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TRANSFORMING FINANCIAL RISK MANAGEMENT AND OPERATIONAL EFFICIENCY: THE IMPACT OF AI ADOPTION IN INDONESIAN BANKS

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Abstract

This study investigates the impact of Artificial Intelligence (AI) adoption on operational efficiency and financial risk management in six major Indonesian banks: BNI, BRI, BCA, Danamon, Mandiri, and CIMB Niaga. The research implements Difference-in-Difference (DiD) methodology coupled with Bayesian Vector Autoregression (BVAR) Scenario Testing to assess how AI affects financial indicators comprising NPLs, ROA, CAR, and LDR. The study shows that AI adoption yields minor, immediate results but does not produce substantial improvements in financial performance or risk management when moving beyond Level 3. AI improves operational performance by enabling automated processes and optimised decision-making, leading financial institutions to enhance their fraud detection, credit risk management, and liquidity risk management. The study demonstrates the value of implementing AI through an orderly strategic plan while mandating that organisations establish rules and ethical guidelines for AI use throughout its adaptation stages. The implementation of AI by Indonesian banks offers multiple prospects to enhance their operational performance, risk management capabilities, and financial stability over the years.

Keywords: *artificial intelligence, financial technology, banking digitalisation, operational efficiency, risk management, Indonesian banks, scenario testing*

I. INTRODUCTION

Artificial Intelligence (AI) is among the most rapidly developing technologies across different industries in recent years, and the banking sector was not an exception (Umamaheswari, Valarmathi 2023). The banking industry in Indonesia, a crucial part of the state economy, is faced with a variety of challenges related to optimising operational efficiency, mitigating multifaceted financial risks, and improving service quality. AI also offers an unprecedented opportunity for Indonesian banks to not only automate daily processes but also innovate in key areas, including customer service, risk management, and the development of new financial products and services.[1]

The banking industry can use AI to process large volumes of data, thereby helping financial organisations identify emerging trends, make data-driven decisions, and streamline various activities. The benefits of AI implementation are multifaceted, resulting in increased productivity, better decision-making, cost savings, and a better customer experience. Hence, the banking and financial services industry would benefit from the application of AI to provide tools for more effective data management, risk prediction, and customer service delivery.[2] With such technologies, Indonesian banks should be able to streamline decision-making, continue developing their financial risk management methods, and improve their operational performance.

One of the most significant aspects of AI in the banking industry is its application to enhance financial risk management. There are market risk, operational risk, and credit risk that require institutions to keep a vigilant eye on the field and manage these risks, and AI can provide a highly effective means of improving risk evaluation. Using credit risk as an example, indicators such as the Non-Performing Loan (NPL) ratio will be used to evaluate the level of non-performing debts. Similarly, Return on Assets (ROA) is regarded as the standard method for measuring market risk, and operational risk is measured by Risk-Weighted Assets (RWA).[3] AI enables banks to assess these risks more accurately, thereby enhancing the Capital Adequacy Ratio (CAR) and overall financial stability.[4]

Some of the major Indonesian banks, including Bank Mandiri, Bank Negara Indonesia (BNI), Bank Rakyat Indonesia (BRI), Bank Central Asia (BCA), CIMB Niaga, and Danamon, have already implemented AI in different areas of their operations, including fraud detection, customer service, credit risk analysis, etc. Indeed, AI-enabled chatbots will be deployed to address

[1] Rita Jain, "Role of Artificial Intelligence in Banking and Finance," *Journal of Management and Science* 13, no. 3 (2023): 1–4, https://doi.org/10.26524/jms.13.27.

[2] Amer Awad Alzaidi, "Impact of Artificial Intelligence on Performance of Banking Industry in Middle East," *IJCSNS International Journal of Computer Science and Network Security* 18, no. 10 (2018): 140, http://paper.ijcsns.org/07_book/201810/20181021.pdf; Dede Arisko Agustiawan, "Digital Banking Transformation AI Enhances Efficiency and Customer Experience Seminar Perspective Industry," *WACANA: Jurnal Ilmiah Ilmu Komunikasi* 23, no. 1 (2024): 191–200, https://journal.moestopo.ac.id/index.php/wacana/article/view/4130/1579.

[3] Nitin Liladhar Rane et al., "Artificial Intelligence-Driven Corporate Finance: Enhancing Efficiency and Decision-Making Through Machine Learning, Natural Language Processing, and Robotic Process Automation in Corporate Governance and Sustainability," *Studies in Economics and Business Relations* 5, no. 2 (2024): 1–22, https://doi.org/10.48185/sebr.v5i2.1050.

