0.1054	0.0146
CIR	-0.1551	-0.1965	-0.2060	-0.1562	-0.1025	0.1398	0.2297	1.0000	0.0098	-0.0680	-0.0833
M2	-0.0090	0.1255	0.0540	0.0746	0.0967	0.2191	-0.1378	0.0098	1.0000	0.2152	-0.1560
GDP	0.0805	0.0208	0.0797	-0.0096	0.0840	-0.0302	-0.1054	-0.0680	0.2152	1.0000	0.0586
COVID	0.0771	-0.0156	0.0577	-0.0075	0.0263	-0.0886	0.0146	-0.0833	-0.1560	0.0586	1.0000

As shown in Table 6 and Table 7, all correlation coefficients among the independent variables were below 0.90. Therefore, the regression models did not exhibit serious multicollinearity.

Heteroskedasticity Test

Heteroskedasticity was tested using the Park test. A model is considered free from heteroskedasticity when the probability values of the independent variables exceed 0.05 (Winarno, 2023). The results for the ROA and ROE models are presented in Tables 8 and 9.

Table 8. Heteroskedasticity Test for Model 1 (ROA)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-11.44472	17.45280	-0.655753	0.5158
DT	14.78535	17.31630	0.853840	0.3984
SIZE	0.737238	0.967103	0.762316	0.4505
DT*SIZE	-1.052300	0.971419	-1.083260	0.2853
DEPOSITO	0.004199	0.004674	0.898425	0.3745
LABA	-0.046203	0.048607	-0.950542	0.3477
CAR	-0.208479	2.131917	-0.097790	0.9226
NPL	0.216981	0.198802	1.091445	0.2818
CIR	0.183499	0.850643	0.215717	0.8303
M2	-0.256737	0.410417	-0.625553	0.5353
GDP	67.30343	34.27340	1.963722	0.0567
COVID	1.612104	0.865320	1.863013	0.0700

Table 9. Heteroskedasticity Test for Model 2 (ROE)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.210134	4.181960	-1.006737	0.3603
DT	6.854090	4.176028	1.641294	0.1617
SIZE	0.222021	0.226230	0.981397	0.3715

International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 09 Issue 06 June 2026
DOI: 10.47191/ijcsrr/V9-i6-64, Impact Factor: 8.048
IJCSRR @ 2026
www.ijcsrr.org

DT*SIZE	-0.418563	0.228886	-1.828699	0.1270
DEPOSITO	0.003033	0.001301	2.331853	0.0671
LABA	-0.015123	0.006716	-2.252004	0.0741
CAR	-0.270370	0.243140	-1.111997	0.3167
NPL	-0.008101	0.025554	-0.317019	0.7640
CIR	0.493768	0.232169	2.126755	0.0868
M2	0.077804	0.036093	2.155660	0.0836
GDP	5.887769	6.339667	0.928719	0.3957
COVID	0.226275	0.103844	2.178986	0.0812

Based on Tables 8 and 9, all independent variables in both models had p-values above 0.05. These results indicate that the models did not exhibit heteroskedasticity.

Autocorrelation Test

Autocorrelation was assessed using the Durbin–Watson statistic, as reported in Table 10 and Table 11. The Durbin–Watson value was 1.6327 for the ROA model and 1.3828 for the ROE model.

Table 10. Autocorrelation Test Results for Model 1 (ROA)

Statistik Durbin-Watson			
Durbin-Watson stat			1.632717
n	k	dL	dU
240	11	1,0995	1,6010

Table 11. Autocorrelation Test Results for Model 2 (ROE)

Statistik Durbin-Watson			
Durbin-Watson stat			1.382762
n	k	dL	dU
235	11	1,1012	1,5995

However, in panel-data settings, the Durbin–Watson statistic is less applicable, as it is more appropriate for single-equation time-series regression. Accordingly, these autocorrelation results should be interpreted with caution and should not serve as the sole basis for evaluating model adequacy (Gujarati et al., 2010; Ekananda, 2016).

Panel Regression Results

Simultaneous Significance Test (F-test)

The F-test was used to assess the joint significance of all independent variables in explaining the dependent variable (Winarno, 2023). The results are presented in Tables 12 and 13.

Table 12. F-Test Results for Model 1 (ROA)

F-statistic	26.10387
Prob(F-statistic)	0.000000

Table 13. F-Test Results for Model 2 (ROE)

F-statistic	32.02087
Prob(F-statistic)	0.000000

As shown in Table 12, the F-statistic for Model 1 (ROA) was 26.10387, with a probability value of 0.000000. Table 13 shows that the F-statistic for Model 2 (ROE) was 32.02087, also with a probability value of 0.000000. Since both probability values were below 0.05, both regression models were statistically significant overall.

