1ST ICEFCI: INTERNATIONAL CONFERENCE ON ECONOMICS, FINANCE AND CREATIVE INDUSTRY 2026
PROCEEDING AND CALL FOR PAPER

Fintech Impact on Indonesian Bank Performance via Credit Risk

Devi Intan Sari[1], Novita Mardiani[2]

[1] Management Study Program, Faculty of Economics and Business, Institut Teknologi dan Bisnis (ITEBIS) PGRI Dewantara Jombang, Indonesia- 2261167@itebisdewantara.ac.id

[2] Management Study Program, Faculty of Economics and Business, Institut Teknologi dan Bisnis (ITEBIS) PGRI Dewantara Jombang, Indonesia- novita.mardiani@itebisdewantara.ac.id

ARTICLE INFORMATION

Available online: July, 2026.

KEYWORDS

Financial technology, credit risk, financial performance, mediating variable

CORRESPONDENCE

E-mail: 2261167@itebisdewantara.ac.id

A B S T R A C T

This study aims to analyze the effect of financial technology on the financial performance of conventional commercial banks in Indonesia during the 2023-2025 period, both directly and through credit risk as a mediating variable. The study employs a quantitative causal approach using panel data, focusing on financial technology, credit risk, and financial performance. The study population consists of 45 conventional commercial banks listed on the Indonesia Stock Exchange, with the sample selected through purposive sampling, resulting in 13 banks and 39 observations over the 2023-2025 period. The data were analyzed using panel data regression with EViews 12 software, followed by a mediation test. The results indicate that financial technology does not have a significant direct effect on either credit risk or financial performance. Credit risk, proxied by Non-Performing Loans (NPL), has a significant negative effect on Return on Assets (ROA); however, credit risk was not found to mediate the effect of financial technology on financial performance. These findings indicate that Non-Performing Loans (NPL) were the dominant determinant of bank profitability during this period, while the adoption of financial technology has not yet had a significant impact, either directly or through improvements in credit quality.

INTRODUCTION

Digital transformation in the financial industry has become an inevitable global phenomenon. Internet penetration in Indonesia reached 79% with more than 180 million smartphone users in 2024, while e-commerce transactions surpassed 52.93 billion U.S. dollars in 2023 [1]. In line with this, the number of financial technology companies in Indonesia has increased sixfold over the past decade, from 51 active players in 2011 to 336 in 2023 (Statista, 2025), with a market value reaching 20.93 billion U.S. dollars in 2025 and projected to grow to 32.67 billion U.S. dollars by 2030 [2]. This momentum is supported by the 2025-2030 Indonesian Payment System Blueprint developed by Bank Indonesia to promote secure and integrated financial digitalization [1].

Amid this acceleration, the quality of bank credit has improved, with the gross Non-Performing Loan (NPL) ratio declining to 2.20% in October 2024 [3]. However, performance among banks continues to vary significantly; for example, Bank Mandiri has faced pressure on its Return on Assets (ROA) and Return on Equity (ROE) in the post-pandemic period, while BRI has demonstrated more stable profitability [4], raising fundamental questions about the mechanisms underlying the impact of financial technology on bank performance.

The empirical literature on the direct relationship between financial technology and financial performance remains inconclusive. Indrianti et al. [5], Yulastri & Negara [6], and Sahara et al. [7] found a positive effect of mobile banking on ROA and NIM, whereas Naya et al. [8] and Ayuningtyas & Sufina [9] found no significant effect; in fact, Ovenc & Nabiyev [10] found a negative effect. This inconsistency suggests the presence of an intermediary mechanism that has not been extensively tested: credit risk. Several studies have begun to confirm this pathway: Yudaruddin et al. [11], Chai & Sun [12], Ally et al. [13], and Cheng & Qu [14] have consistently found that the adoption of financial technology reduces NPL by improving the accuracy of credit scoring and enabling real-time monitoring of borrowers (Jagtiani & Lemieux, [15]; Y. He & Fan, [16], while Wang et al. [17] and D. He et al. [18] demonstrate that a reduction in credit risk serves as an indirect transmission channel leading to improved bank performance. On the other hand, the relationship between credit risk and financial performance has been consistently documented; Mulyati & Nurfauziah

[19] and Saleh & Abu Afifa [20]demonstrate that NPL have a significant negative impact on ROA and ROE, although Masruro & Panglipursari [21] found an exception during the OJK's credit restructuring relaxation period from 2020 to 2023.

The 2023-2025 period is relevant for study because two structural changes occurred simultaneously: the accelerated adoption of financial technology following the pandemic [22] and the conclusion of the OJK's credit restructuring program in March 2024, which restored the pressure of credit risk on profitability to normal conditions. Based on the above analysis, previous studies generally examined the direct effect of financial technology on performance without considering the possibility of credit risk mediation, even though Zouari-Hadiji [23], Astuti & Ningsih [24], Aryani [25], and Mulyani et al. [19] have demonstrated the mediating role of credit risk in other banking contexts. Furthermore, most previous studies used overly broad proxies for financial technology and relied solely on NPLs as the sole indicator of credit risk, while the forward-looking Loan Loss Provision (LLP) as defined by PSAK 71 remains rarely used in the Indonesian context (Ally et al., [13]; Cheng & Qu, [14]. In addition, the broader literature on digital banking ecosystems and AI-driven banking innovation such as the systematic review of fintech, digital payments, and e-wallet research by Ungratwar et al. [42] and evidence on the association between AI-enabled FinTech adoption and bank performance by Hamdouni [43] remains only marginally integrated into empirical fintech-performance studies in the Indonesian banking context, despite AI-based credit-assessment tools being repeatedly identified as a key mechanism linking digital transformation to improved financial performance.

This study is designed to address this gap by empirically testing the role of credit risk as a mediating variable in the relationship between financial technology and the financial performance of conventional commercial banks in Indonesia during the 2023–2025 period. This study contributes by combining financial technology proxies at the individual bank level (the number of mobile banking users and the volume of digital transactions) with two credit risk indicators (NPL and LLP) in a single mediation model that has not been widely tested in the context of Indonesia's conventional banking sector following the end of the OJK's credit relaxation measures. Based on this background, the study poses four research questions: (1) Does financial technology have a significant effect on credit risk? (2) Does financial technology have a significant effect on financial performance? (3) Does credit risk have a significant effect on financial performance? and (4) Does credit risk mediate the effect of financial technology on the financial performance of conventional commercial banks in Indonesia for the period 2023-2025?

Financial technology refers to the use of innovative technology to provide financial services and products in a more efficient, secure, and accessible manner for customers [26]. In this study, financial technology is proxied by the number of mobile banking users and the volume of digital transactions sourced from each bank's annual reports, as used by Indrianti et al. [5] and Yulastri & Negara [6].

Credit risk is the risk of loss arising from a debtor's failure to meet its financial obligations [27], measured through Non-Performing Loans (NPL) which are backward-looking and Loan Loss Provisions (LLP) which are forward-looking in accordance with PSAK 71 standards [28].

