

Determinants of Banking Return on Assets in Indonesia: An Analysis of Aggregate Fintech Expansion, Electronic Transaction Intensity, and Non-Performing Asset Ratio

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Abstract

Purpose – This study aims to empirically examine the impact of aggregate financial technology (fintech) expansion, electronic transaction intensity, and non-performing asset ratio on bank profitability, proxied by Return on Assets (ROA).

Design/methodology/approach – A quantitative approach is employed using panel data multiple linear regression. The sample comprises 161 firm-year observations from conventional banking companies listed on the Indonesia Stock Exchange over the 2020–2024 period.

Findings – The results reveal that aggregate fintech expansion positively and significantly affects ROA, supporting the synergy theory over pure disruption. As expected, the non-performing asset ratio significantly degrades profitability. Interestingly, electronic transaction intensity shows no significant impact on ROA, validating the Information Technology (IT) Productivity Paradox during the banks' technological transition phase.

Originality/value – This research synthesizes external disruption pressures, internal digital adaptation, and risk mitigation into a single comprehensive framework. It challenges traditional disruption theories by proving that fintech expansion serves as a collaborative profitability driver for conventional banks rather than a mere substitute.

Implications – Managerially, banks should expand collaborative channeling partnerships with fintech platforms and strictly optimize IT capital expenditures. Policymakers are encouraged to formulate accommodating regulations for hybrid financial ecosystems.

Keywords: Return on Assets; Fintech Expansion; Electronic Transactions; Non-Performing Assets; Bank Profitability

1. Introduction

The structural transformation in the banking sector driven by technological disruption necessitates rapid strategic adaptation (Thakor, 2020; Vives, 2019). The aggressive expansion of financial technology (fintech) triggers competitive pressures, compelling banks to accelerate the intensity of electronic transactions and digital service channels (Gomber et al., 2018; Zhao et al., 2022). This practice creates a cost-efficiency trade-off amidst the imperative to mitigate non-performing assets, especially during periods of macroeconomic volatility (Ari et al., 2021). Consequently, the balance between digital service adoption and asset quality protection has become a primary determinant of modern banks' profitability sustainability, moving beyond traditional intermediation functions.

Despite its urgency, literature over the past decade indicates that the evaluation of bank profitability in the digital era is generally still examined in a fragmented manner. On one hand, Stulz (2022) found that fintech credit expansion induces competition that suppresses traditional bank profitability and erodes market share. Conversely, empirical research by Chen, Wu, and Yang (2022) confirmed that the adoption of valuable fintech innovations positively impacts financial performance by creating long-term operational efficiency. A comprehensive review by Murinde, Rizopoulos, and Zachariadis (2022) highlighted these mixed results, while Cornelli et al. (2023) emphasized that digital innovation must be strictly accompanied by asset risk mitigation, as aggressive digitalization without robust credit scoring increases default risks. This literature gap reveals the absence of an integrative conceptual approach to simultaneously measure the interaction of external ecosystem shocks, internal digital adaptations, and credit risk management.

Addressing this gap, this study aims to empirically examine and analyze the determination of Aggregate Fintech Expansion, Electronic Transaction Intensity, and Non-Performing Asset Ratio on the Return on Assets (ROA) in the banking sector. Therefore, the central research question guiding this study is: *How do aggregate fintech expansion, electronic transaction intensity, and non-performing asset ratio simultaneously and partially affect banking profitability performance?* The novelty and contribution of this research lie in its holistic synthesis. This study diverges from the partial examination of disruption phenomena by simultaneously integrating external pressure (fintech expansion), internal digital adaptation (electronic transactions), and asset quality mitigation (non-performing assets) into a comprehensive econometric model. By doing so, it extends the Technology Acceptance Model (TAM) and Credit Risk Theory within a unified macro-financial framework (Amnas et al., 2025; Ash Shidiqie et al., 2024). The findings are expected to enrich contemporary financial literature and provide practical insights for bank management and supervisory authorities in formulating resilient banking stability strategies in the modern digital ecosystem.