International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 09 Issue 06 June 2026
DOI: 10.47191/ijcsrr/V9-i6-64, Impact Factor: 8.048
IJCSRR @ 2026
www.ijcsrr.org

Partial Significance Test (t-test)

The t-test was used to evaluate the partial significance of each regression coefficient in the multiple regression model (Gujarati & Porter, 2015). The regression results for the ROA and ROE models are presented in Tables 14 and 15, respectively.

Table 14. Regression Results for Model 1 (ROA)

Variable	Coefficient	Std. Error	t-Statistic
C	-16.70104***	5.910157	-2.825819
DT	16.01217***	5.842806	2.740493
SIZE	0.948461***	0.321300	2.951944
DT*SIZE	0.753909**	0.322077	2.340772
DEPOSITO	-0.004503**	0.002090	-2.154740
LABA	0.055956***	0.014236	3.930611
CAR	1.245130***	0.346900	3.589308
NPL	-0.274233***	0.031394	-8.735316
CIR	-1.070485***	0.232471	-4.604812
M2	-0.187854	0.191462	-0.981154
GDP	9.878056	13.38582	0.737949
COVID	-0.005623	0.488331	-0.011515
Ket : * (p < 0,1); ** (p < 0,05); *** (p < 0,01)			

Table 15. Regression Results for Model 2 (ROE)

Variable	Coefficient	Std. Error	t-Statistic
C	-18.89715***	5.014371	-3.768598
DT	19.24356***	5.005321	3.844620
SIZE	1.081708***	0.273045	3.961654
DT*SIZE	0.945157***	0.275179	3.434702
DEPOSITO	-0.004360*	0.001796	-2.427929
LABA	0.056229***	0.012565	4.475015
CAR	0.821799***	0.316046	2.600251
NPL	-0.288071***	0.027374	-10.52362
CIR	-1.069737***	0.202569	-5.280844
M2	-0.171710***	0.055036	-3.119931
GDP	9.958564**	4.923006	2.022862
COVID	-0.012075	0.118790	-0.101654
Ket : * (p < 0,1); ** (p < 0,05); *** (p < 0,01)			

In Model 2 (ROE), DT again had a positive and significant coefficient (β = 19.24356; t = 3.844620). SIZE was positive and significant (β = 1.081708; t = 3.961654), and the interaction term DT*SIZE was also positive and significant (β = 0.945157; t = 3.434702). Profit and CAR remained positive and significant, whereas NPL and CIR remained negative and significant. In this model, M2 was negative and significant, and GDP was positive and significant. Deposits were negatively associated with ROE and were significant at the 10% level, while COVID remained statistically insignificant.

Overall, the regression results indicate that digital transformation positively affects bank profitability, both directly and through its interaction with bank size. These findings support the view that larger banks are better positioned to convert digital transformation into improved financial performance.

International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 09 Issue 06 June 2026
DOI: 10.47191/ijcsrr/V9-i6-64, Impact Factor: 8.048
IJCSRR @ 2026
www.ijcsrr.org

Coefficient of Determination

The coefficient of determination (R^2) was used to measure the proportion of variation in the dependent variable explained by the independent variables in the regression model (Winarno, 2023). The results are presented in Tables 16 and 17.

Table 16. Coefficient of Determination Results for Model 1 (ROA)

R-squared	0.557404
Adjusted R-squared	0.536051

As reported in Table 16, Model 1 (ROA) had an R-squared of 0.557404 and an adjusted R-squared of 0.536051, indicating that approximately 53.61% of the variation in ROA was explained by the independent and control variables included in the model.

Table 17. Coefficient of Determination Results for Model 2 (ROE)

R-squared	0.612329
Adjusted R-squared	0.593206

Similarly, Table 17 shows that Model 2 (ROE) had an R-squared of 0.612329 and an adjusted R-squared of 0.593206. This indicates that the model explained approximately 59.32% of the variation in ROE. Overall, the ROE model provided slightly greater explanatory power than the ROA model.

DISCUSSION

Effect of Digital Transformation on Bank Profitability

The results show that digital transformation has a positive and significant effect on bank profitability, as measured by Return on Assets (ROA) and Return on Equity (ROE). This finding indicates that a higher level of digital transformation enhances banks' ability to use assets more efficiently and generate stronger returns on equity. Empirically, this result supports the view that digitalization is not merely a tool for service modernization but also a strategic factor that improves financial performance.