Financial performance reflects a bank's ability to effectively generate profits from its operational activities [29], proxied by Return on Assets (ROA), which measures the effectiveness of asset utilization, and Net Interest Margin (NIM), which represents the profitability of the intermediation function [20].

The relationship among these variables is supported by several theoretical frameworks. Schumpeter's innovation theory (1934) explains that the adoption of financial technology during the diffusion stage has the potential to improve banks' operational efficiency and profitability [30]. Diamond & Dybvig's financial intermediation theory (1983) asserts that financial technology strengthens banks' delegated monitoring function, thereby reducing credit risk, which in turn affects financial performance. Jensen and Meckling's (1976) agency theory explains that failures in debtor monitoring reflected in rising NPL are manifestations of governance failures that harm shareholders (Berger & Deyoung, 1997) [31].

Based on the theoretical framework and empirical findings above, this study proposes the following hypotheses:

H1: Financial technology has a significant effect on the credit risk of conventional commercial banks in Indonesia during the 2023-2025 period.

H2: Financial technology has a significant effect on the financial performance of conventional commercial banks in Indonesia during the 2023-2025 period.

H3: Credit risk has a significant effect on the financial performance of conventional commercial banks in Indonesia during the 2023-2025 period.

H4: Credit risk mediates the effect of financial technology on the financial performance of conventional commercial banks in Indonesia during the 2023-2025 period.

METHODS

Research Design

This study employs a quantitative research approach with a causal (explanatory) design, intended to test the effect of financial technology on the financial performance of conventional commercial banks in Indonesia, both directly and indirectly through credit risk as a mediating variable [32]. The analytical method used is panel data regression, processed with EViews 12 software, which combines cross-sectional and time-series data to produce more efficient and informative estimates [33]. The most appropriate estimation model was selected through the Chow Test, Hausman Test, and Lagrange Multiplier Test, followed by classical assumption testing to ensure the estimation results are BLUE (Best Linear Unbiased Estimator). The mediating effect of credit risk was tested using the three-step procedure of Baron and Kenny (1986), complemented by the Sobel Test.

This study uses secondary data obtained from the annual financial reports of conventional commercial banks listed on the Indonesia Stock Exchange (IDX) during the 2023-2025 period. The data were collected from the official IDX website (www.idx.co.id) as well as each bank's official website. The population of this study consists of 45 conventional commercial banks listed on the IDX based on data from the Financial Services Authority (OJK) and the IDX for the 2023–2025 period, with the sample determined using a purposive sampling technique based on data completeness criteria.

Population

The population of this study consists of 45 conventional commercial banks listed on the Indonesia Stock Exchange (IDX) during the 2023-2025 period, based on OJK and IDX data. Samples were selected using a purposive sampling technique based on data-completeness criteria relevant to the research variables. Of the 45 banks in the population, 13 banks met all sampling criteria and were designated as the research sample, yielding a total of 39 firm-year observations (13 banks × 3 years).

Variables and Operational Definitions

This study uses three types of variables: an independent variable, a mediating variable, and a dependent variable. Financial technology (X) is the independent variable, proxied by the number of mobile banking users and the volume of digital transactions, both obtained from each bank's annual report [26]. Credit risk (Z) is the mediating variable, proxied by Non-Performing Loan (NPL) and Loan Loss Provision (LLP) [27]. Financial performance (Y) is the dependent variable, proxied by Return on Assets (ROA) and Net Interest Margin (NIM) [34]. Each variable, its indicators, formulas, and data sources are summarized in Table 1.

Table 1. Operational Definition of Variables and Indicators

Variabel	Indicator	Formula/Measurement	Data source
Financial technology (X)	Number of mobile banking users	Ln (Number of registered users per year)	Annual Report Bank
	Digital Transaction Volume	Ln (Total annual digital transaction value)	Annual Report Bank
Credit Risk (Z)	NPL	$\frac{\text{Non Performing Loans}}{\text{Total credits}} \times 100\%$	Annual Report Bank
	Loan Loss Provision	$\frac{\text{CKPN}}{\text{Total credits}} \times 100\%$	Annual Report Bank
Financial Performance (Y)	ROA	$\frac{\text{Net Profit}}{\text{Total Assets}} \times 100\%$	Annual Report Bank
	NIM	$\frac{\text{Net Interest Income}}{\text{Productive Assets}} \times 100\%$	Annual Report Bank

Source: Researcher's processed data (2026)

Data Types, Sources, and Collection Technique

This study uses secondary, quantitative panel data a combination of cross-sectional data from 13 sampled banks and time-series data spanning 2023-2025 obtained from two official sources: the Indonesia Stock Exchange (www.idx.co.id), which provides audited annual reports containing ROA, NIM, NPL, and LLP data, and each sampled bank's official website, which provides mobile banking user and digital transaction volume data not always available through IDX. Data were collected using the documentation technique, in which relevant figures were identified and recorded systematically from each bank's annual report, compiled into a panel-data matrix in Microsoft Excel, cross-verified against OJK's Indonesian Banking Statistics publication, and imported into EViews 12 for further processing [32]. Specifically, mobile banking user figures and digital transaction volumes were extracted from the digital performance highlights section of each annual report, NPL figures from the credit risk management disclosures, LLP figures from the notes to the financial statements under the allowance for impairment losses, and ROA and NIM figures from the financial summary section. The 13 banks used as the final sample were selected from an initial population of 45 conventional commercial banks listed on the IDX, through a purposive sampling technique based on the completeness and consistent availability of these data points throughout the 2023-2025 period, resulting in a total of 39 bank-year observations.

Data Analysis Technique

To answer the research questions and test the proposed hypotheses regarding the direct and indirect effects of financial technology adoption on bank financial performance through credit risk, the collected panel data comprising 45 conventional commercial banks in Indonesia over the 2023-2025 period were analyzed using EViews 12 software through the following stages.

Descriptive statistics were used to describe the mean, standard deviation, maximum, and minimum values of the six measurement variables prior to model estimation [35]. Next, panel data regression was estimated, with the most appropriate model selected through the Chow Test, Hausman Test, and Lagrange Multiplier Test. Hypothesis testing was then conducted using the partial t-test to examine the effect of each independent variable, along with the coefficient of determination (R^2) to assess the model's overall explanatory power. Finally, the mediating role of credit risk was tested using the three-step procedure of Baron and Kenny (1986), complemented by the Sobel Test to confirm the significance of the indirect effect.

Panel data regression was used to test the hypothesized relationships through two separate equations. The first equation tests the effect of financial technology on credit risk:

$$RK_{it} = \propto + \beta_1 MB_{it} + \beta_2 VT_{it} + \epsilon_{it} \qquad (1)$$

The second equation tests the joint effect of financial technology and credit risk on financial performance, following the third step of the Baron and Kenny (1986) [36] mediation procedure:

$$KK_{it} = \propto + \beta_1 MB_{it} + \beta_2 VT_{it} + \beta_3 RK_{it} + \epsilon_{it} \quad (2)$$

Where KK_{it} is financial performance (ROA, NIM), RK_{it} is credit risk (NPL, LLP), MB_{it} is the number of mobile banking users, VT_{it} is digital transaction volume, α is the constant, β is the regression coefficient, and $\epsilon_{it}$is the error term for bank i in period t [33]. Prior to estimation, MB and VT were transformed into natural logarithms (Ln) to address scale differences and stabilize variance [33].

