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Digital Transformation Moderates Liquidity and Operational Efficiency Effects on Banking Stock Performance in Indonesia

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ABSTRACT

Purpose: *This study examines the moderating role of digital transformation on the effect of liquidity and operational efficiency on bank stock performance.* ***Methodology:*** *A quantitative approach using panel data regression (Random Effect Model) and Moderated Regression Analysis was applied to 110 observations from 22 conventional banks listed on the Indonesia Stock Exchange (2020–2024).* ***Results:*** *Liquidity negatively and significantly affects stock performance, whereas operational efficiency has an insignificant negative effect. Digital transformation significantly amplifies liquidity's negative impact but does not moderate operational efficiency.* ***Findings:*** *Investors tolerate short-term operational inefficiencies as necessary digital investments but penalize forced digital expansion during tight liquidity due to heightened fundamental risks.* ***Originality/Novelty:*** *By integrating Signaling Theory, this research introduces digital transformation as a moderator to resolve empirical inconsistencies, demonstrating that market appreciation of a bank's digital capabilities relies heavily on its fundamental liquidity.* ***Conclusion:*** *Massive digital investments alongside high loan-to-deposit ratios create a market-penalized double burden. Banks must balance technological expansion with liquidity stability.* ***Type of Paper:*** *Research Article.*

INTRODUCTION

Global economic dynamics during the 2020–2024 period were characterized by structural uncertainty triggered by geopolitical escalations and contractionary monetary policies, specifically the "higher-for-longer" interest rate phenomenon that tightened global liquidity (Boccaletti et al., 2026; Cobbinah et al., 2024). As a cornerstone of macroeconomic stability, the banking sector is required to maintain more adaptive liquidity resilience, given that shocks from non-bank institutions can now transmit rapidly to the banking system (Beqiraj et al., 2025; Sarmiento, 2025). In Indonesia, the capital market responds sensitively to these dynamics, where investors are highly responsive to corporate action signals and shifts in financial structures that influence firm value (Sihotang et al., 2024).

The primary challenge currently facing the banking industry is structural disruption caused by the emergence of financial technology (fintech), which has fundamentally altered customer behavior and expectations (Angreni et al., 2024). This condition compels conventional banks to implement digital transformation as a strategic imperative to enhance operational efficiency and risk management accuracy (Yansi et al., 2025). The utilization of technology is expected to optimize a bank's fundamental pillars, namely liquidity (Loan to Deposit Ratio/LDR) and operational efficiency (BOPO), which serve as key determinants of profitability and stock performance (Price to Book Value/PBV) (Wang et al., 2024; Wediyanto et al., 2025).

Although theoretical frameworks suggest that strong fundamentals should linearly enhance market value, empirical findings remain inconsistent. While some studies identified a significant positive impact of liquidity on market performance (Adare et al., 2015), others detected insignificant effects or even a weakening of liquidity creation due to digital disruption (Silitonga & Manda, 2022; Tang et al., 2024). To bridge this research gap, this study positions digital transformation as a moderating variable. This approach is predicated on the premise that modern capital markets evaluate the "digital quality" underlying financial ratios to mitigate risk and ensure sustainable efficiency (Dietrich & Gehrig, 2025; Yu & Liu, 2025). Consequently, this research aims to analyze the role of digital transformation in moderating the impact of liquidity and operational efficiency on the stock performance of banks listed on the Indonesia Stock Exchange for the 2020–2024 period.

Stock Performance

Stock performance reflects the market's assessment of a company's ability to create future wealth for shareholders. In this study, stock performance is measured using the Price to Book Value (PBV) ratio, which compares a stock's market closing price to its book value of equity. According to Signaling Theory, a high PBV serves as a strong signal of market confidence in the company's earnings prospects. Empirical findings by Wediyanto et al. (2025) demonstrate that fundamental structures, such as liquidity, simultaneously have a significant effect on PBV. Furthermore, banks with robust capital and liquidity are often observed to outperform during crisis periods, as investors perceive them to possess higher resilience.