This finding is consistent with Do et al. (2022), who show that digital transformation improves the performance of commercial banks. Through service digitalization, process automation, and the use of information systems, banks can increase operational efficiency, accelerate business processes, and broaden service reach. In turn, these improvements are reflected in higher profitability, driven by lower operating costs and improved service quality. The result is also in line with Xie And Wang (2023), who argues that digital transformation in banking extends beyond technology-based services to include changes in strategy, business processes, and digital management that strengthen competitiveness and performance.

In the Indonesian context, this finding is also relevant given the growing demand for banking services that are fast, convenient, secure, and accessible in real time. As a result, technologies such as mobile banking, internet banking, and data analytics have become important tools for maintaining competitiveness. This interpretation supports Anabel and Hidayat (2025), who note that digital transformation in Indonesia's banking sector is driven by rapid technological development and is directed toward improving business performance through changes in information, communication, and connectivity-based activities.

From a theoretical perspective, this result also supports the Resource-Based View (RBV), which suggests that sustainable competitive advantage can be derived from strategic resources and capabilities. In this sense, digital transformation can be understood as a strategic capability that enables banks to integrate technology, data, and organizational competence to create value. This interpretation is consistent with Lantip and Daljono (2023) and Bakkara and Sihotang (2024), who find that digital transformation positively affects banking financial performance through greater efficiency and the creation of value-added services.

Overall, this study reinforces the literature suggesting that digital transformation is an important determinant of bank profitability. It also provides practical evidence that digital investment should be viewed not simply as a short-term cost, but as a source of long-term financial gains when implemented effectively and strategically (Do et al., 2022; Xie & Wang, 2023; Anabel & Hidayat, 2025).

Moderating Role of Bank Size

The results further indicate that the interaction between digital transformation and bank size has a positive and significant effect on profitability, for both ROA and ROE. This suggests that bank size strengthens the positive effect of digital transformation on profitability. In other words, larger banks tend to benefit more from digital transformation than smaller banks.

This finding is consistent with Do et al. (2022), who report that the positive effect of digital transformation on bank performance increases with bank size. A plausible explanation is that large banks typically have stronger capital, more advanced technological infrastructure, and greater human resource capacity to support digital transformation on a broader scale. They are also better able to absorb the initial costs of digital investment, including software development, system upgrades, cybersecurity, and business process adjustment. Consequently, digital transformation in large banks is more likely to produce measurable economic benefits.

The result also aligns with Lantip and Daljono (2023), who show that firm size moderates the relationship between digital transformation and financial performance. Larger institutions generally possess greater resources, technical expertise, managerial commitment, and awareness of digital opportunities, allowing them to implement new technologies more effectively. In the Indonesian banking sector, this interpretation is particularly relevant because digital capacity remains uneven across banks, with larger banks generally better prepared to build integrated digital ecosystems.

At the same time, this result differs from studies suggesting that smaller banks may benefit more from digitalization because of their greater organizational flexibility. Xiang and Jiang (2023) find that the profitability effect of digitalization may be stronger for small and medium-sized banks, whereas Nguyen-Thi-Huong et al. (2023) emphasize that digital transformation can exert negative pressure on performance when investment costs are not yet offset by economic returns. This difference suggests that the moderating effect of bank size is likely shaped by institutional context, digital maturity, and organizational readiness. In Indonesia, the advantages associated with the resource base of large banks appear to outweigh the flexibility of smaller institutions.

Therefore, this study adds evidence that bank size is not merely a control characteristic, but an important factor shaping how effectively digital transformation translates into profitability. The gains from digital transformation are thus not uniform across banks but depend on organizational capacity.

Contributions to Knowledge and Practice

This study contributes to both academic knowledge and managerial practice. Academically, it strengthens the literature on the relationship between digital transformation and bank profitability by providing empirical evidence from Indonesia, where such evidence remains relatively limited. It also extends understanding of heterogeneity in the effects of digital transformation by showing that bank size acts as a significant moderating variable. These findings support the argument that the benefits of digitalization are not universal, but depend on organizational capacity, resources, and implementation readiness (Do et al., 2022; Lantip & Daljono, 2023; Anabel & Hidayat, 2025).

Practically, the findings suggest that banks should treat digital transformation as a medium- to long-term strategic investment rather than merely a response to technological change or competition. Banks also need to align their digital strategies with internal capacity, particularly in financing, cybersecurity, and human capital development. For regulators such as BI and OJK, the results imply that digitalization policies should account for disparities in bank capacity. Support for small and medium-sized banks is therefore important to ensure that the benefits of digital transformation are distributed more evenly across the banking industry (Bousrih, 2023; Uli et al., 2024).