Model selection among the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM) was conducted sequentially using the Chow Test (CEM vs. FEM), the Hausman Test (FEM vs. REM), and, where applicable, the Lagrange Multiplier Test (CEM vs. REM). Classical assumption tests were subsequently conducted to ensure the selected model produces unbiased and efficient (BLUE) estimates before hypothesis testing.

Hypothesis testing was conducted using the partial t-test, in which the null hypothesis (regression coefficient = 0) is rejected if the t-statistic probability is below 0.05, indicating a significant effect at the 95% confidence level. The coefficient of determination (R^2) was used to measure the proportion of variance in the dependent variable explained jointly by the independent variables [33]. Mediation testing was conducted using the Sobel Test to determine the significance of the indirect effect (a × b) of financial technology on financial performance through credit risk:

$$Z = \frac{a \times b}{\sqrt{b^2 S_a^2 + a^2 S_b^2 + S_a^2 S_b^2}} \quad (3)$$

where a is the coefficient of financial technology on credit risk, b is the coefficient of credit risk on financial performance, and S_a and S_b are their respective standard errors. The indirect effect is considered significant indicating that credit risk mediates the relationship if $Z > 1.96$ or the probability value is below 0.05 [37], calculated using the Sobel Test calculator developed by Preacher and Leonardelli based on the EViews 12 regression output.

RESULTS AND DISCUSSION

Overview of the Research Object.

The object of this study is conventional commercial banks listed on the Indonesia Stock Exchange (IDX) during the 2023–2025 period. Based on OJK and IDX data for 2024, 45 conventional commercial banks were recorded as active issuers on the IDX and served as the study's population reference. Of these 45 banks, 13 were selected as the sample through purposive sampling based on data completeness, including the consistent annual disclosure of mobile banking user figures, digital transaction volume, and other financial indicators throughout the study period. The 13 qualifying banks were Bank Central Asia Tbk. (BBCA), Bank KB Indonesia Tbk. (BBKP), Bank Negara Indonesia (Persero) Tbk. (BBNI), Bank Rakyat Indonesia (Persero) Tbk. (BBRI), Bank Tabungan Negara (Persero) Tbk. (BBTN), Bank Maspion Indonesia Tbk. (BMAS), Bank Mandiri (Persero) Tbk. (BMRI), Bank CIMB Niaga Tbk. (BNGA), Bank Permata Tbk. (BNLI), Bank Mayapada Internasional Tbk. (MAYA), Bank Mega Tbk. (MEGA), Bank Multiarta Sentosa Tbk. (MASB), and Bank JTrust Indonesia Tbk. (BCIC), yielding a total of 39 firm-year observations (13 banks × 3 years).

The sample reflects a representative range of characteristics within Indonesia's conventional banking industry, spanning state-owned banks (BRI, BNI, Bank Mandiri, BTN), large national private banks (BCA, CIMB Niaga), and small-to-medium private banks (Bank Maspion, Bank Mayapada, Bank Permata, Bank Mega, Bank Multiarta Sentosa, Bank KB Indonesia, and Bank JTrust Indonesia). This diversity of scale and ownership provides sufficient variation in financial technology adoption, credit risk profile, and financial performance, so that the model estimates can more broadly reflect the dynamics of Indonesia's conventional banking industry. IDX-listed banks were chosen as the unit of analysis for two reasons: first, they are subject to transparent, standardized, and publicly accountable financial reporting requirements, ensuring greater data quality and consistency; second, conventional commercial banks are the segment most directly affected by, and most active in, the digital transformation of Indonesian banking services, making empirical testing on this group the most relevant to the research objective. All data were sourced from each bank's annual reports published on the official IDX website (www.idx.co.id) and on each bank's official website, covering the 2023-2025 period.

Descriptive Statistics of Research Variables

Descriptive statistical analysis was carried out to provide a general picture of the data distribution of all research variables over the 2023-2025 period across 39 observations (13 banks × 3 years). This analysis presents the mean, median, maximum, minimum, and standard deviation values for each of the six research variables, namely financial technology adoption, credit risk, and financial performance. The results of this descriptive analysis are summarized in Table 4.1 below.

Table 2. Descriptive Statistics

	ROA	NPL	PM	VT	NIM	LLP
Mean	1.297436	2.955897	4.231028	17.66965	5.304103	1.889202
Median	1.700000	2.520000	3.453157	17.49003	4.000000	0.900991
Maximum	4.030000	9.970000	17.17519	24.79192	24.60000	16.83178
Minimum	-7.710000	0.970000	0.104360	1.504077	0.780000	0.049577
Std. Dev.	2.571241	2.069096	3.800543	4.194348	5.578884	3.197905
Observations	39	39	39	39	39	39

Source: EViews output, processed data (2026).

ROA shows a mean of 1.2974%, which falls into the "fair" category under POJK No. 17/POJK.03/2023, while its minimum value of -7.71% indicates that at least one sampled bank experienced a loss in a given period. NPL averages 2.9559%, which remains below the 5% tolerance threshold set by OJK Circular Letter No. 14/SEOJK.03/2017, although its maximum value of 9.97% shows that at least one bank exceeded this limit at some point. LLP shows a wide gap between its mean (1.8892%) and median (0.9010%), reflecting considerable divergence in risk-management behavior across the sampled banks. PM and VT, the two proxies for financial technology, display very wide ranges, indicating substantial heterogeneity in digital capacity between large and small-to-medium banks in the sample. NIM has the largest standard deviation of all variables (5.5789), pointing to the greatest heterogeneity in intermediation efficiency among the six variables. Overall, the wide variation observed across all variables reflects differences in scale, technological capacity, and risk-management strategy among the sampled banks, providing favorable conditions for testing the effect and mediation relationships proposed in this study's hypotheses.

Panel Data Model Selection

Selecting the appropriate panel-data estimation model was carried out through a sequential testing procedure, namely the Chow Test, the Lagrange Multiplier (LM) Test, and the Hausman Test, each of which serves to narrow down the choice among the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM) before proceeding to hypothesis testing. The results and interpretation of each test are presented as follows..

Chow Test

The Chow Test was conducted to determine whether the Common Effect Model (CEM) or the Fixed Effect Model (FEM) is more appropriate for estimating the panel data, with the hypotheses formulated as H_0: the Common Effect Model is more appropriate, and H_1: the Fixed Effect Model is more appropriate. Table 3 presents the results of this test.

Table 3. Chow Test Results

Test	Statistic	d.f.	Prob.	Decision
Cross-section F	2,7773	(12,25)	0,0150	H_0 rejected
Cross-section Chi-square	33,0408	12	0,0010	H_0 rejected

Source: EViews output, processed data (2026).