$$PBV = \frac{Closing\ Price}{Book\ Value\ per\ Share}$$

Liquidity

Liquidity represents a bank's capacity to provide adequate funds to meet maturing obligations and support credit intermediation. The Loan to Deposit Ratio (LDR) is utilized as a proxy as it reflects a bank's aggressiveness in channeling third-party funds into productive loans. Empirical discussions regarding LDR yield mixed results; Novita (2022) identified a significant positive influence on stock prices due to interest income optimization, while Aji & Manda (2021) cautioned about a trade-off where an excessively high LDR increases liquidity risk, triggering a negative market response. Additionally, Bragaglia et al. (2026) emphasized that funding liquidity regulations directly impact profitability, serving as a primary signal for investor valuation decisions..

$$LDR = \left(\frac{\text{Total Loans Granted}}{\text{Total Third Party Funds}}\right) x100\%$$

Operational Efficiency

Operational efficiency measures management's capability to control input costs while maximizing revenue output, proxied by the ratio of Operating Expenses to Operating Income (BOPO). According to monetary authority regulations, a BOPO ratio below 90% is categorized as healthy, reflecting a dominant profit margin. Empirical studies by Setyowati (2019) dan Wijono (2023) prove that a decrease in BOPO (increased efficiency) has a significant positive impact on profitability and stock prices. However, Wang et al. (2024) highlighted that in the digital era, efficiency is no longer merely about manual cost-cutting but is the result of mature technological orchestration; thus, short-term technology investments may momentarily pressure efficiency but are appreciated by the market in the long run.

$$BOPO = \left(\frac{\text{Total Operating Expenses}}{\text{Total Operating Revenue}}\right) x100\%$$

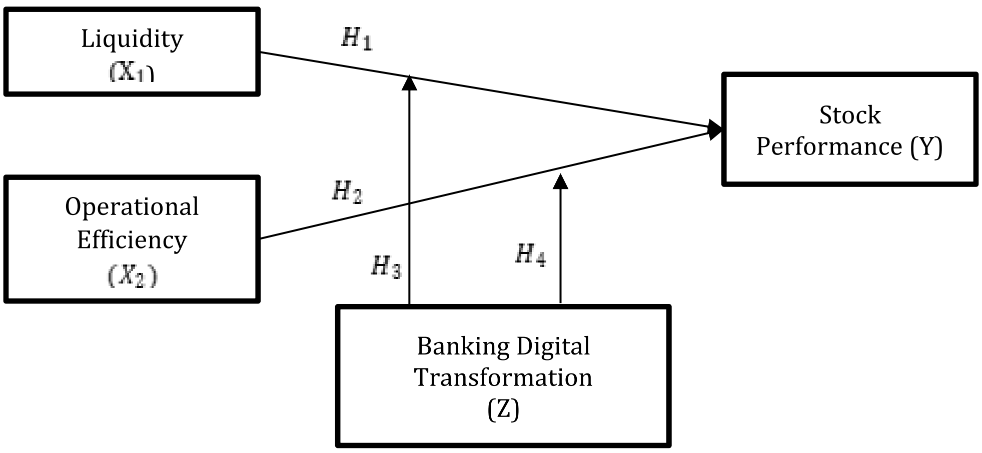
Digital Transformation (Moderating Variable)

Digital transformation involves integrating new technologies into all aspects of banking business to enhance transparency and risk management accuracy. This variable is measured using the IT Investment ratio to capture a bank's financial commitment to building future capabilities. As a moderating variable, digital transformation is believed to alter the influence of fundamental variables on market valuation. According to the Resource-Based View (RBV) approach, banks that allocate significant investments to digital resources will possess a sustainable competitive advantage (Yansi et al., 2025). Furthermore, Yu & Liu (2025) found that digitalization significantly reduces a bank's risk-taking levels; therefore, aggressive credit expansion (high LDR) is evaluated more favorably by the market if supported by robust data analytics technology. Similarly, AI technology has been shown to drastically improve time efficiency and reduce operational risks, strengthening the positive impact of cost efficiency on stock valuation.

$$IT\ Investment\ Ratio = \left(\frac{\text{Information Technology Expenses}}{\text{Total Operating Expenses}}\right) x100\%$$

Theoretical Framework

Figure 1. Conceptual Framework



Source: Conceptual Framework created, 2025

Hypothesis:

H_1 : Liquidity is suspected to influence stock performance.

