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Digital Transformation As A Moderator Of Bank Stability, Risk, And Efficiency Effects On Profitability: Evidence From Indonesia

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Abstract—This study examines whether digital transformation (DT) moderates the effects of banking stability, liquidity, credit risk, and operating efficiency on the profitability of Indonesian banks. Bank profitability remains under structural pressure from margin compression, intensifying financial-technology competition, and the lasting disruption of the COVID-19 pandemic, while banks continue to allocate substantial resources to digitalization whose payoff remains empirically contested. Using an unbalanced panel of 40 Indonesian commercial banks with 400 bank-year observations, profitability is measured by return on equity (ROE) and explained by banking stability (Z-Score), the loan-to-deposit ratio (LDR), non-performing loans (NPL), and the operating expense to operating income ratio (BOPO), with the COVID-19 period, economic growth, and the Bank Indonesia policy rate as control variables. Because profitability is dynamic and the regressors are potentially endogenous, the model is estimated using one-step System Generalized Method of Moments (System GMM); Fisher-type panel unit root tests confirm that all series are stationary, and the Arellano–Bond AR(2) and Hansen tests support the validity of the specification and instruments. The results show that stability strongly increases ROE, whereas LDR and BOPO reduce it. DT has no significant direct effect on ROE, but it significantly moderates the stability–profitability and efficiency–profitability relationships negatively and the liquidity–profitability relationship positively. These findings imply that digitalization is not an automatic source of profit: it pays off mainly through improved intermediation, while imposing transition costs on stable and cost-inefficient banks. The study contributes a dynamic-panel moderation perspective to the digital banking literature and offers guidance for bank managers and regulators in sequencing digital investment.

Keywords—digital transformation; bank profitability; banking stability; System GMM; Indonesia

1. Introduction

The banking industry is undergoing one of the most profound structural changes in its history. Digital technologies — mobile banking, application programming interfaces, big-data analytics, cloud computing, and artificial intelligence — are redefining how banks acquire customers, distribute products, manage risk, and organize their internal processes (Vial, 2019; Scardovi, 2017). In Indonesia, this shift has been accelerated by three forces that operate simultaneously: the rapid adoption of digital financial services by a young and mobile-first population, the entry of financial-technology (fintech) firms and digital-only banks that compete directly with incumbent lenders, and the COVID-19 pandemic of 2020–2022, which forced banks to migrate services to digital channels while simultaneously depressing loan demand and asset quality. Against this backdrop, Indonesian banks have committed very large capital expenditure to digital transformation programs, and both the Financial Services Authority (OJK) and Bank Indonesia have made digitalization a central pillar of their banking development agendas.

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Yet the fundamental economic question remains unsettled: does digital transformation actually improve bank performance, and if so, through which channels? The international evidence is mixed. Some studies find that digitalization improves bank profitability and market value by lowering distribution costs, expanding fee income, and improving customer analytics (Gupta & Sharma, 2021; Zhang & She, 2024). Others emphasize that digital transformation is costly, organizationally disruptive, and slow to pay off, so that its short-run effect on earnings can be negligible or even negative, particularly for banks that digitize without a coherent strategy (Kane et al., 2015; Hess et al., 2016).

The strategic-management literature reconciles these views by arguing that technology creates value only when it is orchestrated together with the firm's other resources and capabilities (Barney, 1991; Sirmon et al., 2011; Teece, 2014). From this perspective, digital transformation should not be modeled primarily as a direct determinant of profitability, but as a contingency — a moderator — that changes how effectively a bank converts its fundamentals, such as stability, liquidity, credit quality, and cost efficiency, into profit.