The Chow test was used to check which model fits better, the Common Effect Model or the Fixed Effect Model. The results show that the probability values, both for the Cross-section F (0.0150) and the Cross-section Chi-square (0.0010), are lower than 0.05. This means the Fixed Effect Model is more suitable than the Common Effect Model for this study.

Lagrange Multiplier (LM) Test

Although the Chow Test pointed toward FEM, the LM Test was still conducted as a confirmatory step to compare the Common Effect Model (CEM) against the Random Effect Model (REM), with the hypotheses formulated as H_0: the Common Effect Model is more appropriate, and H_1: the Random Effect Model is more appropriate. Table 3 presents the results of this test.

Table 4. Lagrange Multiplier Test Results

Test	Cross-section	Prob.	Decision
Breusch-Pagan	3,4664	0,0626	H_0 not rejected
Honda	1,8618	0,0313	-
King-Wu	1,8618	0,0313	-

Source: EViews output, processed data (2026).

The Lagrange Multiplier test was used to compare the Common Effect Model with the Random Effect Model, serving as a confirmatory step following the Chow Test. Based on the Breusch-Pagan statistic, the result shows a cross-section probability value of 0.0626, which is higher than the significance level of 0.05. This means the null hypothesis fails to be rejected, so the Common Effect Model is considered more suitable than the Random Effect Model, which at the same time confirms that the Random Effect Model is not an appropriate choice for this research model.

Hausman Test

Because the Chow and LM Tests pointed in different directions, the Hausman Test was performed to confirm the choice between the Fixed Effect Model (FEM) and the Random Effect Model (REM), with the hypotheses formulated as H_0: the Random Effect Model is more appropriate, and H_1: the Fixed Effect Model is more appropriate. Table 4 presents the results of this test..

Table 5. Hausman Test Results

Test	Chi-Sq. Statistik	Chi-Sq. d.f.	Prob.	Decision
Cross-section random	4,1869	3	0,2420	H_0 not rejected

Source: EViews output, processed data (2026).

The Hausman test was used to compare the Fixed Effect Model with the Random Effect Model, with the hypotheses formulated as H_0: the Random Effect Model is more appropriate, and H_1: the Fixed Effect Model is more appropriate. Based on the cross-section random Chi-Square statistic, the result shows a probability value of 0.2420, which is higher than the significance level of 0.05. This means the null hypothesis fails to be rejected, so the Random Effect Model is considered more suitable than the Fixed Effect Model according to the Hausman test.

Taken together, the Chow Test rejected CEM in favor of FEM, while the Hausman Test failed to reject REM in favor of FEM a pattern commonly found in panel studies with a limited number of periods (here, three periods, 2023-2025). Since the Hausman Test is considered more decisive for the final choice between FEM and REM, and the LM Test also indicated no meaningful cross-sectional random effect at the 5% level, this study adopts the **Random Effect Model (REM)** as its estimation model. This choice is also consistent with the nature of the data, in which the sampled conventional commercial banks are treated as a random sample from a larger population, so that inter-bank differences are assumed uncorrelated with the independent variables in the model.

Hypothesis Testing

Partial t-Test

The partial significance test (t-test) was used to examine the individual effect of each independent variable on the dependent variable, holding other variables constant, using a significance criterion of α = 0.05. Because this study uses dual proxies for both credit risk (NPL and LLP) and financial performance (ROA and NIM), testing was carried out across eight equation combinations, as summarized in Table 6.

Table 5. Partial t-Test Results

Dep. Var	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Remarks
NPL	PM	-0,0284	0,0254	-1,1217	0,2694	Not significant
	VT	-0,0263	0,0263	-1,0020	0,3230	Not significant
LLP	PM	-0,3841	0,6088	-0,6309	0,5321	Not significant
	VT	0,2263	0,5516	0,4103	0,6840	Not significant
ROA	PM	0,0300	0,0640	0,4684	0,6423	Not significant
	VT	-0,0865	0,0653	-1,3242	0,1938	Not significant
NIM	PM	-0,0088	0,0192	-0,4584	0,6495	Not significant
	VT	-0,0386	0,0200	-1,9344	0,0610	Not significant
ROA + NPL	PM	-0,0063	0,0626	-0,1002	0,9207	Not significant
	VT	-0,0766	0,0614	-1,2475	0,2205	Not significant
	NPL	-0,8884	0,1766	-5,0297	0,0000	significant
ROA + LLP	PM	0,0261	0,0693	0,3769	0,7085	Not significant
	VT	-0,0862	0,0670	-1,2860	0,2069	Not significant
	LLP	-0,0037	0,0185	-0,2019	0,8412	Not significant
NIM + NPL	PM	-0,0144	0,0197	-0,7321	0,4690	Not significant
	VT	-0,0438	0,0203	-2,1544	0,0382	significant
	NPL	-0,1891	0,1511	-1,2514	0,2191	Not significant
NIM + LLP	PM	-0,0082	0,0210	-0,3920	0,6974	Not significant
	VT	-0,0387	0,0205	-1,8934	0,0666	Not significant
	LLP	0,0004	0,0056	0,0752	0,9405	Not significant

Source: EViews output, processed data (2026).

Based on Table 6, neither mobile banking users nor digital transaction volume significantly affects credit risk under either proxy: probabilities of 0.2694 and 0.3230 against NPL, and 0.5321 and 0.6840 against LLP, all well above α = 0.05 H1 is rejected for both credit-risk proxies. Before the mediator is introduced, neither variable significantly affects financial performance either: probabilities of 0.6423 and 0.1938 against ROA, and 0.6495 and 0.0610 against NIM. Although the probability for digital transaction volume against NIM (0.0610) approaches the threshold, it remains above α = 0.05, so H2 is rejected for both performance proxies. Once the mediator is introduced, results vary by combination: mobile banking users remain insignificant across all combinations (p = 0.4690-0.9207); digital transaction volume is significant only for the NIM-NPL combination (coefficient -0.0438; p = 0.0382); and among the mediators, only NPL significantly and negatively affects ROA (coefficient -0.8884; p = 0.0000) each one-unit increase in NPL is associated with a 0.8884-point decrease in ROA, ceteris paribus. NPL's effect on NIM (p = 0.2191), LLP effect on ROA (p = 0.8412), and LLP effect on NIM (p = 0.9405) are all not significant. H3 is therefore accepted only for the NPL-ROA combination and rejected for the others.

Coefficient of Determination (R^2)

Table 7 presents the coefficient of determination for all estimated equations, using the adjusted R-squared as the primary reference and the unweighted R-squared to reflect overall explanatory power under Panel EGLS Random Effect estimation. The coefficient of determination (R^2) test was conducted to measure the extent to which each model explains variation in its dependent variable, with the adjusted R-squared accounting for the number of independent variables included, thereby providing a more conservative and comparable benchmark across equations with different numbers of predictors. The results show a fairly consistent pattern across all eight equations, ranging from models with financial technology alone as predictors of credit risk and financial performance, to models that incorporate credit risk as a mediating variable in explaining financial performance.