The remainder of this article is structured as follows: Section 2 outlines the literature review and hypothesis development. Section 3 details the research methodology, including the data sample and econometric model. Section 4 presents the empirical results and discussion. Finally, Section 5 concludes the paper, highlighting managerial implications, limitations, and avenues for future research.

2. Literature Review and Theoretical Development

This study evaluates banking financial performance through the lens of profitability, specifically proxied by the Return on Assets (ROA). ROA is a fundamental construct that measures the extent to which total assets managed by bank management can efficiently revolve and convert into net profit (Brigham & Houston, 2019; Kasmir, 2018). Rather than treating digital disruption and risk management as isolated phenomena, this research synthesizes two grand theories the Technology Acceptance Model (TAM) and Credit Risk Theory to explain the theoretical mechanisms driving modern bank profitability.

TAM, originally postulated by Davis (1989), explains technology adoption through perceived usefulness and perceived ease of use. In the contemporary financial sector, TAM provides the theoretical foundation for the shifting customer behavior toward digital banking (Singh, Sahni, & Kovid, 2022). This shift compels banks to adapt by increasing their electronic transaction intensity, driven by customer demands for ease of use and trust in digital platforms (Al Nawayseh, 2022). Concurrently, Credit Risk Theory, rooted in Merton's (1974) structural model, governs the banking sector's fundamental intermediation function. It posits that the materialization of default probability directly degrades financial health. This principle is heavily

embedded in modern regulatory frameworks, such as the Basel Accords, to ensure long-term resilience and profitability (Bessis, 2023). By integrating these theories, this study establishes a comprehensive framework to examine how banks balance the external pressures of fintech ecosystem expansion, the internal transition costs of digital transactions, and the inherent risks of non-performing assets to sustain their ROA in a volatile market. Furthermore, to isolate these main effects and identify boundary conditions, the model integrates Firm Size and Leverage as control constructs, accounting for economies of scale and structural funding risks, respectively.

2.1. Hypothesis or Proposition Development

Aggregate Fintech Expansion and Profitability

The modern financial landscape positions non-bank technological innovations as a catalyst for structural change. Aggregate Fintech Expansion is conceptualized as the total volume of funds disbursed by national Peer-to-Peer (P2P) lending platforms, representing the magnitude of fintech intervention in the banking market. Theoretical debates present two opposing mechanisms: the substitution effect (disruption) and the complementary effect (synergy) (Nguyen, 2021; Tarawneh et al., 2024). While traditional views suggest fintech erodes market share, recent collaborative frameworks indicate that banks act as institutional lenders for P2P platforms via channeling schemes. This synergy allows banks to penetrate unbanked sectors without incurring high customer acquisition costs, thereby transforming external digital disruption into a new revenue stream (Thakor, 2020; Vives, 2019). Based on this synergistic mechanism, the proposed hypothesis is directional:

H1. Aggregate fintech expansion has a positive effect on the Return on Assets (ROA).

Electronic Transaction Intensity and Profitability

As a strategic response to digitalization, banks undergo operational transformations, captured by the construct of Electronic Transaction Intensity. This reflects the shift in customer behavior from conventional to digital channels (e-channels), driven by the TAM constructs of perceived ease of use and usefulness (Ashoer et al., 2024). The theoretical mechanism underlying this relationship is based on the trade-off theory and operational efficiency. Ideally, a high volume of digital transactions acts as a catalyst to reduce conventional operational costs (cost center reduction), thereby boosting profitability (Theiri & Hadoussa, 2024; Berisha & Rayfield, 2025). Although early adoption phases may encounter the "IT Productivity Paradox"—where massive capital expenditures on IT infrastructure temporarily suppress net margins—the theoretical consensus posits that digitalization ultimately generates long-term economies of scale. Therefore, the hypothesis is formulated as follows:

H2. Electronic transaction intensity has a positive effect on the Return on Assets (ROA).