Most empirical work on Indonesian bank profitability, however, still treats digitalization (when it is included at all) as a simple additional regressor in a static panel model. This creates two gaps. First, the moderating role of digital transformation on the classic determinants of bank profitability — stability, liquidity, credit risk, and efficiency — has rarely been tested formally, even though the theoretical argument for moderation is strong. Second, bank profitability is well known to be dynamic and persistent, and its determinants are plausibly endogenous (profitable banks can afford more digital investment, better risk management, and stronger capital positions), so static estimators such as pooled OLS or fixed effects are likely to be biased. Dynamic panel estimators of the Arellano–Bond and Blundell–Bond family address both problems by instrumenting the endogenous regressors with their own lags (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998; Roodman, 2009), and they have become the standard tool in modern banking research (Guill, 2016).

This study addresses these gaps by asking three research questions. First, do banking stability (Z-Score), the loan-to-deposit ratio (LDR), non-performing loans (NPL), and the operating expense to operating income ratio (BOPO) determine the return on equity (ROE) of Indonesian banks? Second, does digital transformation (DT) directly affect ROE? Third — and centrally — does digital transformation moderate the effect of stability, liquidity, credit risk, and efficiency on ROE? The analysis uses a panel of 40 Indonesian commercial banks with 400 bank-year observations and controls for the COVID-19 period, macroeconomic growth, and the Bank Indonesia policy rate. Estimation is carried out with one-step System GMM, supported by Fisher-type panel unit root tests, a correlation analysis, and the standard Arellano–Bond and Hansen diagnostics.

The study contributes to the literature in three ways. Conceptually, it reframes digital transformation as a moderating capability rather than a stand-alone profit driver, consistent with the resource-based and dynamic-capabilities views (Barney, 1991; Teece, 2018; Warner & Wäger, 2019). Methodologically, it applies a dynamic System GMM design with interaction terms, which controls for profit persistence, unobserved heterogeneity, and endogeneity simultaneously. Empirically, it provides new evidence from Indonesia — one of the largest and fastest-digitizing banking markets in Southeast Asia — covering a period that includes the COVID-19 shock, which makes it possible to separate the digitalization effect from the pandemic effect. The remainder of the paper is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and methodology. Section 4 presents the results and discussion. Section 5 concludes with implications, limitations, and directions for future research.

2. Literature Review and Hypothesis Development

2.1 Theoretical Framework: Resource-Based View and Dynamic Capabilities

The theoretical anchor of this study is the resource-based view (RBV) of the firm, which holds that sustained competitive advantage arises from resources that are valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991). Digital technologies by themselves rarely satisfy these conditions, because hardware, software, and even fintech partnerships can be purchased by any bank with sufficient budget. What differentiates banks is the way resources are bundled and deployed — what Sirmon et al. (2011) call resource orchestration, and what the human-capital literature describes as the architecture through

which skills are allocated and developed inside the firm (Lepak & Snell, 1999). The dynamic-capabilities extension of the RBV makes the argument explicitly temporal: in fast-moving environments, performance depends on the capacity to sense opportunities, seize them, and reconfigure the resource base accordingly (Teece, 2014, 2018). Digital transformation is best understood as such a reconfiguration process — an ongoing strategic renewal of the business model rather than a one-off technology purchase (Warner & Wäger, 2019; Vial, 2019).

Two implications follow for empirical modeling. First, the direct effect of digital transformation on profitability is theoretically ambiguous: digitalization simultaneously generates revenue opportunities (new channels, fee income, customer analytics) and large transition costs (capital expenditure, cybersecurity, cannibalization of branch networks, organizational friction) (Hess et al., 2016; Kane et al., 2015; Scardovi, 2017). Second, and more fundamentally, digital transformation should alter the productivity of the bank's other fundamentals. A digitally capable bank can convert a given level of liquidity into more earning assets, monitor a given loan portfolio more intensively, and run a given cost base more efficiently. In econometric terms, digital transformation is a moderator of the relationships between bank fundamentals and profitability. This moderation logic parallels the intellectual-capital literature, which finds that intangible, knowledge-based resources create value primarily by enhancing the efficiency of other value drivers (Pulic, 2004; Vidyarthi, 2019).