Strengths and Limitations

This study has several strengths. First, it uses panel data on Indonesian conventional banks over the 2018–2023 period, allowing the analysis to capture both cross-bank and intertemporal variation. Second, profitability is measured using both ROA and ROE, providing a more comprehensive view of financial performance. Third, the inclusion of both internal and macroeconomic control variables improves the model's explanatory power.

However, several limitations should also be acknowledged. First, digital transformation is measured using the ratio of digital intangible assets to total intangible assets, which may not fully capture broader dimensions of digital transformation, such as digital service quality, digital transaction intensity, or innovation capability. As noted by Xie and Wang (2023), digital transformation in banking also encompasses strategic, business, and managerial dimensions. Second, the sample includes only conventional banks listed on the IDX, which limits the generalizability of the findings to Islamic or non-listed banks. Third, the analysis focuses on a linear relationship, whereas prior studies suggest that the relationship between digitalization and profitability may be nonlinear or

U-shaped (Xiang & Jiang, 2023). Fourth, the financial effects of digital transformation may emerge gradually, and a longer observation period may provide deeper insight.

Implications for Future Research

The main implication of this study is that digital transformation is a relevant driver of bank profitability and that its benefits are stronger for larger banks. Accordingly, banks should pursue digital transformation not only through technology adoption but also through business process integration, employee digital literacy, technology risk management, and stronger digital governance. The findings also suggest that regulators should adopt more inclusive policies so that small and medium-sized banks are not left behind in the digitalization process.

Future research may extend this study in several ways. First, digital transformation could be measured using more multidimensional indicators, such as the number of digital transactions, mobile banking adoption, information technology expenditure, or digital disclosure scores in annual reports. Second, future studies could examine possible nonlinear relationships between digital transformation and profitability, as suggested by Xiang and Jiang (2023). Third, additional moderating or mediating variables—such as risk, operational efficiency, governance quality, or ownership structure—could be incorporated. Fourth, comparative studies between conventional and Islamic banks, or, more specifically, between large and small banks, may provide deeper insight into the heterogeneous effects of digital transformation on banking performance.

Overall, this study demonstrates that digital transformation is a strategic factor contributing to higher bank profitability in Indonesia. It further shows that bank size strengthens this relationship, highlighting the importance of organizational capacity in determining the success of digital transformation. These findings enrich the academic literature while also offering an empirical basis for managerial decision-making and banking digitalization policy in Indonesia.

CONCLUSION

This study examined 41 banks using multiple regression analysis to assess the effect of digital transformation on bank profitability, with firm size as a moderating variable. The findings can be summarized as follows:

Digital transformation has a positive and significant effect on Return on Assets (ROA). This result indicates that adopting digital technology in banking operations improves asset utilization efficiency and contributes to higher profitability relative to total assets.

The interaction between digital transformation and firm size has a positive and significant effect on ROA. This suggests that larger banks are better positioned to optimize the benefits of digitalization in improving asset efficiency, despite their greater operational complexity.

Digital transformation has a positive and significant effect on Return on Equity (ROE). This finding implies that the implementation of digital technology enhances returns to shareholders, particularly through improved service-based revenue generation and greater cost efficiency.

The interaction between digital transformation and firm size also has a positive and significant effect on ROE. Larger banks are therefore more likely to benefit from economies of scale, stronger technological infrastructure, and broader innovation in digital services, all of which contribute to higher equity-based profitability.

Overall, the results confirm that digital transformation is an important driver of bank profitability in Indonesia and that its positive effect is strengthened by firm size.

Implications

This study offers value to multiple stakeholders: for academics, it deepens understanding of how digital transformation affects bank profitability, particularly by considering firm size as a moderating factor, and provides a useful methodological reference through its panel regression approach; for the banking industry, it highlights the importance of optimizing digital technologies such as mobile banking, internet banking, and big data analytics to improve efficiency, diversify revenue, and strengthen risk management in areas like cybersecurity and regulatory compliance; for regulators such as Bank Indonesia and OJK, it provides empirical insights to support more inclusive and adaptive digitalization policies that reflect differences in bank readiness while addressing data protection, system security, and infrastructure needs; and for the fintech industry, it underscores growing opportunities for collaboration with banks to develop digital financial solutions that enhance efficiency, profitability, financial inclusion, and the broader national financial ecosystem.