Non-Performing Asset Ratio and Profitability

In executing their intermediation function, banks are constantly exposed to inherent risks, operationalized as the Non-Performing Asset Ratio. This construct measures the percentage of credit facilities in arrears or default relative to the total credit portfolio, serving as a primary barometer of asset quality (Saunders & Cornett, 2018). The theoretical mechanism, grounded in Credit Risk Theory, is deductive and strictly penalizing. The deterioration of asset quality triggers a multiplier effect on profit contraction: it not

only halts expected interest income but also triggers regulatory boundary conditions requiring banks to freeze a portion of their retained earnings as Allowance for Impairment Losses (Diaz, 2025; Fahmi, 2020). This mandatory provisioning aggressively depletes net operational profit. Hence, the hypothesis posits a clear negative direction:

H3. Non-performing asset ratio has a negative effect on the Return on Assets (ROA).

Simultaneous Effect on Profitability

In addition to the isolated partial effects, the structural integration of external ecosystem pressures, internal digital adaptation, and risk mitigation collectively shapes the overall financial resilience of a bank. Evaluating these constructs simultaneously is crucial to understanding the holistic impact of modern banking dynamics on profitability. Therefore, the simultaneous hypothesis is formulated as follows:

H4. Aggregate fintech expansion, electronic transaction intensity, and non-performing asset ratio simultaneously have a significant effect on the Return on Assets (ROA).

3. Method

3.1. Research Design

This study employs a quantitative paradigm with a causal-explanatory research approach. The research design is structured to empirically test the causal relationships between external technological disruption, internal digital adaptation, risk mitigation, and financial performance. The unit of analysis is the institutional level, specifically publicly listed banking companies in Indonesia. The selection of a quantitative panel data design is justified as it provides a robust, holistic framework to simultaneously capture the dynamics of cross-sectional differences among banks and time-series fluctuations over the observation period.

3.2. Population, Sample, and Data Collection

The target population comprises all banking companies actively listed and traded on the Indonesia Stock Exchange (IDX) during the observation period of 2020 to 2024. The selection of publicly traded banks as the sampling frame is justified by the availability of transparent, independently audited annual financial reports, thereby minimizing information bias (Kasmir, 2018). From an initial population of 46 banking companies, a non-probability purposive sampling technique was employed. This technique focuses on specific inclusion and exclusion criteria to ensure the selected specimen has empirical relevance and strong representation of the operational phenomena being tested (Sugiyono, 2019).

The criteria stipulate that companies must not have engaged in corporate actions such as mergers during the study period (to prevent the distortion of asset structures) and must have consistently disclosed complete data for all research variables. Based on this screening, one company was excluded due to a merger, leaving 45 banking entities and generating 225 initial firm-year observations across the five-year period. Furthermore, 64 observations were excluded due to incomplete secondary data. Consequently, the final valid sample size ready for panel data regression estimation is 161 observations. Data collection was conducted retrospectively using archival data from official annual reports and national financial statistics.

3.3. Measures and Operationalization

As this study utilizes secondary macro-financial and corporate data, the constructs are operationalized using standardized financial ratios, substituting the need for traditional survey scale validation (validity and reliability) with statutory audit assurances provided by independent public accountants.