H_2 : Operational efficiency is suspected to influence stock performance.

H_3 : Digital transformation is suspected to moderate the effect of liquidity on stock performance.

H_4 : Digital transformation is suspected to moderate operational efficiency on stock performance.

METHOD

This study is a quantitative study using a causal-associative approach aimed at empirically testing the cause-and-effect relationship among variables. The population of this study comprises 47 conventional banking sector companies listed on the Indonesia Stock Exchange (IDX) for the period

2020–2024. The research sample was selected using purposive sampling based on specific criteria, namely conventional commercial banks that published annual reports and audited financial statements in full for consecutive years, and explicitly listed details of information technology investment costs. Based on the screening of these criteria, a final sample of 22 companies was obtained. The total observations used over a 5- year period amounted to 110 data points. The data analyzed consisted of secondary panel data extracted from the official IDX website and the respective banks' websites.

Table 1. Sample Selection Criteria

No	Criteria	Number of Companies
1	All companies in the banking sector listed on the Indonesia Stock Exchange (IDX) during the 2020–2024 period.	47
2	Companies that are Sharia Commercial Banks. Excluded due to differences in operational principles and financial reporting structures compared to conventional banks.	-4
3	Companies that have not published an Annual Report for consecutive years, do not have explicit IT Investment Cost data, or conducted an IPO/Delisting during the observation period (Incomplete Time Series Data).	-21
	Final Sample Total (Companies)	**22**
	Total Observations (28 Companies x 5 Years)	**110**

Source: Processed data, 2025

Table 2. Sample Selection Considerations

No	Kode	Company Name
1	AGRS	PT Bank IBK Indonesia Tbk
2	BABP	PT Bank MNC Internasional Tbk
3	BACA	PT Bank Capital Indonesia Tbk
4	BBCA	PT Bank Central Asia Tbk
5	BBKP	PT Bank KB Bukopin Tbk
6	BBNI	PT Bank Negara Indonesia (Persero) Tbk
7	BBRI	PT Bank Rakyat Indonesia (Persero) Tbk
8	BBTN	PT Bank Tabungan Negara (Persero) Tbk
9	BDMN	PT Bank Danamon Indonesia Tbk
10	BINA	PT Bank Ina Perdana Tbk
11	BJBR	PT Bank Pembangunan Daerah Jawa Barat dan Banten Tbk
12	BMRI	PT Bank Mandiri (Persero) Tbk
13	BNGA	PT Bank CIMB Niaga Tbk
14	BNII	PT Bank Maybank Indonesia Tbk
15	BNLI	PT Bank Permata Tbk
16	BTPN	PT Bank BTPN Tbk
17	BVIC	PT Bank Victoria International Tbk
18	MAYA	PT Bank Mayapada Internasional Tbk
19	MEGA	PT Bank Mega Tbk
20	NISP	PT Bank OCBC NISP Tbk
21	PNBN	PT Bank Pan Indonesia Tbk
22	SDRA	PT Bank Woori Saudara Indonesia 1906 Tbk

Source: Processed data, 2025

The dependent variable in this study is stock performance, measured using the Price to Book Value (PBV) ratio by comparing the closing stock price with the book value per share. The independent variables consist of liquidity, proxied using the Loan to Deposit Ratio (LDR), calculated as total loans divided by total third-party funds, and operational efficiency, measured through the Operational Expense to Operating Income Ratio (BOPO). Banking digital transformation acts as a moderating variable measured through the IT Investment ratio, calculated as the proportion of information technology costs to the bank's total operating expenses.