2.2 Determinants of Bank Profitability

A large empirical literature examines the internal and external determinants of bank profitability, typically measured by return on assets (ROA) or return on equity (ROE). Dietrich and Wanzenried (2011), studying Swiss banks before and during the global financial crisis, show that profitability depends on bank-specific factors such as efficiency, funding structure, and growth, and that these relationships shift in crisis periods — a finding directly relevant to the COVID-19 window covered by the present sample. Bitar et al. (2018), using OECD data, show that capital strength and risk profiles significantly shape bank efficiency and profitability. Within this tradition, four bank-specific fundamentals are standard for emerging markets and for Indonesia in particular.

Banking stability is commonly proxied by the Z-Score, which combines capitalization and the level and volatility of returns into a distance-to-default measure, an approach rooted in Altman's (1968) insight that accounting ratios can predict financial distress. More stable banks enjoy cheaper funding, greater depositor confidence, and larger buffers to pursue profitable lending, so stability is expected to raise profitability. Liquidity and intermediation intensity are proxied by the loan-to-deposit ratio (LDR). Its effect is theoretically two-sided: higher LDR means more earning assets, but an over-stretched LDR raises funding costs and liquidity risk, which can compress equity returns. Credit risk is proxied by non-performing loans (NPL); higher NPL forces provisioning and write-offs that reduce earnings. Operating efficiency is proxied by BOPO, the ratio of operating expenses to operating income widely used by Indonesian supervisors; a higher BOPO indicates inefficiency and is expected to reduce profitability.

Bank profitability is also shaped by the macroeconomic environment. Economic growth expands loan demand and improves borrower repayment capacity, while the policy interest rate affects net interest margins and the cost of funds (Dietrich & Wanzenried, 2011). The COVID-19 pandemic represents a distinct structural shock: it depressed credit demand and asset quality but also accelerated digital adoption, so it must be controlled for explicitly in any Indonesian sample that spans 2020–2022.

2.3 Digital Transformation and Bank Performance

Digital transformation is defined as the process by which organizations use combinations of information, computing, communication, and connectivity technologies to fundamentally change how value is created and delivered (Vial, 2019). In banking, this covers digital distribution channels, process automation, data-driven credit scoring, and ecosystem partnerships with fintech firms (Scardovi, 2017). Empirically, Gupta and Sharma (2021) find that digital transformation is associated with stronger financial performance in the banking sector, while Zhang and She (2024) show that digitalization and the associated build-up of intangible assets improve corporate performance in the banking industry. However, the strategy literature warns that

the returns to digitalization are conditional on strategy and organization rather than on technology itself (Kane et al., 2015; Hess et al., 2016), and case evidence shows that incumbents frequently experience a prolonged period in which digital investment inflates costs before revenues respond (Warner & Wäger, 2019). These considerations motivate a direct-effect hypothesis stated in the alternative form, while acknowledging that the net short-run effect may be weak.

2.4 Hypothesis Development

Based on the theoretical framework and prior evidence, the following hypotheses are proposed. First, regarding the direct effects of bank fundamentals: H1 — banking stability (Z-Score) has a positive effect on ROE; H2 — the loan-to-deposit ratio has a significant effect on ROE; H3 — non-performing loans have a negative effect on ROE; H4 — BOPO (cost inefficiency) has a negative effect on ROE. Second, regarding digitalization: H5 — digital transformation has a positive direct effect on ROE.

Third, and central to this study, digital transformation is hypothesized to moderate each fundamental-profitability relationship: H6a — DT moderates the effect of banking stability on ROE; H6b — DT moderates the effect of LDR on ROE, strengthening the conversion of intermediation into profit; H6c — DT moderates the effect of NPL on ROE, mitigating the earnings damage of credit risk through better monitoring and collection; and H6d — DT moderates the effect of BOPO on ROE. The direction of H6a and H6d is theoretically ambiguous: digital capability may amplify the value of stability and efficiency (complementarity), or the transition costs of digitalization may fall hardest precisely on stable, branch-heavy incumbents and on banks whose cost base is already bloated, in which case the interaction would be negative (Hess et al., 2016; Warner & Wäger, 2019). The empirical analysis lets the data decide.