Table 1. Operational Definition and Measurement of Variables

Variable	Definition	Measurement
Return on Assets (Dependent Variable / Y)	Measures the extent to which total assets managed by the bank's management can efficiently revolve and convert into net profit.	$ROA = (\text{Net Income} / \text{Total Assets}) \times 100\%$
Aggregate Fintech Expansion (Independent Variable / X1)	Measures the total accumulated volume of funds disbursed by national P2P lending platforms, representing the magnitude of fintech intervention in the banking market.	Total National P2P Loan Disbursements
Electronic Transaction Intensity (Independent Variable / X2)	Measures the shift in customer behavior from conventional to digital services, reflecting the utilization of banking technology.	Nominal Value of Electronic Transactions / Total Assets
Non-Performing Asset Ratio (Independent Variable / X3)	Measures the percentage of credit facilities in arrears or default relative to the entire credit portfolio, representing default risk.	Total Non-Performing Loans / Total Disbursed Credit
Firm Size (Control Variable)	Measures the scale or aggregate size of the company based on its total assets.	Natural Logarithm (Ln) of Total Assets
Leverage (Control Variable)	Measures the intensity of debt utilization within the company's capital structure.	$Lev = (\text{Total Debt} / \text{Total Assets}) \times 100\%$

Note. This table outlines the operational definitions and measurement formulas for the dependent, independent, and control variables used in the panel data regression model. The variables are constructed using secondary data derived from audited annual reports and national macroeconomic statistics.

3.4. Analytical Procedure

The analytical procedure employs panel data multiple linear regression to accommodate the combined time-series (2020–2024) and cross-sectional nature of the dataset. Data estimation and processing were conducted using statistical software, such as the Statistical Package for the Social Sciences (SPSS). The analysis systematically proceeds through three stages. First, descriptive statistics (minimum, maximum, mean, and standard deviation) are generated to map the data distribution. Second, model specification and robustness are evaluated through a series of classical assumption tests including residual normality, multicollinearity, heteroscedasticity, and autocorrelation tests ensuring the model parameters are free from econometric bias and satisfy the Best Linear Unbiased Estimator (BLUE) criteria. Missing data issues were resolved during the sampling phase via listwise deletion (resulting in the exclusion of 64 incomplete observations). Finally, hypothesis testing is executed via individual parameter significance tests (t-tests) to prove the direction, magnitude, and partial significance of the independent and control variables on ROA.

3.5. Ethics and Data Governance

Since this study relies entirely on secondary, publicly available macroeconomic data and audited corporate annual reports accessed via the Indonesia Stock Exchange (IDX) and relevant financial authorities, institutional ethical approval and informed consent were not required. No human subjects were directly involved, and no personally identifiable information was processed, inherently ensuring strict privacy protections. Data availability is transparent, as the utilized financial datasets can be publicly accessed and independently verified by third parties for research replication purposes.

4. Results

4.1. Sample Selection

This study observes the banking sector listed on the Indonesia Stock Exchange (IDX) for the 2020–2024 period. The sample selection process employed a purposive sampling method based on predetermined criteria, the results of which are detailed in Table 2.

Table 2. Sample Selection Criteria

Sample Criteria	Total
Banking companies listed on the IDX during 2020–2024	46
Companies undergoing mergers during the observation period	(1)
Total Eligible Banking Companies	45
Total Initial Observations (45 banks × 5 years)	225
Observations excluded due to incomplete data	(64)
Final Valid Research Sample	161

Note. This table outlines the purposive sampling stages. From an initial population of 46 banks, 1 entity was excluded due to corporate merger actions, and 64 firm-year observations were removed due to incomplete data disclosures, resulting in a final panel data sample of 161 observations.

4.2. Descriptive Statistics

Descriptive statistics were conducted to map the distribution, central tendency, and dispersion of the data across the 161 valid observations, as presented in Table 3.

Table 3. Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Return on Assets (ROA)	161	-1.43	3.93	1.2742	1.03514
Aggregate Fintech Expansion	161	0.00	1.00	0.3000	0.45900
Non-Performing Asset Ratio	161	0.00	5.69	2.6260	1.22260
Electronic Transaction Intensity	161	2.71	5.79	4.3168	0.61435
Firm Size	161	15.50	21.61	18.1300	1.61031
Leverage	161	0.61	0.92	0.8064	0.06996

Note: Descriptive statistics of the variables used in the panel data regression.