Data analysis was conducted using panel data regression and Moderated Regression Analysis (MRA) with the assistance of EViews 13 software. The selection of the best-fitting estimation model was conducted through the Chow Test, Hausman Test, and Lagrange Multiplier (LM) Test, with the results of these three tests consistently pointing toward the use of the Random Effects Model (REM) with the Generalized Least Squares (GLS) approach. The testing of classical assumptions focused on normality and multicollinearity tests to ensure an unbiased model. Hypothesis testing was conducted using partial tests (t-tests) and simultaneous model suitability tests (F-tests) at a 5% significance level. The MRA equation in this study is formulated as follows:

$$Y_{it} = \alpha + \beta_1 X1_{it} + \beta_2 X2_{it} + \dots + e_{it}$$

To test the hypotheses and the moderating effect, adjusted for the variables in this study, the MRA equation used is:

$$Y_{it} = \alpha + \beta_1 X1_{it} + \beta_2 X2_{it} + \beta_3 Z_{it} + \beta_4 (X1_{it} * Z_{it}) + \beta_5 (X2_{it} * Z_{it}) + e_{it}$$

RESULTS AND DISCUSSION

RESULTS

Descriptive Statistical Analysis

Table 3. Results of Descriptive Statistical Analysis

	Y	X1	X2	Z
Mean	1.843812	88.09716	91.09054	15.29179
Median	0.929539	85.70329	72.21636	14.64572
Maximum	8.647090	159.9554	607.5739	32.16242
Minimum	0.315047	12.35090	33.26742	0.878040
Std. Dev.	1.836717	24.77973	89.72690	6.361453
Skewness	1.638841	0.254885	4.411428	0.453559
Kurtosis	5.023689	4.395375	22.56444	3.771544
Jarque-Bera	68.00989	10.11513	2111.130	6.499824
Probability	0.000000	0.006361	0.000000	0.038778
Sum	202.8193	9690.687	10019.96	1682.097
Sum Sq. Dev.	367.7147	66929.79	877550.0	4411.022
Observations	110	110	110	110

Source: processed data Eviews 13, 2026

Based on the results of the data processing, descriptive statistical analysis was conducted to provide an overview of the data distribution from 22 banking company samples during the 2020–2024 period (110 data observations). The test results show that the price-to-book value (PBV) ratio has an average of 1.84 with a range of values between 0.31 and 8.64, indicating that, in general, the market assigns a premium valuation above the companies' book value. The liquidity ratio (LDR) recorded an average of 88.09%, indicating that the majority of banks operate at a fairly aggressive intermediation level but remain within regulatory limits. Meanwhile, operational efficiency (BOPO) averaged 91.09%, and the technology investment ratio (IT Investment), as a representation of digital transformation, recorded an average allocation of 15.29% of total operating expenses. The standard deviation of all variables is smaller than their mean values, indicating a well-distributed data set that is representative for further analysis.

Chow Test

Table 4. Results of the Chow Test

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	15.535819	(21,83)	0.0000
Cross-section Chi-square	175.504010	21	0.0000

Source: processed data Eviews 13, 2026

The Chow test was conducted to compare and select the best model between the Common Effect Model (CEM) and the Fixed Effect Model (FEM). Based on the data processing results, the Cross-section Chi-square probability value was 0.0000 (< 0.05). This result indicates that the null hypothesis is rejected, concluding that the Fixed Effect Model (FEM) is more appropriate to use than the Common Effect Model (CEM).

Hausman Test

Table 5. Results of the Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	8.668060	5	0.1231

Source: processed data Eviews 13, 2026

Following the selection of FEM in the Chow Test, the Hausman Test was conducted to compare the Fixed Effect Model (FEM) with the Random Effect Model (REM). The test results showed a Cross-section random probability value of 0.1231 (> 0.05). Because the probability value exceeds the 5% significance level, the null hypothesis is accepted. Statistically, this proves that the Random Effect Model (REM) is a more appropriate and efficient model to use compared to the FEM.