3. Research Method

3.1 Research Design, Population and Sample

This study uses a quantitative explanatory design with secondary panel data. The population is Indonesian commercial banks; the sample consists of 40 banks observed annually over ten years, yielding 400 bank-year observations. Sampling criteria, e.g., purposive sampling of banks listed on the Indonesia Stock Exchange with complete annual reports throughout 2016–2025. Data are collected from published annual reports and financial statements of the sample banks, complemented by macroeconomic series from Bank Indonesia and Statistics Indonesia (BPS).

3.2 Variables and Measurement

The dependent variable is profitability, measured by return on equity (ROE), defined as net income divided by total equity. ROE is preferred to ROA here because it captures the return delivered to shareholders, who ultimately fund digital transformation programs. The independent variables are four bank fundamentals. Banking stability is measured by the Z-Score, computed as the sum of the capital-to-assets ratio and ROA divided by the standard deviation of ROA, so that a higher value indicates greater distance from insolvency (Altman, 1968; Bitar et al., 2018). Liquidity and intermediation intensity are measured by the loan-to-deposit ratio (LDR), total loans divided by total deposits. Credit risk is measured by the non-performing loan ratio (NPL), non-performing loans divided by total loans. Operating efficiency is measured by BOPO, operating expenses divided by operating income, where a higher ratio means lower efficiency.

The moderating variable is digital transformation (DT), an index capturing the intensity of each bank's digitalization. DT measurement with a composite disclosure index from annual reports, the ratio of IT/digital investment to total assets. The interaction terms DTZ (DT × Z-Score), DTLDR (DT × LDR), DTNPL (DT × NPL), and DTBOPO (DT × BOPO) operationalize the moderation hypotheses H6a–H6d. Three control variables complete the model: COVID, a dummy equal to 1 for 2020–2022 and 0 otherwise; ECGRWTH, Indonesia's annual real economic growth rate; and BIINTRST, the Bank Indonesia policy interest rate.

3.3 Model Specification

Because bank profitability is persistent and its determinants are potentially endogenous, a dynamic panel model is specified in which current ROE depends on its own lags, the fundamentals, DT, the interaction terms, and the controls:

$$ROE_{it} = \alpha_1 ROE_{i,t-1} + \alpha_2 ROE_{i,t-2} + \beta_1 DT_{it} + \beta_2 ZSCORE_{it} + \beta_3 LDR_{it} + \beta_4 NPL_{it} + \beta_5 BOPO_{it} + \beta_6 COVID_t + \beta_7 ECGRWTH_t + \beta_8 BIINTRST_t + \gamma_1 DTZ_{it} + \gamma_2 DTLDR_{it} + \gamma_3 DTNPL_{it} + \gamma_4 DTBOPO_{it} + \mu_i + \varepsilon_{it},$$

where μ_i is an unobserved bank-specific effect and ε_{it} is the idiosyncratic error. Two lags of the dependent variable are included to fully capture the dynamics of profitability and to remove residual serial correlation.

3.4 Estimation Strategy: System GMM

Estimating this equation by pooled OLS or fixed effects would be biased: the lagged dependent variable is correlated with the bank effect (dynamic panel bias), and regressors such as DT, LDR, and BOPO are plausibly determined jointly with profitability. The study therefore uses the System Generalized Method of Moments (System GMM) estimator, which combines the equation in first differences, instrumented by lagged levels, with the equation in levels, instrumented by lagged differences (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). System GMM is particularly suitable for panels with a moderate number of cross-sections and short time dimension, and is the workhorse estimator in contemporary banking research (Roodman, 2009; Guill, 2016). A one-step estimator with collapsed instruments is applied to avoid instrument proliferation; following Roodman (2009), the number of instruments (35) is kept below the number of banks (40).