The descriptive analysis reveals that the dependent variable, Return on Assets (ROA), has a mean value of 1.2742% (ranging from -1.43% to 3.93%), indicating relatively dynamic profitability resilience among the sampled banks. For the independent variables, Aggregate Fintech Expansion averages 0.30, while the Non-Performing Asset Ratio and Electronic Transaction Intensity record mean values of 2.6260 and 4.3168, respectively. The control variables demonstrate an average Firm Size of 18.1300 and a Leverage posture of 0.8064. Overall, the standard deviations for the majority of the variables are smaller than their respective means, reflecting a reasonable and homogenous data distribution without extreme outliers that could disrupt the stability of the econometric model.

4.3. Classical Assumption Tests

To ensure the regression model fulfills the Best Linear Unbiased Estimator (BLUE) criteria, a series of classical assumption tests were performed.

Table 4. Normality Test (One-Sample Kolmogorov-Smirnov Test)

		Unstandardized Residual
N		161
Normal Parameters	Mean	0.0000000
	Std. Deviation	0.71043454
Most Extreme Differences	Absolute	0.070
	Positive	0.070
	Negative	-0.059
Test Statistic		0.070
Asymp. Sig. (2-tailed)		0.052
Monte Carlo Sig. (2-tailed)	Sig.	0.052
	99% Confidence Interval Lower Bound	0.046

Note: The normality test uses the Monte Carlo significance method to assess the distribution of the regression residuals.

Based on Table 4, the normality test on the unstandardized residuals yields an Asymptotic Significance (2-tailed) and a Monte Carlo Significance of 0.052. Because this value exceeds the standard error tolerance threshold ($\alpha = 0.05$), the residuals are confirmed to be normally distributed. This validates that the data is symmetrically distributed and free from extreme variance bias, making the parameter estimation reliable for hypothesis testing.

Table 5. Multicollinearity Test

Model	Collinearity Statistics	
	Tolerance	VIF
1 (Constant)		
Aggregate Fintech Expansion	0.823	1.216
Non-Performing Asset Ratio	0.918	1.089
Electronic Transaction Intensity	0.784	1.275
Firm Size	0.860	1.163
Leverage	0.910	1.098

Note: Assessment of multicollinearity among independent and control variables.

Table 5 demonstrates the absence of strong linear correlation among the explanatory variables. The Collinearity Statistics reveal that all independent and control variables consistently exhibit a Tolerance value greater than the 0.10 threshold. Concurrently, the Variance Inflation Factor (VIF) outputs are ideally distributed well below the maximum limit of 10 (ranging from 1.089 to 1.275). Satisfying these criteria empirically confirms that the regression model is free from multicollinearity, ensuring that each variable is orthogonal and reliable for estimating ROA without information overlap.

Table 6. Heteroscedasticity Test

Model	t	Sig.
1 (Constant)	2.797	0.006
Aggregate Fintech Expansion	0.657	0.512
Non-Performing Asset Ratio	-1.491	0.138
Electronic Transaction Intensity	-1.089	0.278
Firm Size	-0.375	0.708
Leverage	-0.914	0.362

Note: Heteroscedasticity assessment using the Glejser test (regressing independent variables against absolute residuals).

As shown in Table 6, the evaluation of heteroscedasticity indicates that none of the independent or control variables have a statistically significant effect on the absolute residuals. The probability (Sig.) values for Aggregate Fintech Expansion (0.512), Non-Performing Asset Ratio (0.138), Electronic Transaction Intensity (0.278), Firm Size (0.708), and Leverage (0.362) all far exceed the standard 0.05 significance level. This confirms that the variance of the residuals remains constant across observations (homoscedasticity), fulfilling a critical prerequisite for a robust linear estimation.

Table 7. Autocorrelation Test

Model	Durbin-Watson
1	1.004

Note: The Durbin-Watson statistic assesses the presence of serial correlation in the residuals.