Lagrange Multiplier Test

Table 6. Results of the Lagrange Multiplier Test (LM Test)

Lagrange Multiplier Tests for Random Effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided (all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	95.64727 (0.0000)	2.297945 (0.1295)	97.94521 (0.0000)

Source: processed data Eviews 13, 2026

The LM test was utilized as a final verification to choose between the Common Effect Model (CEM) and the Random Effect Model (REM). The LM Test results yielded a Breusch-Pagan probability value of 0.0000 (< 0.05). This highly significant value rejects the null hypothesis, meaning the Random Effect Model (REM) is absolutely superior to the CEM.

Classical Assumption Tests

The most appropriate regression model for this study is the Random Effects Model (REM), which was selected based on the results of the Chow, Hausman, and Lagrange Multiplier tests. Therefore, this study employs the Generalized Least Squares (GLS) approach in the REM model to test the hypotheses, rather than Ordinary Least Squares (OLS) (Baltagi, 2005:14-16; Gujarati & Porter, 2003:602-204).

In the normality test, the Jarque-Bera probability result indicates that the residual data are not normally distributed. However, this violation of the assumption does not affect the validity of the model estimation because the sample size is relatively large, namely 110 observations (n > 30). Referring to the Central Limit Theorem, as the sample size increases, the distribution of the estimator will asymptotically approach a normal distribution regardless of the shape of the original population distribution (Gujarati & Porter, 2003:602-204). Therefore, the GLS estimator in the REM model is confirmed to remain consistent and valid for use in hypothesis testing.

Table 7. Results of the Multicollinearity Test

	LDR	BOPO
LDR	1.00000	0.139826
BOPO	0.139826	1.00000

Source: processed data Eviews 13, 2026

The multicollinearity test shows that the correlation values between independent variables are below 0.80, so it can be confirmed that there are no serious multicollinearity issues in this research data.

Table 8. Results of the Heteroscedasticity Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.622826	0.839379	1.933366	0.0559
X1	0.000736	0.008524	0.086364	0.9313
X2	-0.001816	0.002111	-0.860590	0.3914
Z	0.053558	0.053562	0.999924	0.3197
X1Z	-0.000670	0.000480	-1.394749	0.1661
X2Z	-5.28E-05	0.000164	-0.322008	0.7481

Source: processed data Eviews 13, 2026

Based on the Glejser test results, the probability values for all independent and moderating variables were greater than the 0.05 significance level (> 0.05). This result confirms that the null hypothesis is accepted, leading to the conclusion that the regression model is free from heteroscedasticity issues and that the residual variance is constant (homoscedastic).

Table 9. Results of the Autocorrelation Test

R-squared	0.055450	Mean dependent var	0.452550
Adjusted R-squared	0.028717	S.D. dependent var	0.835447
S.E. of regression	0.823364	Sum squared resid	71.86040
F-statistic	2.074244	Durbin-Watson stat	1.303408
Prob(F-statistic)	0.108008		

Source: processed data Eviews 13, 2026

The autocorrelation test result obtained is 1.303408 < 1.7262, or DW < dU, indicating positive autocorrelation; however, the GLS approach automatically corrects for violations of the assumptions of heteroscedasticity and autocorrelation, since the estimates in the REM model use the Generalized Least Squares (GLS) method rather than Ordinary Least Squares (OLS)) (Baltagi, 2005:14-16; Gujarati & Porter, 2003:602-204).

Multiple Linear Regression Analysis

Table 10. Results of Multiple Linear Regression Using the Random Effects Method, Model 1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.579122	0.805676	4.442383	0.0000
X1	-0.015954	0.007738	-2.061739	0.0417
X2	-0.003621	0.002369	-1.528675	0.1293
Effects Specification				
			S.D.	Rho
Cross-section random			1.469569	0.7696
Idiosyncratic random			0.804127	0.2304
Weighted Statistics				
R-squared	0.051282	Mean dependent var		0.438266
Adjusted R-squared	0.033549	S.D. dependent var		0.829045
S.E. of regression	0.815020	Sum squared resid		71.07550
F-statistic	2.891914	Durbin-Watson stat		1.326001
Prob(F-statistic)	0.059817			