Three groups of diagnostic tests validate the specification. First, Fisher-type panel unit root tests based on the inverse chi-squared statistic verify that all variables are stationary, so the regression is not spurious. Second, the Arellano–Bond test for second-order autocorrelation, AR(2), checks the key identifying assumption that the errors are not serially correlated beyond first order. Third, the Hansen J test of over-identifying restrictions checks the joint validity of the instruments. The Wald test assesses the joint significance of the regressors. Pairwise correlations are inspected to rule out severe multicollinearity among the fundamentals (interaction terms are, by construction, correlated with their components; this does not bias GMM coefficients).

4. Result and Discussion

4.1 Descriptive Statistics

Table 1 summarizes the 400 bank-year observations. Average ROE is 2.39% with a large standard deviation of 14.05% and a minimum of −123.93%, indicating that the sample contains banks experiencing severe losses alongside profitable institutions (maximum 25.25%); this heterogeneity underlines the importance of controlling for bank-specific effects. The digital transformation index averages 0.0455 with a maximum of 0.5620, showing that digitalization intensity is still low on average but varies widely across banks — exactly the variation needed to identify moderation effects. The mean Z-Score of 0.3719 with wide dispersion (−2.61 to 2.82) reflects heterogeneous stability. The average LDR of 86.49% lies within Bank Indonesia's traditional intermediation corridor, although the maximum of 197.66% shows some banks lend far beyond their deposit base. Mean NPL is 3.41%, below the 5% supervisory threshold, but reaches 60.58% at the extreme. Mean BOPO of 89.55% indicates that operating costs absorb almost ninety percent of operating income for the average bank, and values above 1 reveal banks operating at a loss. Thirty percent of observations fall in the COVID window, consistent with three pandemic years in a ten-year panel; economic growth averages 4.24% and the policy rate 5.08%.

TABLE I. DESCRIPTIVE STATISTICS

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
ROE	Return on Equity	400	0.0239	0.1405	-1.2393	0.2525
DT	Digital Transformation	400	0.0455	0.1228	0.0000	0.5620
ZSCORE	Banking Stability	400	0.3719	0.5899	-2.6100	2.8200
LDR	Loan to Deposit Ratio	400	0.8649	0.2368	0.0547	1.9766
NPL	Non-Performing Loan	400	0.0341	0.0380	0.0001	0.6058
BOPO	Cost to Income (Operations) Ratio	400	0.8955	0.2320	0.0166	1.8062
COVID	COVID period 2020–2022 = 1, 0 otherwise	400	0.3000	0.4588	0	1
ECGRWTH	Indonesia's Economic Growth	400	0.0424	0.0215	-0.0207	0.0531
BIINTRST	Indonesia Central Bank Rate	400	0.0508	0.0101	0.0350	0.0600
DTZ	DT × ZSCORE	400	0.0288	0.0864	-0.0173	0.4624
DTLDR	DT × LDR	400	0.0408	0.1113	0.0000	0.4624
DTNPL	DT × NPL	400	0.0013	0.0036	0.0000	0.0205
DTBOPO	DT × BOPO	400	0.0353	0.0942	0.0000	0.4664

Source: authors' calculations.

4.2 Panel Unit Root Tests

TABLE II. FISHER-TYPE PANEL UNIT ROOT TEST RESULTS

Variable	Test Statistic	p-value	Conclusion
ROE	Inverse chi-squared (P) = 218.58	0.0000	Stationary
DT	Inverse chi-squared (P) = 167.78	0.0000	Stationary
ZSCORE	Inverse chi-squared (P) = 237.91	0.0000	Stationary
LDR	Inverse chi-squared (P) = 210.23	0.0000	Stationary
NPL	Inverse chi-squared (P) = 269.52	0.0000	Stationary
BOPO	Inverse chi-squared (P) = 239.99	0.0000	Stationary
COVID	Inverse chi-squared (P) = 147.21	0.0000	Stationary
ECGRWTH	Inverse chi-squared (P) = 265.03	0.0000	Stationary

Variable	Test Statistic	p-value	Conclusion
BIINTRST	Inverse chi-squared (P) = 244.41	0.0000	Stationary
DTZ	Inverse chi-squared (P) = 222.80	0.0000	Stationary
DTLDR	Inverse chi-squared (P) = 205.47	0.0000	Stationary
DTNPL	Inverse chi-squared (P) = 243.75	0.0000	Stationary
DTBOPO	Inverse chi-squared (P) = 229.36	0.0000	Stationary

Note: Fisher-type test based on the inverse chi-squared statistic; the null hypothesis is that all panels contain a unit root.