[4] José Xiaoan Zhan et al., "Driving Efficiency and Risk Management in Finance through AI and RPA," *Journal of Advanced Computing Systems* 4, no. 5 (2024): 1-9, https://doi.org/10.69987/JACS.2024.40501.

customer queries more often, and machine learning algorithms will be optimised to enhance the precision and effectiveness of lending decisions. These are AI systems that can handle large volumes of data, enabling banks to make better-informed investment decisions, improve their fraud-prevention models, and streamline risk-management operations.[5]

The six major Indonesian banks examined in the study include BRI and BCA. The rationale behind the choice of the banks is the significance of their contribution at the national level and the big influence they have on asset financing and their impact on customers. Our sample, comprising six major conventional banks, allows us to conduct a comparative analysis of various risk management practices. Furthermore, these banks are not similar because they are trendsetters in digital transformation, where their use of technology in approaches to enhancing risk governance and operational efficiency is innovative. Such banks are particularly suitable when one wants to conduct a research project because of the detailed data transparency and strong compliance with regulations. Such banks should be examined for their significant contributions to financial stability and policy orientation, which will advance risk management methods and the strength of actions within the Indonesian banking sector.

Besides enhancing financial performance, the use of AI has also led to a substantial increase in operational efficiency by automating routine tasks. This has enabled banks to reduce the time taken to execute transactions, manage their accounts, and carry out better data analysis, which has led to reduced operational costs and increased productivity. This automation also enables the worker to concentrate on more strategic, value-added work, further improving the bank's efficiency and customer satisfaction.[6]

Although these benefits are numerous, there are challenges associated with adopting AI in Indonesian banks. Employee resistance to automation is one of the major barriers because the workers are afraid of losing their jobs or being relocated to other positions as AI systems take over manual jobs. Moreover, AI systems, especially deep learning-based ones, are usually more correct than human decision-makers and are not able to justify their decision-making process. Such a deficiency in transparency may lead to prejudices and fallacies when making key decisions, particularly critical ones, such as the management of credit risk.[7]

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[5] Jain, "Role of Artificial Intelligence."

[6] Agustiawan, "Digital Banking Transformation."

[7] Ahmad Ghandour, "Opportunities and Challenges of Artificial Intelligence in Banking: Systematic Literature Review," *TEM Journal* 10, no. 4 (2021): 1581–1587, https://doi.org/10.18421/TEM104-12.

Additionally, the digital divide is another issue with the adoption of AI in banking, particularly in a country with a diverse and economically diverse population such as Indonesia. Although urban clients are also embracing AI-based banking services at a very high rate, lower-socioeconomic clients might lack digital literacy and access to these services. This might create an access disparity in financial services, which ultimately impacts customer loyalty and satisfaction.[8] Moreover, there are data privacy issues because AI use requires large amounts of customer information, which may be at risk of hacking unless effectively safeguarded. To reduce such risks, banks should adopt strong data protection policies that would consider the privacy regulations.[9]

The purpose of this paper is to discuss how AI can make operations in the Indonesian banking industry more efficient and less financially risky. Using case studies of major Indonesian banks, including Bank Mandiri, BNI, BRI, BCA, CIMB Niaga, and Danamon, this paper discusses the banks' use of AI and evaluates its effects on their performance. The results will be useful for understanding the practical issues and value of applying AI in the real world and will provide recommendations for Indonesian banks to make them more competitive amid rapid, sustainable technological change.

To address these gaps, this paper provides a comprehensive understanding of the role of AI in the Indonesian banking industry, shedding light on its long-term effects on banks' operational performance, financial risk, and overall banking performance.

II. LITERATURE REVIEW

With AI, banking institutions have experienced a revolution focused on achieving high levels of operational excellence, lower expenses, and improved customer service. The integration of machine learning-based AI and natural language processing (NLP) and automated processes has spawned tsunamis in the manner the banks are run and supported by systems as well as financial measurement systems. The application of AI has had a positive effect on performance indicators such as Cost-to-Income Ratio (CIR), ROA, Loan-to-Deposit Ratio (LDR), and credit growth indicators. The use of AI led to drastic changes in four financial risk indicators: NPL, Capital CAR, Risk-Weighted Assets (RWA), and Total Assets (TA). Banks have optimised workflows and decision-making systems to improve customer interactions in the same way

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8 Ghandour, "Opportunities and Challenges."