Table 7. Coefficient of Determination (R^2)

Dep. Var	Mediator	Weighted R²	Adjusted R²	Unweighted R²
NPL	-	0,0706	0,0190	-0,0140
LLP	-	0,0140	-0,0408	0,0140
ROA	-	0,0498	-0,0030	-0,0114
NIM	-	0,1101	0,0606	0,0093
ROA	NPL	0,4227	0,3732	0,5830
ROA	LLP	0,0524	-0,0288	-0,0066
NIM	NPL	0,1515	0,0787	0,0479
NIM	LLP	0,1120	0,0359	0,0090

Source: researcher's processed data (2026).

The explanatory power of the model is fairly consistent across equations. Financial technology alone explains only a small share of the variation in credit risk (adjusted $R^2 = 0.0190$ for NPL) and is even negative for LLP (-0.0408); adjusted R^2 is likewise negative for ROA (-0.0030) and very low for NIM (0.0606) before the mediator is added indicating that, within this sample, variation in credit risk and financial performance is driven more by bank-specific characteristics than by the level of financial technology adoption. This picture changes markedly once NPL is added to the ROA equation: weighted R^2 jumps to 0.4227 and unweighted R^2 reaches 0.5830, up from 0.0498 without the mediator showing that NPL is the principal explanatory factor for ROA. By contrast, adding LLP to the ROA equation yields an adjusted R^2 of only -0.0288, lower than without the mediator, adding no explanatory power. For NIM, adding either NPL or LLP raises adjusted R^2 only marginally (to 0.0787 and 0.0359, respectively); variation in NIM across banks instead appears to be driven mainly by bank-specific factors, consistent with the very high cross-section random Rho values (0.9961-0.9962) found across all NIM-based equations.

Robustness Check

As outlined in the Methods section, this study employs dual proxies for both credit risk (NPL and LLP) and financial performance (ROA and NIM), which serves as a robustness check on the consistency of the findings across alternative measurements, complementing the model-selection procedure reported above. The check compares results across proxy combinations in Table 6 rather than through additional model re-estimation.

For the effect of financial technology on credit risk (H1), the finding proves robust: neither mobile banking users nor digital transaction volume significantly affects credit risk under either proxy, with probabilities of 0.2694 and 0.3230 against NPL and 0.5321 and 0.6840 against LLP. The consistent non-significance across both proxies indicates that the rejection of H1 is not an artifact of the credit-risk measure chosen. By contrast, the effect of credit risk on financial performance (H3) is not robust and instead proves sensitive to proxy choice: NPL significantly and negatively affects ROA (coefficient -0.8884; $p = 0.0000$), but its effect on NIM is not significant ($p = 0.2191$), while LLP affects neither ROA ($p = 0.8412$) nor NIM ($p = 0.9405$). Support for H3 therefore holds only for the NPL-ROA combination and does not extend to the other three combinations, consistent with the earlier observation that LLP in this sample likely functions more as an income-smoothing device [41] than as a sensitive indicator of credit risk. The mediation result (H4) is robust in a different sense: the precondition for mediation, a significant effect of financial technology on the mediator, fails for both credit-risk proxies, so the conclusion that mediation does not occur holds regardless of which proxy is used.

Taken together, the robustness check indicates that the findings for H1 and H4 are stable across proxies, whereas the finding for H3 is proxy-dependent and holds specifically for the NPL-ROA channel. This sensitivity reinforces the limitations discussed below and underscores that future studies with a larger sample should complement proxy variation with additional robustness checks, such as re-estimating the ROA-NPL equation under the Fixed Effect Model or examining the results after winsorizing extreme values.

Mediation Test (Sobel Test)

Mediation testing focused on the ROA-NPL combination, the only pathway in which the mediator proved significant, since credit risk proxied by Non-Performing Loan (NPL) was the sole credit risk indicator that showed a significant relationship with financial performance, while Loan Loss Provision (LLP) did not meet this precondition. Using the three-step procedure of Baron and Kenny (1986) complemented by the Sobel test, the indirect effect of financial technology on financial performance through credit risk was examined along two paths, namely mobile banking users (PM) and digital transaction volume (VT) as proxies for financial technology adoption. Table 7 presents the results of this mediation test..

Table 7. Mediation Test Results

Jalur Mediasi	Efek Tidak Langsung (a×b)	Nilai z	Prob.	Hasil
PM-NPL-ROA	0,0252	1,091	0,275	Tidak Signifikan
VT-NPL- ROA	0,0234	0,981	0,327	Tidak Signifikan

Source: researcher's processed data (2026).

Both z-values fall below the critical value of 1.96, with probabilities of 0.275 and 0.327 respectively, so H4 is rejected. Credit risk, proxied by NPL, is not found to mediate the effect of financial technology on the financial performance of conventional commercial banks in Indonesia over the 2023-2025 period.

Discussion

Effect of Financial Technology on Credit Risk (H1). Testing the first hypothesis shows that financial technology measured through the number of mobile banking users and digital transaction volume has no significant effect on credit risk, whether proxied by NPL or LLP; H1 is not supported. This contrasts with Yudaruddin et al. [11] on Indonesian commercial banks and with Chai and Sun ([12]) and Ally [13] on Chinese and Tanzanian banking, all of whom found that financial technology reduces non-performing loans. This divergence can plausibly be explained by three factors. First, the wide digital-capacity gap among sampled banks ranging from technologically mature banks such as BCA and Bank Mandiri to banks still at an early digitalization stage such as Bank Maspion and Bank Multiarta Sentosa likely causes bank-level effects to offset one another at the sample average. Second, the study period coincided with the end of OJK's credit restructuring program in March 2024; during this transition, rising non-performing loans at several banks were more likely driven by macroeconomic conditions and the withdrawal of credit relaxation policy than by fintech adoption. Third, the proxies used here mobile banking users and digital transaction volume capture the customer-service dimension of fintech rather than the credit-assessment and monitoring dimension, such as AI-based credit scoring or early-warning systems for problematic debtors; Gambacorta et al. [38] and Zhang et al. [39] found that credit-risk reduction operates mainly through that latter dimension, suggesting the proxies used in this study may not capture the fintech dimension most relevant to reducing credit risk. This interpretation is consistent with the broader AI-driven banking innovation literature, which finds that internally adopted AI-enabled technologies such as machine-learning credit assessment are the channel most strongly associated with improved bank outcomes, rather than customer-facing digital services alone [43]. This finding aligns with Naya et al. [8], who likewise found no effect of digitalization on Indonesian banking performance over a nearby period, reinforcing the argument that the benefits of banking-technology investment in Indonesia have not yet been fully realized in the short run.