Table 2 reports Fisher-type panel unit root tests. For every variable, the inverse chi-squared statistic is large and the p-value is 0.0000, so the null hypothesis of a unit root is rejected at the 1% level for all series, including the interaction terms. All variables are stationary in levels, which means the dynamic panel regression does not risk producing spurious results and the variables can enter the GMM specification without differencing for stationarity reasons.

4.3 Correlation Analysis

TABLE III. CORRELATION MATRIX

	ROE	DT	ZSCORE	LDR	NPL	BOPO	COVID	ECGRWTH	BIINTRST
ROE	1								
DT	0.2180***	1							
ZSCORE	0.5561**	0.1643**	1						
LDR	-0.0437***	0.0498***	0.2159**	1					
NPL	-0.2616***	-0.0624***	-0.2657***	0.0389*	1				
BOPO	-0.6851**	-0.1924***	-0.5121*	-0.0136***	0.2129***	1			
COVID	-0.0693***	0.0069***	-0.0426**	-0.1218**	0.0852***	0.0647***	1		
ECGRWTH	0.0453***	0.0003***	0.0280***	0.0479***	-0.1694**	-0.0740**	-0.5887**	1	

	ROE	DT	ZSCORE	LDR	NPL	BOPO	COVID	ECGRWTH	BIINTRST
BIINTRST	0.0923***	0.0088***	0.0354***	0.1341***	-0.1116***	-0.1041***	-0.4824***	0.6311***	1

*Notes: *** significant at 1%, ** significant at 5%, * significant at 10%.*

Table 3 presents pairwise correlations. ROE correlates positively with DT (0.218) and strongly with the Z-Score (0.556), and negatively with NPL (−0.262) and especially BOPO (−0.685), giving a first indication that stability supports profitability while credit risk and cost inefficiency erode it. Correlations among the independent variables are generally moderate; the largest, between economic growth and the policy rate (0.631) and between COVID and growth (−0.589), involve the macroeconomic controls and are expected, since the pandemic years combined recession with monetary easing. No correlation among the bank-level fundamentals approaches the conventional 0.80 multicollinearity threshold, so the regressors can be included jointly.

4.4 System GMM Estimation Results

TABLE IV. DYNAMIC PANEL SYSTEM GMM ESTIMATION RESULTS (DEPENDENT VARIABLE: ROE)

Variables	Coefficient	t-Statistic
Lagged dependent variable (ROEt−1)	-0.2723***	-4.8697
Second lag (ROEt−2)	-0.0659***	-3.0420
DT	4.4158	1.3201
ZSCORE	0.2815***	7.2118
LDR	-0.1970*	-1.6782
NPL	-0.4325	-0.4755
BOPO	-0.1107*	-1.7948
COVID	0.0174	0.7975
ECGRWTH	-0.4111	-0.5276
BIINTRST	1.8280*	1.8150
DTZ (DT × ZSCORE)	-4.5428***	-2.7867
DTLDR (DT × LDR)	7.2225**	2.3424
DTNPL (DT × NPL)	21.4965	0.4773
DTBOPO (DT × BOPO)	-9.3025***	-2.8051

Variables	Coefficient	t-Statistic
Diagnostic tests		
Observations	280	
Number of banks	40	
Number of instruments	35	
Wald test	126.995***	
Arellano–Bond AR(2) (p-value)	0.9398	
Hansen test (p-value)	0.5000	