9 David Mhlanga, "Industry 4.0 in Finance: The Impact of Artificial Intelligence (AI) on Digital Financial Inclusion," *International Journal of Financial Studies* 8, no. 3 (2020): 1–14, https://doi.org/10.3390/ijfs8030045.

through recent advancements. These measures show that AI promotes cost savings and plays an essential role in the development of risk management and credit transformation.[10]

AI enhances CIR performance, helping banks improve their operational efficiency in cost and income. When a bank has a lower CIR ratio, it is more efficient in its operations, as it indicates it is performing better in competitive markets. The introduction of AI-based automation systems is one of the main factors in CIR reduction, as it reorganises workflows, reduces opportunities for human interaction in routine work, and optimises customer service processes.[11] Current activities rely on multiple AI chatbots and virtual assistants to respond to customer queries and minimise the need for human customer support agents, thereby reducing staffing costs and delivering high-quality service. The combination has been critical in ensuring that businesses reduce operational costs while maintaining a high level of customer satisfaction. Recent studies by Al-Ababneh et al.[12] and Tsapa[13] reveal that AI automation reduces CIR rates by enabling faster service delivery. These research studies combine interviews and case studies as qualitative methods to study the consequences of AI in the banking sector and utilise pre- and post-AI implementation financial performance metrics as a quantitative approach to estimate the effects on operational efficiency.

A more efficient AI system will be achieved through the integration of NLP tools, as they will automate the process of extracting information from customer communications, thus decreasing administrative workloads and increasing the time available to respond to communications. The combination of these technologies means that the banks can manage operations more effectively, consequently lowering their CIR. Studies by Akbary et al., Bahman Zohuri & Farhang Mossavar-Rahmani 14, and Fethi & Pasiouras 15 found that automation improves CIR. The comparisons were based on regression models to assess the impact of AI automation on cost efficiency and service delivery between AI-using and non-using banks.

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[10] Isolde Castillo-Martínez et al., "AI in Higher Education: A Systematic Literature Review," *Frontiers in Education* 9, no. 2 (2024), https://doi.org/10.3389/feduc.2024.1391485.

[11] Utsav Goswami and Rashi Mittal, "The Role of Artificial Intelligence in Financial Decision-Making," *International Journal of Scientific Research in Engineering and Management* 8, no. 4 (2024): 1–5, https://doi.org/10.55041/ijsrem32690.

[12] Hassan Ali Al-Ababneh et al., "Performance of Artificial Intelligence Technologies in Banking Institutions" *WSEAS Transactions on Business and Economics* 20 (2022): 307–317, https://doi.org/10.37394/23207.2023.20.29.

[13] Joseph Aaron Tsapa, "Predictive Analytics for Proactive Risk Management in FinTech Lending and Investment," *Journal of Artificial Intelligence & Cloud Computing* 3, no. 1 (2024): 1–4, https://doi.org/10.47363/JAICC/2024(3)309.

The significant boosts in CIR are due to AI, but the technology is fundamental to maximising such financial ratios as Loan-to-Deposit Ratio (LDR). LDR can be used to assess a bank's liquidity position by balancing deposits and loans. A bank must maintain a stable LDR to issue loans while managing liquidity risks. The key input of AI systems is manifested in the development of the process of credit and risk evaluation. This is because AI systems can analyse large volumes of traditional and non-traditional data to improve the evaluation process, which has relied on past data and subjective decisions in credit evaluation. AI has been successful in updating credit scoring models according to Alzaidi[14] and Al-Ababneh et al.,[15] which has led to improved lending accuracy as compared to conventional methods. The study used machine learning models that processed massive transaction and social media datasets, enabling banks to better determine the creditworthiness of their clients.

Early recognition of financial distress, such as AI-driven detection of abnormal spending, helps banks take preventive action to prevent potential loan defaults, thereby stabilising the LDR. The adoption of AI-powered analytics, replacing traditional risk assessment models, will be a significant shift in how banking institutions manage credit and ensure liquidity stability. Additionally, Zhan et al.,[16] Doumpos et al.,[17] and Barongo & Mbelwa[18] found that the indication of AI can be used to improve the management of liquidity and prediction. These research papers combined predictive analytics and live safety warnings, based on machine learning technology, to identify proactive changes indicating potential bank financial instability, enabling institutions to initiate remediation efforts before cases of default.