The autocorrelation assumption is evaluated using the Durbin-Watson (DW) statistic, yielding a coefficient of 1.004. Theoretically, a DW value substantially deviating from the ideal equilibrium of 2 (and trending closer to 0) strongly indicates the presence of persistent positive autocorrelation within the estimation. This confirms that observational errors (residuals) in a given period are systematically correlated

with prior periods, a common phenomenon in time-series and panel data structures. This condition suggests the necessity for further methodological interventions such as Generalized Least Squares (GLS) or the inclusion of lag variables to normalize error distribution in future model refinements.

4.4. Hypothesis Testing and Model Fit

The structural relationships and causal determinations are evaluated through multiple linear regression analysis, simultaneously and partially.

Table 8. F-Test (Simultaneous Significance Test)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	90.687	5	18.137	34.813	0.001
	Residual	80.755	155	0.521		
	Total	171.442	155			

Note: Evaluates the collective ability of all independent and control variables in explaining the dependent variable (ROA).

Based on the simultaneous significance test (F-Test) presented in Table 8, the calculated F-statistic is 34.813 with a probability level (Sig.) of 0.001. Because the significance value falls significantly below the $\alpha = 0.05$ threshold, the statistical hypothesis stating a simultaneous effect is accepted. This confirms that all estimated explanatory variables collectively possess a significant capacity to determine the fluctuations in the Return on Assets. This result validates the model's goodness of fit, affirming its reliability in predicting banking profitability dynamics.

Table 9. Coefficient of Determination

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.727	0.529	0.514	0.72180

Note: Indicates the proportion of the variance in ROA that is predictable from the independent variables.

The explanatory power of the structural model is assessed via the Coefficient of Determination. Table 9 shows an Adjusted R-Square value of 0.514. This implies that 51.4% of the variance in ROA is comprehensively explained by the interaction of aggregate fintech expansion, electronic transaction intensity, asset quality, firm size, and leverage. The remaining 48.6% represents residual variance determined by other macroeconomic or managerial dimensions outside the scope of this study.

Table 10. T-Test (Partial Significance Test)

Model	Unstandardized Coefficients	Std. Error	Standardized Coefficients	t	Sig.
	B		Beta		
1 (Constant)	-2.906	0.858		-3.386	0.001
Aggregate Fintech Expansion	0.344	0.137	0.153	2.511	0.013
Non-Performing Asset Ratio	0.294	0.049	-0.347	-6.037	0.001
Electronic Transaction Intensity	-0.061	0.105	-0.036	-0.586	0.559
Firm Size	0.427	0.038	0.664	11.165	0.001
Leverage	-3.249	0.855	-0.220	-3.800	0.001

Note: Evaluates the individual causal determination of each independent and control variable on ROA.

The partial hypothesis testing (T-Test) in Table 10 demonstrates significant causal dynamics for the majority of the observed variables. Aggregate Fintech Expansion is proven to positively and significantly determine profitability, indicated by an unstandardized coefficient (B) of 0.344 with a significance level of 0.013 ($\alpha < 0.05$). Conversely, the Non-Performing Asset Ratio confirms a highly significant negative effect (Sig. 0.001, t-value -6.037), asserting that credit quality deterioration severely degrades profit resilience. Meanwhile, Electronic Transaction Intensity fails to demonstrate a significant partial effect, as its probability

value (0.559) exceeds the standard tolerance threshold. Furthermore, the control variables confirm solid determination at the 0.001 significance level: Firm Size positively impacts profitability ($B = 0.427$), whereas aggressive external debt reliance, proxied by Leverage, exerts sharp negative pressure on profitability ($B = -3.249$).