Effect of Financial Technology on Financial Performance (H2). Testing the second hypothesis likewise finds no significant effect of financial technology on financial performance, on either ROA or NIM, before credit risk is introduced as a mediator; H2 is not supported. Only the relationship between digital transaction volume and NIM approaches significance, though not enough to change the conclusion. This is consistent with Naya et al. [8], who analyzed 44 IDX-listed banks over 2018-2023 and found that digitalization did not affect ROA, ROE, or NIM; the high cost of technology-infrastructure development and low customer trust in digital-transaction security are likely barriers preventing digital-transaction growth from translating directly into higher profitability. Ayuningtyas and Sufina [9] reached a similar conclusion regarding mobile and internet banking's effect on ROA, while Ovenc and Nabiyev (2025) even found that fintech growth suppresses banking profitability. Contrasting evidence comes from Indrianti et al. [5] and Yulastri and Negara [6], who found a positive effect of mobile banking on ROA a difference plausibly attributable to period effects, since their 2017-2021 data captured mobile banking's early growth phase before scale efficiencies were reached, whereas by 2023-2025 adoption among certain customer segments has plateaued, so additional new users no longer contribute meaningfully to profitability. The near-significant relationship between digital transaction volume and NIM still merits attention: with a larger number of observations or a longer study period, this relationship could become more apparent, as found by Indrianti et al. [5] and Liu et al. [40] using larger samples.

Effect of Credit Risk on Financial Performance (H3). Results for the third hypothesis vary by proxy combination. H3 is supported only for the NPL-ROA combination, with a fairly strong negative effect: the higher a bank's non-performing loans, the lower its asset profitability, and the decline is comparatively steep. No significant effect is found for NPL on NIM, LLP on ROA, or LLP on NIM. The NPL-ROA finding is consistent with Mulyati and Nurfauziah (Mulyati & Nurfauziah, 2024) on Indonesian commercial banks (2015–2019), although the effect size here appears larger, suggesting that pressure from non-performing loans on bank profitability intensified in the post-pandemic period after OJK's credit restructuring program ended. Masruro and Panglipursari [21] argue that during the pandemic, the effect of non-performing loans on profitability was cushioned by OJK's relaxation policy, and once that policy was lifted in March 2024, the pressure resumed at full force a pattern also reported by Saleh and Abu Afifa [20] for Jordanian banking and by Andreas et al. [28] for Indonesian commercial banks (2020-2024). This negative effect operates through two reinforcing channels: the obligation to build loan-loss provisions, which directly erodes pre-tax profit, and the loss of accrued interest income recognition on loans reclassified as non-performing, which further reduces operating income [20]. The absence of a significant NPL effect on NIM may reflect that NIM is shaped largely by interest-rate policy and each bank's funding strategy factors outside this model and that banks with high non-performing loan portfolios may already compensate through lending-rate adjustments, muting the short-run impact on NIM. The consistent non-significance of LLP across all combinations suggests that provisioning by the sampled banks over this period functioned more as income smoothing, as argued by Ozili [41], than as a pure reflection of expected credit risk, making LLP a less sensitive signal of credit risk for Indonesian bank profitability during 2023-2025.

The Mediating Role of Credit Risk (H4). Using the Baron and Kenny (1986) [36] procedure with the Sobel test, credit risk is not found to mediate the effect of financial technology on the financial performance of conventional commercial banks in Indonesia over 2023-2025, through either the mobile-banking-user or digital-transaction-volume pathway toward NPL and then ROA; H4 is not supported. This is a logical consequence of H1's rejection, since the Baron and Kenny procedure requires the independent variable to significantly affect the mediator before mediation can occur because financial technology does not significantly affect NPL, no mediation pathway can form, even though NPL itself significantly affects ROA. This contrasts with Chen and Wang [14], who found that credit risk mediates the fintech–operational performance relationship among Chinese commercial banks, and Zouari-Hadiji [23], who found a mediating role of risk management between financial innovation and banking performance in Tunisia. This divergence is plausibly explained by three factors: the limited sample size in this study, which reduces the statistical power to detect mediation effects that typically require larger samples for stable path estimation; the fintech proxies used, which reflect the customer-service dimension more than the credit-assessment technology dimension that directly affects loan-portfolio quality; and the wide heterogeneity in scale, ownership, and technological capacity across sampled banks, which obscures any average effect of fintech on NPL. Despite H4 not being supported, the study still offers a meaningful contribution: the strong, significant negative effect of NPL on ROA and the sharp rise in the model's explanatory power for ROA once NPL is included confirms that credit risk remains a dominant determinant of bank profitability in the post-pandemic period, and that credit-risk management continues to matter far more for financial performance than the current level of fintech adoption. Future research is encouraged to use a larger sample, a longer study period, and fintech proxies that more directly measure back-end credit-assessment technology, so that the mediation mechanism not identified in this study can be more fully characterized.

Limitations and Practical Implications

Several limitations of this study should be acknowledged. First, the sample is relatively small, comprising only 13 banks and 39 firm-year observations drawn from a population of 45 conventional commercial banks, since purposive sampling required consistent disclosure of mobile banking and digital-transaction data throughout the 2023-2025 period; a limited number of cross-sectional units reduces the statistical power of the panel regression, and particularly of the Sobel test used for mediation testing, so the non-significant indirect effect reported for H4 should be interpreted with this power constraint in mind, alongside the substantive explanation offered above. Second, although the choice of the Random Effect Model was supported by the sequential Chow, LM, and Hausman testing procedure and the dual-proxy robustness check reported in the Results section confirms that H1 and H4 hold across both credit-risk measures, no further robustness checks beyond proxy variation were conducted in this study, such as re-estimating the ROA-NPL equation under the Fixed Effect Model as a sensitivity comparison or examining the results after winsorizing extreme values of ROA and LLP; future studies with access to a larger panel are encouraged to perform such checks to confirm the stability of the coefficient estimates reported here. Third, as noted throughout the Discussion, the financial technology proxies used in this study, mobile banking users and digital transaction volume, capture only the customer-facing dimension of digital adoption and do not directly measure back-end credit-assessment technology, which the AI-driven banking innovation literature increasingly identifies as the primary channel linking fintech to credit risk and bank performance [43].

Notwithstanding these limitations, the findings carry practical implications for both bank management and regulators. For bank management, the results indicate that credit-risk management remains a more decisive lever for profitability than customer-facing digital investment alone during 2023-2025; banks are therefore encouraged to prioritize investment in back-end credit-assessment technology, such as machine-learning-based credit scoring and early-warning systems for problematic debtors, rather than customer-service-oriented digital channels alone, if the objective is to improve asset profitability through stronger credit-risk control. For regulators such as OJK and Bank Indonesia, the findings suggest that credit-risk-focused supervision remains warranted even as fintech adoption expands, since digital transformation alone does not automatically translate into lower non-performing loans; regulatory incentives that specifically encourage the adoption of AI-based credit-scoring and monitoring systems, rather than digital adoption in general, may therefore be more effective in strengthening the resilience of Indonesia's conventional banking sector following the conclusion of the credit restructuring relaxation program.