AI provides meaningful improvements to ROA, which evaluates the bank's performance in generating profits from its assets. The effectiveness with which AI systems handle assets will determine the extent to which they affect ROA. The AI platforms analyse large volumes of data to identify low-quality assets, enabling banks to allocate their resources to higher-return opportunities. The integration of AI with market forecast tools like those developed in Kou &

[14] Alzaidi, "Impact of Artificial Intelligence."

[15] Al-Ababneh et al., "Performance of Artificial Intelligence."

[16] Zhan et al., "Driving Efficiency."

[17] Michalis Doumpos et al., "Operational Research and Artificial Intelligence Methods in Banking," *European Journal of Operational Research* 306, no. 1 (2023): 1–16, https://doi.org/10.1016/j.ejor.2022.04.027.

[18] Rweyemamu Ignatius Barongo and Jimmy Tibangayuka Mbelwa, *Using Machine Learning for Detecting Liquidity Risk in Banks*, Machine Learning with Applications 15 (2024): 100511, https://doi.org/10.1016/j.mlwa.2023.100511.

Lu[19] and Milojević & Redzepagic[20] will help banks to make decisions based on the data and increase profitability. AI devices save assets by real-time monitoring of risk that protects the asset against changes in the market to earn more returns on assets. The empirical research, based on simulation models and econometric techniques, measured the effects of AI on financial resources and profitability, providing comprehensive information on AI-driven increases in ROA.

AI is immensely helpful in managing financial risk, as it improves the detection and prediction of risks in the banking sector. Powered by AI, AI analytics will enable financial institutions to generate indicators of default without considering actual borrower behavioural insights or economic data, thereby reducing NPL rates.[21] Machine learning models become more accurate when non-standard data points are used to evaluate risk and identify unsound borrowers earlier in the loan application process. The research used three AI technologies, including predictive analytics with machine learning and real-time data analysis, to assess AI risk prediction models aimed at reducing defaults and improving loan quality during financial stability.

Artificial intelligence contributes to improved CAR performance, as CAR is a crucial indicator of bank financial stability. AI also provides banks with accurate loss prediction tools and effective capital requirement monitoring, enabling them to develop an optimal capital placement strategy and improve financial stability in the face of unexpected events. AI provides accurate risk management, enabling banks to manage capital resources effectively and thereby improving the CAR.[22] Financial modelling AI programs associated with capital allocation modelling enable banks to produce superior forecasts and optimise balance sheet management of their capital requirements.

The role of AI is an important instrument to enhance the measurements of the CAR that defines the financial stability of banks. AI can enable banks to apply its analytical capabilities, which are powerful with large, real-time data,

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[19] Gang Kou and Tang Lu, "FinTech: A Literature Review of Emerging Financial Technologies and Applications," *Financial Innovation* 11, no. 1 (2025): 1–34, https://doi.org/10.1186/s40854-024-00668-6.

[20] Nedad Milojević and Srdjan Redzepagic, "Prospects of Artificial Intelligence and Machine Learning Application in Banking Risk Management," *Journal of Central Banking Theory and Practice* 10, no. 3 (2021): 41–57, https://doi.org/10.2478/jcbtp-2021-0023.

[21] Harsh Daiya, "AI-Driven Risk Management Strategies in Financial Technology," *Journal of Artificial Intelligence General Science (JAIGS)* 5, no. 1 (2024): 194–216, https://doi.org/10.60087/jaigs.v5i1.194; Alison Lui and George William Lamb, "Artificial Intelligence and Augmented Intelligence Collaboration: Regaining Trust and Confidence in the Financial Sector." *Information and Communications Technology Law* 27, no. 3 (2018): 267–283. https://doi.org/10.1080/13600834.2018.1488659.

[22] Carsten Maple et al., "The AI Revolution: Opportunities and Challenges for the Finance Sector," arXiv:2308.16538v1 (2023), https://arxiv.org/abs/2308.16538; Goswami and Mittal, "The Role of Artificial Intelligence."

to enhance the accuracy of risk assessments and forecasts of future capital requirements. Optimised strategies can also enable banks to distribute capital well due to this method, which gives them enough reserves in case of a loss. The integration of AI models can also help banks conduct more complex stress testing, allowing them to simulate different financial scenarios that will inform changes to their capital ratios (Metha et al., 2025). AI systems assist banks in identifying material risks early, allowing them to optimise their positions by adjusting capital in real time. This action will make them financially more robust. As Nallakaruppan et al. (2024) indicate, AI is more effective at monitoring instant credit and market risk, thereby supporting regulatory capital standards and reducing the probability of a capital deficit. Applying AI helps financial institutions better manage their capital, thereby enhancing their CAR values and establishing long-term financial stability amid changing financial conditions.