Source: processed data Eviews 13, 2026

Based on Table 5, the resulting regression model can be expressed as follows:

$$Y_{it} = \alpha + \beta_1 X1_{it} + \beta_2 X2_{it} + \ldots + e_{it}$$

PBV = 3.579122 - 0.015954 (LDR) - 0.003621 (BOPO) + e_{it}

Table 11. Regression Results Using the Random Effects Method, Model 2: Moderation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.364475	0.591473	2.306911	0.0230
Z	0.133588	0.062445	2.139280	0.0347
X1Z	-0.001055	0.000474	-2.226159	0.0281
X2Z	-5.46E-05	0.000203	-0.268931	0.7885

Source: processed data Eviews 13, 2026

Based on Table 6, the resulting regression model can be expressed as follows:

$$Y_{it} = \alpha + \beta_1 X1_{it} + \beta_2 X2_{it} + \beta_3 Z_{it} + \beta_4 (X1_{it} * Z_{it}) + \beta_5 (X2_{it} * Z_{it}) + e_{it}$$

$$Y = 1.364475 - 0.015954\ (X_1) - 0.003621\ (X_2) + 0.133588\ (Z) - 0.001055\ (X_1 * Z) - 0.000054\ (X_2 * Z) + e_{it}$$

Analysis of the Coefficient of Determination R²

Table 12. Coefficient of Determination R²

Coefficient of Determination R²	Value
R-squared	0.047021
Adjusted R-squared	0.020050

Source: processed data Eviews 13, 2026

Table 12 presents the results of the coefficient of determination analysis, revealing an adjusted R-squared coefficient of 0.0200. This indicates that the combination of liquidity, operational efficiency, and the moderating role of digital transformation accounts for approximately 2% of the variation in stock performance (PBV). While this explanatory power appears relatively low, it critically reflects the highly volatile and complex nature of capital market valuations during the 2020–2024 period. The remaining 98% of the unobserved variance suggests that banking stock prices during this disruptive era were overwhelmingly dictated by macroeconomic externalities such as fluctuating benchmark interest rates, post-pandemic regulatory forbearance, and global market sentiment rather than internal operational ratios alone. Furthermore, this low coefficient emphasizes that modern investors evaluate a much broader spectrum of fundamental indicators not included in this model, such as asset quality (NPL) and return on equity (ROE), when determining a bank's holistic market valuation.

Model Fit Test (F-Test)

The results of the Random Effect Model (REM) estimation show an F-statistic probability value of 0.0598. Although this figure is above the 0.05 threshold, this study refers to Gujarati & Porter's (2003), which states that using a significance level (α) of 10% (0.10) is a standard of testing that is acceptable and widely recognized academically in econometric and social science research. Therefore, with a probability value of 0.0598 < 0.10, the regression model in this study is statistically valid (fit). This concludes that the instrumental variables in the model have sufficient ability to explain fluctuations in stock performance, so that the partial hypothesis testing is valid to proceed.

Significance Test (t-Test)

Partial hypothesis testing (t-test) was conducted to evaluate the significant contribution of each independent variable to the dependent variable individually (Basuki, 2021). Based on the estimation results in Tables 5 and 6:

a. the liquidity variable (LDR) recorded a negative regression coefficient of -0.0159 with a probability value of 0.0417 (< 0.05). This result confirms that the first hypothesis (H_1) is accepted, meaning that the level of liquidity is empirically proven to have a negative and significant effect on stock performance.

b. For the operational efficiency variable (BOPO), the regression coefficient was recorded at -0.0036 with a probability value of 0.1293 (> 0.05). A probability level exceeding the 0.05 threshold indicates that the second hypothesis (H_2) is rejected, so it can be concluded that operational efficiency has a negative but insignificant effect on stock performance valuation.
c. The interaction between the digital transformation variable and liquidity (LDR*IT Investment) yields a negative regression coefficient of -0.0010 with a probability level of 0.0281 (< 0.05). This significance level below 0.05 confirms the acceptance of the third hypothesis (H3), meaning that banking digital transformation is significantly able to moderate and amplify the negative impact of liquidity on stock performance.
d. The interaction between digital transformation and operational efficiency (BOPO*IT Investment) yields a coefficient of -0.00005 with a probability of 0.7885 (> 0.05). Since the probability of this interaction far exceeds the 5% significance level, the fourth hypothesis (H4) is rejected. This concludes that digital transformation capabilities are not proven to moderate the influence of operational efficiency on banking stock performance