CONCLUSIONS

This study concludes that financial technology does not have a significant effect on credit risk among conventional commercial banks in Indonesia during the 2023–2025 period, indicating that the movement of credit risk in this period was driven more by macroeconomic conditions and the expiration of the OJK credit restructuring relaxation program in March 2024 than by banks' level of financial technology adoption. Financial technology likewise shows no significant direct effect on financial performance, suggesting that investment in digital banking technology has not yet translated into short-term profitability gains. Credit risk, proxied by Non-Performing Loan (NPL), is found to have a significant negative effect on financial performance, proxied by Return on Assets (ROA), confirming that credit quality remains a critical determinant of bank profitability, particularly after the withdrawal of the credit restructuring relaxation policy. However, credit risk is not proven to mediate the effect of financial technology on financial performance, a logical consequence of the non-significant relationship between financial technology and credit risk. Taken together, these findings indicate that during 2023-2025, credit risk rather than the level of financial technology adoption is the more decisive factor in shaping the financial performance of conventional commercial banks in Indonesia, lending support to the bad management hypothesis in agency theory and the delegated monitoring function in financial intermediation theory. Future research is encouraged to employ more specific financial technology proxies focused on credit-risk assessment technology, such as machine learning-based credit scoring or partnerships with fintech lending companies, and to extend the sample coverage and observation period for a more comprehensive understanding of the relationship between financial technology, credit risk, and bank financial performance..

ACKNOWLEDGMENT

The authors gratefully acknowledge the guidance and support provided throughout this research, particularly from the supervising lecturer and the Faculty of Economics and Business, Institut Teknologi dan Bisnis (ITEBIS) PGRI Dewantara Jombang. The authors also thank the Indonesia Stock Exchange for providing access to the financial statement data of the sampled banks used in this study.

REFERENCES

[1] U.S. Department of Commerce, " Indonesia - Financial Services (Financial Technology)," International Trade Administration. Accessed: Apr. 18, 2026. [Online]. Available: https://www.trade.gov/country-commercial-guides/indonesia-financial-services-financial-technology

[2] Mordor Intelligence, "INDONESIA FINANCIAL TECHNOLOGY SERVICES MARKET SIZE & SHARE ANALYSIS - GROWTH TRENDS AND FORECAST (2026 - 2031) Source: https://www.mordorintelligence.com/industry-reports/indonesia-financial-technology-services-market," Mordor Intelligence. Accessed: Apr. 18, 2026. [Online]. Available: https://www.mordorintelligence.com/industry-reports/indonesia-financial-technology-services-market

[3] OJK, "Press Release: Reflection 2024: Indonesian Banking Remains Solid and Optimistic Amid Global Economic Uncertainty," OJK. Accessed: Apr. 18, 2026. [Online]. Available: https://ojk.go.id/en/berita-dan-kegiatan/siaran-pers/Pages/Reflection-2024-Indonesian-Banking-Remains-Solid-and-Optimistic-Amid-Global-Economic-Uncertainty.aspx

[4] D. S. K. Wardani, A. Wahyuningtyas, and E. C. Suhatmi, "Analisis Return on Assets (ROA) dan Return on Equity (ROE) pada PT Bank Rakyat Indonesia Tbk. Dan PT Bank Mandiri Tbk. Tahun 2022-2024," 2026. Accessed: Apr. 18, 2026. [Online]. Available: https://ojs.udb.ac.id/HUBISINTEK/article/view/5872/3949

[5] S. Indrianti, R. R. Gamayuni, R. Yuni, and N. Susilowati, "PENGARUH FINANCIAL TECHNOLOGY TERHADAP KINERJA KEUANGAN PERBANKAN KONVENSIONAL YANG TERDAFTAR DI BURSA EFEK INDONESIA (BEI) TAHUN 2017-2021," 2022.

[6] Y. D. Yulastri and I. K. Negara, "Pengaruh Adopsi Financial Technology Terhadap Profitabilitas Bank Umum Konvensional yang Terdaftar di Otoritas Jasa Keuangan Periode 2017-2022," ALEXANDRIA (Journal of Economics, Business, & Entrepreneurship), vol. 5, no. 2, pp. 186–192, Sep. 2024, doi: 10.29303/alexandria.v5i2.628.

[7] I. Sahara, W. P. Sari, L. Lores, and A. Prayudi, "Pengaruh Penggunaan Mobile Banking, Internet Banking Dan ATM Terhadap Kinerja Keuangan Pada Perusahaan Perbankan yang Terdaftar di Bursa Efek Indonesia Periode 2018-2023," Journal of Education, Humaniora and Social Sciences (JEHSS), vol. 8, no. 1, pp. 33–40, May 2025, doi: 10.34007/jehss.v8i1.2641.

[8] F. E. Naya, D. Aulia, T. Kristanto, and K. Aditasari, "ANALISIS PENGARUH DIGITALISASI TERHADAP KINERJA KEUANGAN PADA SEKTOR PERBANKAN PERIODE 2018-2023," Indo-Fintech Intellectuals: Journal of Economics and Business, vol. 5, no. 3, pp. 6849–6863, Sep. 2025, doi: 10.54373/ifijeb.v5i3.3960.

[9] M. Ayuningtyas and L. Sufina, "Pengaruh Penggunaan Mobile Banking, Internet Banking, dan Atm terhadap Kinerja Keuangan Perbankan (Studi Kasus Sektor Bank Konvensional yang Terdaftar di Bursa Efek Indonesia) Tahun 2017- 2021," Jurnal Keuangan dan Perbankan, 2023, doi: https://doi.org/10.35384/jkp.v19i2.394.

[10] G. Ovenc and A. B. Nabiyev, "Discover how fintech is transforming bank performance: insights from an emerging economy," Cogent Economics and Finance, vol. 13, no. 1, 2025, doi: 10.1080/23322039.2025.2477676.

[11] R. Yudaruddin et al., "Liquidity and Credit Risk in Indonesia: The Role of FinTech Development," Sage Open, vol. 14, no. 2, Apr. 2024, doi: 10.1177/21582440241245248.

[12] Y. Chai and S. Sun, "Can the development of Fintech mitigate non-performing loan risk?," Financ. Res. Lett., vol. 67, p. 105889, Sep. 2024, doi: 10.1016/j.frl.2024.105889.

[13] O. J. Ally, Y. J. Kulindwa, and L. Mataba, "Financial technology and credit risk management: the case of non-performing loans in Tanzanian banks," Cogent Economics and Finance, vol. 13, no. 1, 2025, doi: 10.1080/23322039.2025.2459188.

[14] M. Cheng and Y. Qu, "Does bank FinTech reduce credit risk? Evidence from China," Pacific-Basin Finance Journal, vol. 63, p. 101398, Oct. 2020, doi: 10.1016/j.pacfin.2020.101398.

[15] J. Jagtiani and C. Lemieux, "The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform," Federal Reserve Bank of Philadelphia, Philadelphia, PA, Jan. 2019. doi: 10.21799/frbp.wp.2018.15.

[16] Y. He and W. Fan, "FinTech, bank risk-taking, and credit allocation," Humanit. Soc. Sci. Commun., vol. 12, no. 1, Dec. 2025, doi: 10.1057/s41599-025-05931-4.