Asset management has also become a core use case for AI, as it has been applied to Industry 4.0, enabling greater connectivity of systems under Asset Administration Shell (AAS) schemes. This framework improves the interoperability of system data and enables better management of the asset lifecycle by enabling more effective predictive maintenance and optimising asset performance. According to Rauh et al.,[23] the implementation of AI enables superior asset monitoring, reduced downtime, and improved asset performance during operation.

AI-based models bring changes to the tracking and management of digital assets and therefore lead to a transformation of processes. The AI TRiSm (Trustworthy, Reliable, and Safe machine Learning) model provides procedures for ensuring that asset-monitoring AI models are efficient and safe while remaining fully accountable. The AI TRiSm system improves the quality of decisions on asset and resource distribution in industries that require precise asset monitoring. AI TRiSm has been proven effective at increasing the transparency and safety of AI systems operating in asset administration.[24]

The AI technology shows its usefulness as it enhances the management of both critical medical assets such as hospital facilities and medical equipment in healthcare facilities. The study of asset management in healthcare proves that AI increases the efficiency of maintaining the equipment and ordering resources to save money and improve their functionality. The AI solutions

[23] Lukas Rauh et al., "AI Asset Management: A Case Study with the Asset Administration Shell (AAS)." *2022 IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA)* (IEEE, 2022): 1–8, https://doi.org/10.1109/ETFA52439.2022.9921705.

[24] Pinyaphat Tasatanattakool et al., "Digital Asset Management Process Using AI TRiSM." *2024 IEEE International Conference on Cybernetics and Innovations (ICCI)* (IEEE, Chonburi, Thailand, 2024): 1–6, https://doi.org/10.1109/ICCI60780.2024.10532376.

optimise the use of healthcare facilities and reduce unforeseen equipment failures, keeping crucial medical devices on hand when medical services are needed.[25]

Machine learning is another crucial area of AI use in asset management since its algorithms give predictions on the value and trends of assets. Decision Trees, Random Forests, and Gradient-Boosted Trees are machine learning models that have competed against each other in predictive ability for asset value prediction. Recent studies have shown that Gradient-Boosted Trees models for machine-learning-based data prediction are the best tools that asset managers should utilise because of their high accuracy. High-level algorithms reinforce asset prospects and reduce risks in traditional management approaches.[26]

In terms of financial risk management, AI comes in handy by identifying illegal dealings. Real-time control of transaction data, enabled by AI-based systems, will allow them to identify suspicious transactions and facilitate better fraud detection. The implemented technologies help reduce financial risks from fraud and improve banking security. The models used to detect fraud were trained on historical data labelled to identify fraud, and AI algorithms updated their knowledge by processing new transaction data to increase accuracy. These models improve fraud detection over time, as they are supervised learning methods.

This is because the banking industry faces numerous challenges in the overall adoption of AI. The problem is that deploying state-of-the-art AI technologies would be complicated by banks' outdated legacy systems, which would require time-consuming, costly system transitions.[27] The problem of management of AI systems is that human resources become a significant problem, as many institutions, even small ones, do not have qualified professionals who could work and interpret such systems.[28] The dynamic aspect of AI surpasses the current regulatory measures as it introduces new data privacy, security, and ethical issues that hamper the adoption of AI, as per Petrone et al.[29] The

[25] Motheo Meta Tjebane and Innocent Musonda, "Artificial Intelligence in Healthcare Facilities Asset Information Management: Mixed Review," *Infrastructure Asset Management* 12, no. 2 (1015): 94-109, https://doi.org/10.1680/jinam.23.00033.

[26] Supansa Chaising et al., "Comparison of Machine Learning Algorithms for Prediction of Total Assets," *2023 International Conference on Cyber Management and Engineering (CyMaEn)* (IEEE, 2023): 255–259, https://doi.org/10.1109/CyMaEn57228.2023.10051085.

[27] Zhan et al., "Driving Efficiency."

[28] Ashima Narang et al., "Artificial Intelligence in Banking and Finance," *International Journal of Innovative Research in Computer Science and Technology* 12, no. 2 (2024): 130–134, https://doi.org/10.55524/ijircst.2024.12.2.23.