*Notes: one-step System GMM. *** significant at 1%, ** significant at 5%, * significant at 10%.*

The diagnostics validate the model before interpretation. The Arellano–Bond AR(2) p-value of 0.9398 shows no second-order autocorrelation in the differenced residuals, so the moment conditions are valid. The Hansen test p-value of 0.5000 comfortably fails to reject the over-identifying restrictions, indicating that the instrument set is valid, while the number of instruments (35) remains below the number of banks (40), in line with Roodman's (2009) rule of thumb against instrument proliferation. The Wald statistic of 126.995 is significant at 1%, confirming the joint significance of the regressors. The estimation uses 280 observations because two lags of the dependent variable and the internal transformation consume the initial periods of each bank's series.

Both lags of ROE are negative and significant at 1% (−0.2723 and −0.0659). Rather than the profit persistence often found in mature markets (Dietrich & Wanzenried, 2011), Indonesian bank profitability exhibits mean reversion: unusually high (or low) equity returns are partially corrected in subsequent years. This is plausible in a market characterized by intense competition, regulatory pressure on margins, and episodic shocks, and it reinforces the necessity of a dynamic estimator — a static model would confound this reversion with the effects of the regressors.

4.5 Direct Effects of Bank Fundamentals

Banking stability is the dominant positive driver of profitability: the Z-Score coefficient of 0.2815 is significant at 1% (t = 7.21), strongly supporting H1. Stable banks fund themselves more cheaply, retain depositor confidence in downturns, and can sustain lending through the cycle, which translates directly into equity returns (Bitar et al., 2018). LDR carries a negative coefficient (−0.1970) significant at 10%, so H2 is supported but with a sign that warrants attention: at the margin, pushing intermediation harder reduces ROE in this sample, consistent with the funding-cost and liquidity-risk channel dominating the earning-asset channel when LDR is already high — recall the sample mean of 86% and maximum near 198%. BOPO is negative (−0.1107) and significant at 10%, supporting H4: cost inefficiency directly erodes shareholder returns, echoing the efficiency results of Dietrich and Wanzenried (2011). NPL has the expected negative sign but is not statistically significant once the dynamics, controls, and interactions are accounted for, so H3 is not supported statistically; the raw negative correlation in Table 3 appears to be absorbed by BOPO (provisioning costs flow into operating expenses) and by the bank fixed effects.

Among the controls, the policy rate is positive and weakly significant (1.8280, 10%), consistent with higher rates widening lending margins for deposit-funded banks. Neither the COVID dummy nor economic growth is individually significant in the dynamic specification, suggesting that the pandemic's impact on equity returns operated mainly through the bank-level fundamentals — asset quality, efficiency, and stability — that the model already includes.

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4.6 The Moderating Role of Digital Transformation

The direct effect of DT on ROE is positive but statistically insignificant (4.4158; t = 1.32), so H5 is not supported. By itself, digitalization neither raises nor lowers equity returns on average — a result that aligns with the strategy literature's warning that technology adoption without complementary organizational change does not create value (Kane et al., 2015; Hess et al., 2016). The economically meaningful action is in the interactions, three of which are significant.

First, DTLDR is positive and significant at 5% (7.2225; t = 2.34), supporting H6b. Digital transformation reverses the negative marginal effect of intermediation intensity on profitability: for a bank at the sample mean of DT, the marginal effect of LDR is approximately −0.1970 + 7.2225 × 0.0455 ≈ +0.13, and it turns positive for any bank with DT above roughly 0.027. In other words, digitally capable banks convert an aggressive loan-to-deposit position into profit — through cheaper digital deposit gathering, data-driven loan origination, and lower distribution costs — whereas analog banks that stretch their LDR destroy equity value. This is the clearest evidence in the sample that digitalization pays off through the intermediation channel, consistent with Gupta and Sharma (2021) and Zhang and She (2024).