[17] H. Wang, K. Mao, W. Wu, and H. Luo, "Fintech inputs, non-performing loans risk reduction and bank performance improvement," International Review of Financial Analysis, vol. 90, p. 102849, Nov. 2023, doi: 10.1016/j.irfa.2023.102849.

[18] D. He, Y. Wang, S. Wu, X. Wang, and J. Zhang, "Banking on technology: Does FinTech improve bank performance?," The Quarterly Review of Economics and Finance, vol. 105, p. 102102, Jan. 2026, doi: 10.1016/j.qref.2025.102102.

[19] S. Mulyati and Nurfauziah, "Pengaruh penerapan manajemen risiko terhadap kinerja keuangan (Studi pada bank umum kelompok usaha)," Jurnal Kebijakan Ekonomi dan Keuangan, pp. 51–59, Aug. 2024, doi: 10.20885/jkek.vol3.iss1.art7.

[20] I. Saleh and M. Abu Afifa, "The effect of credit risk, liquidity risk and bank capital on bank profitability: Evidence from an emerging market," Cogent Economics and Finance, vol. 8, no. 1, Jan. 2020, doi: 10.1080/23322039.2020.1814509.

[21] Masruro and D. L. Panglipursari, "Pengaruh Risiko Pasar dan Risiko Kredit Terhadap Kinerja Keuangan Bank Umum Konvensional Tbk di Indonesia pada Saat Pandemi COVID-19 dan Sesudahnya," 2024.

[22] G. Methri, “Philippines, Indonesia lead Mobile FinTech Adoption in Southeast Asia,” IBS Intelligence. Accessed: Apr. 17, 2026. [Online]. Available: https://ibsintelligence.com/ibsi-news/philippines-indonesia-lead-mobile-fintech-adoption-in-southeast-asia/

[23] R. Zouari-Hadiji, “Financial innovation characteristics and banking performance: The mediating effect of risk management,” International Journal of Finance & Economics, vol. 28, no. 2, pp. 1214–1227, Apr. 2023, doi: 10.1002/ijfe.2471.

[24] D. D. Astuti and W. F. Ningsih, “PERANAN RESIKO KREDIT SEBAGAI VARIABEL MEDIASI TERHADAP KINERJA KEUANGAN PADA PERUSAHAAN PERBANKAN DI BEI,” Jurnal Ilmu Manajemen (JIMMU), vol. 9, no. 1, pp. 98–124, Apr. 2024, doi: 10.33474/jimmu.v9i1.21478.

[25] K. H. Aryani, “PENGARUH GOOD CORPORATE GOVERNANCE TERHADAP PROFITABILITAS PERBANKAN DENGAN RISIKO KREDIT SEBAGAI VARIABEL INTERVENING (PADA PERBANKAN YANG TERDAFTAR DI BEI PERIODE 2014-2016),” Distribusi - Journal of Management and Business, vol. 7, no. 1, pp. 63–80, Mar. 2019, doi: 10.29303/distribusi.v7i1.45.

[26] S. A. Chand, B. Singh, K. Narayan, and A. Chand, “The Impact of Financial Technology (FinTech) on Bank Risk-Taking and Profitability in Small Developing Island States: A Study of Fiji,” Journal of Risk and Financial Management, vol. 18, no. 7, Jul. 2025, doi: 10.3390/jrfm18070366.

[27] Basel, “Principles for the Management of Credit Risk,” 2000.

[28] Andreas, R. F. Sulthan, H. S. Lestari, and F. M. Leon, “RISK MANAGEMENT, CORPORATE GOVERNANCE, AND FINANCIAL PERFORMANCE: EVIDENCE FROM INDONESIAN COMMERCIAL BANKS (2020–2024),” Ekonomi Digital, vol. 5, no. 1, pp. 65–82, Mar. 2026, doi: 10.55837/ed.v5i1.204.

[29] S. Mulyati and Nurfauziah, “Pengaruh penerapan manajemen risiko terhadap kinerja keuangan (Studi pada bank umum kelompok usaha),” Jurnal Kebijakan Ekonomi dan Keuangan, pp. 51–59, Aug. 2024, doi: 10.20885/jkek.vol3.iss1.art7.

[30] K. Śledzik, “KAROL ŚLEDZIK Schumpeter’s view on innovation and entrepreneurship SCHUMPETER’S VIEW ON INNOVATION AND ENTREPRENEURSHIP,” 2013.

[31] A. N. Berger and R. Deyoung, “Problem loans and cost efficiency in commercial banks,” 1997.

[32] Sugiyono, 7. Sugiyono - Kualitatif, Kuantitatif, R&D (2019). 2019.

[33] D. N. Gujarati and D. C. Porter, Basic Econometrics. 2009.

[34] P. P. Athanasoglou, S. N. Brissimis, M. D. Delis, P. P. Athanasoglou Bank, G. Sophocles, and N. Brissimis, “BANK-SPECIFIC, INDUSTRY-SPECIFIC AND MACROECONOMIC DETERMINANTS OF BANK PROFITABILITY,” 2005.

[35] I. Ghozali and H. Latan, “Partial Least Squares: Concepts, Techniques and Applications using SmartPLS 3,” 2015.

[36] R. M. Baron and D. A. Kenny, “The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations,” Psychological Association, Inc, 1986.

[37] M. E. Sobel, “Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models,” 1982.

[38] L. Gambacorta, Y. Huang, H. Qiu, and J. Wang, “BIS Working Papers No 834 How do machine learning and non-traditional data affect credit scoring? New evidence from a Chinese fintech firm,” 2019. [Online]. Available: www.bis.org

[39] Y. Zhang, S. Ye, J. Liu, and L. Du, “Impact of the development of FinTech by commercial banks on bank credit risk,” Financ. Res. Lett., vol. 55, p. 103857, Jul. 2023, doi: 10.1016/j.frl.2023.103857.

[40] Z. Liu, X. Li, and Z. Li, “Inclusive FinTech, open banking, and bank performance: evidence from China,” Financial Innovation, vol. 10, no. 1, Dec. 2024, doi: 10.1186/s40854-024-00679-3.

[41] P. K. Ozili, “Banking sector earnings management using loan loss provisions in the Fintech era,” 2021. [Online]. Available: https://ssrn.com/abstract=3758468

[42] S. Ungratwar, D. Sharma, and S. Kumar, “Mapping the digital banking landscape: a multi-dimensional exploration of fintech, digital payments, and e-wallets, with insights into current scenarios and future research,” Humanities and Social Sciences Communications, vol. 12, no. 1, p. 1064, 2025, doi: 10.1057/s41599-025-05186-z.

[43] A. Hamdouni, “From ESG to Financial Stability: Unpacking the Multi-Dimensional Impact of AI-Driven FinTech-Related Technology Adoption on Bank Performance,” International Journal of Financial Studies, vol. 13, no. 4, p. 234, 2025, doi: 10.3390/ijfs13040234.