5. Discussion

The empirical findings present a nuanced mechanism of modern banking profitability, heavily influenced by digital disruption, technological transition, and risk mitigation. Contrary to the traditional "Disruption Innovation Theory," which postulates that fintech penetration erodes market share and degrades conventional bank profitability, this study finds a positive and significant effect of Aggregate Fintech Expansion on Return on Assets (ROA). This finding robustly supports the "Complementary and Synergy Theory." The theoretical mechanism driving this outcome is a strategic orientation shift; rather than competing frontally in high-risk micro-retail credit segments, banks have repositioned themselves as institutional lenders for Peer-to-Peer (P2P) platforms via channeling schemes. This collaborative mechanism allows banks to aggressively expand credit to unbanked and underbanked sectors without incurring exorbitant customer acquisition costs, effectively transforming the disruption threat into diversified interest revenue.

Conversely, Electronic Transaction Intensity fails to demonstrate a significant determination on ROA. This finding challenges the initial hypothesis that digitalization inherently leads to immediate cost efficiency and profit acceleration. This insignificance is theoretically justified through the lens of the "IT Productivity Paradox." The escalation of electronic transaction volume is constantly accompanied by drastic surges in operational and capital expenditures (OPEX and CAPEX) for network infrastructure upgrades, cybersecurity enhancements, and system interconnectivity. Consequently, the high depreciation and maintenance costs create a trade-off that offsets the marginal potential of fee-based income. This establishes a critical boundary condition: during the observational period, banks are still trapped in the infrastructure transition phase, failing to reach the economies of scale required to substantially drive core net profit.

Furthermore, aligning with the fundamental expectations of Credit Risk Theory, the Non-Performing Asset Ratio exerts a highly significant negative effect on ROA. The theoretical mechanism operates through a dual multiplier effect on operational profit contraction: the cessation of projected interest liquidity and the regulatory mandate to allocate retained earnings into an Allowance for Impairment Losses. This mandatory provisioning aggressively depletes net operational profit. Finally, the integration of control variables establishes further boundary conditions: Firm Size positively dictates profitability through economies of scale, while aggressive Leverage significantly compresses net interest margins due to high fixed-charge costs stemming from external debt reliance.

5.1. Theoretical Contributions

Prior to this study, existing literature largely evaluated the fintech-banking nexus through a fragmented, zero-sum paradigm, predominantly relying on Disruption Theory to predict market share cannibalization. This study extends and refines the existing theoretical landscape by simultaneously integrating external ecosystem pressures, internal digital adaptation, and risk mitigation.

First, the findings challenge the absolute applicability of Disruption Theory in emerging financial markets, refining it by empirically validating the Complementary and Synergy Theory; fintech platforms serve as an extension of banking intermediation infrastructure rather than mere substitutes. Second, by identifying the insignificance of electronic transactions on profitability, this study integrates the IT Productivity Paradox into the banking digitalization discourse. It extends the theoretical understanding that technological acceptance does not linearly equate to financial efficiency during transitional maturity phases, explaining what prior models which assumed immediate cost reductions from digital adoption failed to capture.

5.2. Managerial and Policy Implications

The empirical evidence translates into actionable strategic decisions for banking executives and regulatory bodies. For bank management, particularly the Board of Directors and Credit Committees, the findings dictate a strategic imperative to scale up collaborative channeling partnerships with registered P2P lending platforms, leveraging them as cost-efficient acquisition engines rather than attempting direct, high-risk micro-lending. Concurrently, Chief Information Officers (CIOs) must rigorously calibrate IT capital expenditures; digitalization strategies must pivot from merely chasing transaction volume to optimizing the Return on Investment (ROI) of technological infrastructure to overcome the IT Productivity Paradox. Additionally, risk management divisions must strictly tighten credit scoring protocols to suppress non-performing assets, as default risks remain the most destructive force to firm value.