International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 09 Issue 06 June 2026
DOI: 10.47191/ijcsrr/V9-i6-64, Impact Factor: 8.048
IJCSRR @ 2026
www.ijcsrr.org

Recommendations

This study has several limitations. First, the data cover only a specific period and therefore may not fully reflect the long-term dynamics of banking digitalization. Second, digital transformation was measured using quantitative indicators only and did not capture other relevant dimensions, such as human resource readiness or organizational culture. Third, the only moderating variable examined was firm size, although other factors may also influence the relationship between digitalization and profitability.

Future research is therefore encouraged to use a longer observation period and a more diverse sample. Additional variables, such as technology strategy or service innovation, may also be incorporated. Moreover, future studies may consider alternative profitability measures, such as Net Interest Margin (NIM), to provide a more comprehensive understanding of banking performance.

REFERENCES

1. Anabel, S., & Hidayat, T. (2025). The effect of digital transformation on bank financial performance with fee-based income as an intervening variable in commercial banks listed on the IDX in the 2020–2023 period. Jurnal Ekonomi, Manajemen, dan Perbankan. https://journal.ibs.ac.id/index.php/jemp
2. Bakkara, L., & Sihotang, R. B. (2024). The effect of banking digitalization on return on assets and return on equity in KBMI IV banking companies listed on the Indonesia Stock Exchange.
3. Bousrih, J. (2023). The impact of digitalization on the banking sector: Evidence from fintech countries. Asian Economic and Financial Review, 13(4), 269–278. https://doi.org/10.55493/5002.v13i4.4769
4. Chen, Y., Huang, R., Zhang, Y., & Shuai, Q. (2024). The impact of digital transformation of commercial banks on household income: Evidence from China. PLOS ONE, 19(9). https://doi.org/10.1371/journal.pone.0310277
5. Dang, C., Li, Z., & Yang, C. (2018). Measuring firm size in empirical corporate finance. Journal of Banking and Finance, 86, 159–176. https://doi.org/10.1016/j.jbankfin.2017.09.006
6. Do, T., Pham, H., Thalassinos, E. I., & Le, H. A. (2022). The impact of digital transformation on performance: Evidence from Vietnamese commercial banks. Journal of Risk and Financial Management, 15(1). https://doi.org/10.3390/jrfm15010021
7. Ferli, Lestari, & Kusumawardhani. (2022). Digital products increase fee-based income banking in Indonesia. Jurnal Ilmu Manajemen dan Ekonomika.
8. Gujarati, D. N., & Porter, D. C. (2010). Essentials of econometrics (4th ed.). McGraw-Hill/Irwin.
9. Lantip, & Daljono. (2023). Pengaruh transformasi digital terhadap kinerja keuangan dengan ukuran perusahaan sebagai variabel moderasi (Studi empiris pada perusahaan perbankan yang terdaftar di BEI tahun 2019–2022).
10. Nguyen-Thi-Huong, L., Nguyen-Viet, H., Nguyen-Phuong, A., & Van Nguyen, D. (2023). How does digital transformation impact bank performance? Cogent Economics & Finance, 11(1). https://doi.org/10.1080/23322039.2023.2217582
11. Sugiyono. (2020). Metode penelitian pendidikan: Pendekatan kuantitatif, kualitatif, dan R&D. Alfabeta.
12. Uli, A., Irmayani, R., Hadis, R., & Gibran, F. (2024). Transformasi ekonomi digital di Indonesia: Tantangan, peluang, dan dampaknya pada perekonomian nasional. Prosiding Seminar Nasional, 3(1).
13. Winarno, W. W. (2023). Analisis ekonometrika dan statistika dengan EViews (5th ed.). UPP STIM YKPN.
14. Xiang, X., & Jiang, L. (2023). Digitalisation and commercial bank performance: A test of heterogeneity from Chinese commercial banks. Finance Research Letters, 58. https://doi.org/10.1016/j.frl.2023.104303
15. Xie, X., & Wang, S. (2023). Digital transformation of commercial banks in China: Measurement, progress and impact. China Economic Quarterly International, 3(1), 35–45. https://doi.org/10.1016/j.ceqi.2023.03.002

Cite this Article: Silvyani Putri Sihotang, S.P. (2026). Digital Transformation and Bank Profitability in Indonesia: The Role of Firm Size as a Moderating Variable. International Journal of Current Science Research and Review, 9(6), pp. 3584-35. DOI: https://doi.org/10.47191/ijcsrr/V9-i6-64