DISCUSSION

The Effect of Liquidity on Stock Performance

The analysis results demonstrate that liquidity (LDR) has a negative and significant effect on banking stock performance. A high LDR ratio indicates a large proportion of credit disbursement, leading to a tightening of the bank's cash availability. In the digital era (2020– 2024), capital markets respond to excessive credit aggressiveness as a signal of liquidity risk that could jeopardize fundamental stability, especially if the underlying investment quality is low (Dietrich & Gehrig, 2025). These findings are supported by Tang et al. (2024) who state that the development of fintech has been shown to weaken the liquidity creation capacity of traditional banking. Modern capital market investors evaluate this risk comprehensively, so that liquidity constraints resulting from high LDRs tangibly trigger negative sentiment that depresses bank stock valuations.

The Impact of Operational Efficiency on Stock Performance

Operational efficiency (BOPO) has been shown to have a negative but insignificant impact on stock performance. Although theoretically, rising operational costs erode profits and depress corporate value, the insignificance of this finding reflects investor rationality. Conventional banks are currently forced to absorb massive short-term spikes in operational costs to modernize their technological infrastructure and undertake system transformations. Investors view this cost increase not as managerial inefficiency, but as an absolutely necessary strategic step to enhance the company's future stability (Yu & Liu, 2025). Therefore, a surge in BOPO does not automatically result in a significant decline in stock prices on the stock exchange.

Digital Transformation Moderates the Impact of Liquidity on Stock Performance

Test results show that digital transformation in the banking sector is significantly capable of moderating (mitigating) the negative impact of liquidity on stock performance. These findings demonstrate that forcing digital expansion amid tight liquidity conditions (high LDR) actually creates a double burden that is met with a negative response from the capital market. Investors perceive signals of increased default risk when massive technology capital expenditures are undertaken without adequate underlying liquidity support. Although digital transformation is designed to reduce banks' risk-taking levels (Yu & Liu, 2025), these benefits or "digital quality" will only be appreciated and increase corporate value if banks can maintain their liquidity ratios within safe limits.

Digital Transformation Moderates the Effect of Operational Efficiency on Stock Performance

Banking digital transformation has not been shown to moderate the impact of operational efficiency levels on stock performance. The insignificance of this moderation aligns with the rational response of modern capital markets. The digitalization process inherently demands significant costs in the initial phase, which distorts efficiency (increasing the BOPO). Since investors have come to accept this phenomenon as a reasonable form of long-term investment, the interaction between the scale of digitalization allocation and cost efficiency no longer creates a surprise signal that drastically alters stock valuation decisions. The true efficiency benefits of implementing technology (Rodrigues et al., 2023), take time to materialize, so the presence of digital transformation within this observation period has not yet been able to moderate investor responses to banking efficiency components.

CONCLUSION

This study concludes that liquidity (LDR) has a significant negative impact on stock performance (PBV), while operational efficiency (BOPO) has an insignificant negative effect. Digital transformation significantly moderates and amplifies the negative impact of liquidity, but no moderation was found in the relationship between operational efficiency and stock performance. Theoretically, this research contributes to the advancement of Signaling Theory by demonstrating that the capital market evaluates digital investment signals conditionally and massive technological investments during periods of tight liquidity are perceived as fundamental risks that increase a bank's risk profile rather than a competitive advantage.

Bank management is advised to balance digitalization ambitions with fundamental liquidity stability to prevent negative market sentiment. For regulators, there is a need to strengthen macroprudential oversight regarding the liquidity risks of banks undergoing aggressive transformation. Future research should extend the observation period and include additional proxies, such as the non-performing loan (NPL) ratio, to provide a more comprehensive assessment of banking fundamental quality.

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