For policymakers and financial supervisory authorities (such as the Financial Services Authority / OJK), the evidence underscores the necessity of formulating accommodating regulations that govern hybrid financial ecosystems. Authorities should design regulatory sandboxes and risk-sharing frameworks that protect inter-institutional channeling schemes while incentivizing shared digital infrastructure. Such resources and regulatory conditions are expected to accelerate the banking sector's transition out of the IT Productivity Paradox toward true economies of scale and sustainable financial stability.

6. Conclusion

This study aimed to empirically examine the simultaneous and partial effects of aggregate fintech expansion, electronic transaction intensity, and asset quality mitigation on the profitability of the banking sector. Addressing this objective directly, the empirical results conclude that the structural dynamics of fintech ecosystem pressures, internal digital adaptation, and default risk management collectively determine the fluctuations in banking Return on Assets (ROA). Partially, this study concludes that aggregate fintech expansion exerts a positive and significant effect on banking profitability. This affirms that the banking sector has successfully leveraged fintech platforms through collaborative channeling schemes, turning external disruption into a profitable synergy. Conversely, electronic transaction intensity does not significantly affect profitability, confirming that banks are currently experiencing the IT Productivity Paradox, where massive technological infrastructure costs offset the short-term financial gains from digital transactions. Furthermore, consistent with fundamental risk theories, the non-performing asset ratio has a highly significant negative effect on ROA, acting as the primary destructor of profit due to the loss of interest income and mandatory impairment provisioning. Finally, the control variables confirm that larger firm size strengthens profitability through economies of scale, while aggressive reliance on external debt (leverage) compresses financial performance.

6.1. Limitations and Future Research

Despite providing a robust integrative framework, this study acknowledges several limitations that serve as boundary conditions for the findings, subsequently opening specific avenues for future research. First, the explanatory power of the structural model is bounded at an Adjusted R-Square of 51.4%, indicating that nearly half of the variance in banking profitability remains unexplained by the current constructs. Future research should expand the model's boundary conditions by integrating external macroeconomic indicators (such as inflation and central bank benchmark interest rates) and internal Good Corporate Governance (GCG) metrics to capture a more exhaustive determinant framework.

Second, the findings are constrained by a five-year observation period (2020–2024). This timeframe bounds the empirical evidence to a transitional phase of digitalization and post-pandemic economic recovery, which justifies the observed IT Productivity Paradox but may not reflect long-term technological maturity. Future studies must extend the longitudinal observation window to a decade or more to accurately capture the long-term payoff and economies of scale of banking IT investments.

Finally, the econometric boundary condition is marked by the presence of serial correlation in the residuals, as indicated by a Durbin-Watson statistic of 1.004. This suggests that static panel data approaches may not perfectly isolate time-dependent error variances. Therefore, it is highly recommended that future research adopts dynamic panel data estimators, specifically the Generalized Method of Moments (GMM), to effectively resolve autocorrelation issues, accommodate endogeneity, and capture the time-lagged behavioral effects of digital investments on profitability.

Declarations

Declaration	Required statement
Author contributions	Use the CRediT roles: Conceptualization, Methodology, Data Curation, Formal Analysis, Investigation, Writing, Supervision, Funding Acquisition, and others as applicable.
Funding	State funder and grant number, or “This research received no external funding.”
Conflict of interest	State conflicts or “The authors declare no conflict of interest.”
Data availability	Provide repository/link, justified restriction, or statement that data are available on reasonable request.
Ethics approval	State committee, reference number, and consent process where applicable.
AI use disclosure	Disclose generative AI use for language support or other permitted tasks. Authors remain accountable for all content.
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Technical formatting

Item	Requirement
File	Microsoft Word .docx
Page size	A4
Font	Cambria 11 pt body; headings according to template
Spacing	1.15; 6 pt after paragraphs
Length	Normally 6,000-9,000 words for research articles; other types according to editorial policy
Tables and figures	Editable, numbered consecutively, cited in text, source and notes provided
Language	Academic English, proofread before submission
Similarity	Original work; similarity is evaluated contextually and not solely by a percentage threshold