Second, DTZ is negative and significant at 1% (−4.5428; t = −2.79), supporting H6a but with a negative sign: digital transformation weakens the positive stability–profitability link. Two complementary readings fit the dynamic-capabilities framework. On one side, highly stable, well-buffered incumbents are precisely the banks undertaking the costliest transformation programs — branch rationalization, core-system replacement, cybersecurity — so part of the profit dividend of stability is currently being consumed by transition costs (Warner & Wäger, 2019; Scardovi, 2017). On the other side, digital capability partially substitutes for balance-sheet stability as a source of earnings power: less stable banks gain proportionally more from digital channels, which lower their funding and acquisition disadvantages. Either way, DT and stability act as substitutes rather than complements in the short run.

Third, DTBOPO is negative and significant at 1% (−9.3025; t = −2.81), supporting H6d: digitalization amplifies the profitability penalty of cost inefficiency. For an efficient bank, digital investment layered on a lean cost base is affordable; for a bank whose BOPO is already high, digital spending adds a second cost burden before generating revenue, deepening the drag on ROE. The managerial implication is direct: cost discipline is a precondition for value-creating digitalization, not a substitute for it — resources must be orchestrated in the right sequence (Sirmon et al., 2011). Finally, DTNPL is positive but insignificant (21.4965; t = 0.48), so H6c is not supported: there is no robust evidence yet that digital monitoring and collection technologies offset the earnings damage of credit risk, perhaps because advanced digital credit-risk tools are still nascent among most sample banks.

Taken together, the pattern is coherent with the resource-orchestration view: digital transformation is not a stand-alone profit machine (insignificant direct effect) but a capability that reshapes how fundamentals map into profit — enhancing the return to intermediation (DTLDR > 0), while taxing stability and inefficiency during the transition (DTZ < 0, DTBOPO < 0). Digitalization changes the production function of banking rather than simply shifting it upward.

5. Conclusion

This study examined whether digital transformation moderates the effects of banking stability, liquidity, credit risk, and operating efficiency on the profitability (ROE) of 40 Indonesian commercial banks over ten years (400 bank-year observations), using a one-step System GMM dynamic panel estimator validated by Fisher-type unit root, Arellano–Bond, and Hansen diagnostics. Three main conclusions emerge. First, bank fundamentals matter in the expected way: stability strongly raises equity returns, while cost inefficiency and, at the margin, an over-stretched loan-to-deposit ratio reduce them; profitability itself is mean-reverting rather than persistent. Second, digital transformation has no significant direct effect on ROE. Third, digital transformation significantly moderates the fundamental–profitability nexus: it turns the marginal effect of intermediation intensity positive, but weakens the profit contribution of stability and deepens the penalty of cost inefficiency, while leaving the credit-risk channel unchanged.

The theoretical implication is that digital transformation in banking is best modeled as a dynamic capability that reconfigures

the productivity of other resources, not as an independent profit driver — an operationalization of the resource-based and resource-orchestration views in a dynamic panel setting. The managerial implication is one of sequencing: banks should attach digital investment to their intermediation engine, where it demonstrably pays, and should restore cost discipline before, not after, large transformation programs; stable incumbents should expect and budget for a transition period in which digitalization consumes part of their stability dividend. For regulators such as OJK and Bank Indonesia, the results suggest that digitalization policy will raise systemic profitability most effectively when combined with supervision of efficiency and prudent intermediation, and that digital investment mandates applied uniformly could unintentionally strain inefficient banks.

The study has limitations that map directly into future research. The digital transformation index, while capturing cross-bank variation in digitalization intensity, cannot distinguish between types of digital investment (channels, core systems, analytics); richer, disaggregated measures may reveal which components drive the moderation effects. The sample covers one country and includes the extraordinary COVID-19 window; cross-country replication and post-pandemic extensions would test external validity. Finally, extending the framework to risk-adjusted performance measures, to ROA and net interest margins, and to nonlinear or threshold moderation (e.g., whether the DT–stability substitution reverses at high digital maturity) are promising avenues for subsequent work.

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