[29] Daniele Petrone et al., "An AI Approach for Managing Financial Systemic Risk via Bank Bailouts by Taxpayers," *Nature Communications* 13, no. 1 (2022): 1–18, https://doi.org/10.1038/s41467-022-34102-1.

barriers to implementation and costs do not allow smaller banks to adopt AI technologies, as they lack adequate financial resources to conduct system updates, provide long-term support, and train staff members.[30] The obstacles to AI adoption also create a knowledge gap regarding the long-term impacts of AI on financial systems. Many studies analyse the short-term advantages of AI, whereas researchers have not conducted an extensive investigation into the effects of AI on bank performance and long-term financial stability in relation to bank resilience. The existing sources are quite deficient in the necessary data on the long-term advantages of AI, as it is not known whether AI can retain its material benefits or see its outcomes decline.[31]

Research about AI adoption within emerging economies has not received adequate analysis. Research on implementing AI primarily centres on developed markets with advanced technological infrastructure, while neglecting the assessment of its applications in areas with limited resources, specific regulatory conditions, and lower levels of technological penetration.[32] AI ethics remains a pressing issue that must be addressed due to concerns about the transparency of computer decision-making and algorithmic discrimination in banking institutions. Researchers need to find methods for AI to operate without bias while maintaining clear decision-making so that discrimination does not continue, especially when processing loans and evaluating credit risk.[33] Energy companies should further examine banking regulatory standards to understand how they can meet compliance requirements as they develop innovative approaches to data privacy, security, and AI governance.[34]

The research employs mixed methods to examine how AI affects operational effectiveness and financial risk management functions across Indonesian banking institutions. The research uses Difference-in-Differences (DiD) estimation together with Bayesian Vector Autoregression (BVAR) for dynamic analysis and forecasting, and Scenario Testing to simulate different AI adoption levels. The study examines the BNI, BRI, BCA, Danamon, Mandiri, and CIMB Niaga large banks in Indonesia over the period 2009 to 2023. According to the assumptions, all of these banking institutions began to use AI systems in 2018. One of the studies examines the effects of AI on operational efficiency and risk management practices in finance, based on an

[30] Fethi and Pasiouras, "Assessing Bank Efficiency."

[31] Rane et al., "Artificial Intelligence-Driven Corporate Finance."

[32] Tajudeen Alaburo, "Artificial Intelligence (AI) in the Banking Industry: A Review of Service Areas and Customer Service Journeys in Emerging Economies." *Business & Management Compass* 68, no. 3 (2024): 19-43, https://doi.org/10.56065/9hfvrq20.

[33] Sanjay Moolchandani, "Advancements in Credit Risk Modelling: Exploring the Role of AI and Machine Learning," *International Journal of Management, IT & Engineering* 13, no. 3 (2023): 135–141.

[34] Petrone et al., "An AI Approach."

analysis of performance indicators and risk metrics. Through this method, the study will provide significant results regarding the long-term impacts of AI on the market in developing economies as well as elucidate the aspects of AI integration in the emerging markets and the complexity of ethics and regulations.

III. RESEARCH METHODOLOGY

The study is based on a mixed-methods research design to examine the effects of AI implementation in the banking sector on the operational efficiency of banks and financial risk management in Indonesia. The analysis will include DiD estimation and BVAR to perform dynamic analysis and forecasting, and Scenario Testing to simulate various levels of AI adoption. The research focuses on BNI, BRI, BCA, Danamon, Mandiri, and CIMB Niaga, the largest Indonesian banks, between 2009 and 2023. The assumption will be that all banking institutions will begin adopting AI systems in 2018. The study will examine the impact of artificial intelligence on operational effectiveness and financial risk management practices.

The source of data used in this study is the annual reports of the six banks, namely, BNI, Bank BRI, BCA, Bank Danamon, Bank Mandiri and CIMB Niaga, as well as publicly accessible data in the Central Bank of Indonesia (BI), bank websites and other relevant sources. The data are from 2009 to 2023, enabling the study to compare the pre- and post-implementation periods of AI. The dataset under study consists of several important variables. The table below outlines the key study variables:

Table 1.
Variable Descriptions

VARIABLES	TYPE	DEFINITIONS
Cost-to-Income Ratio (CIR)	Dependent	Reflects the efficiency of the bank in managing costs relative to income.
Return on Assets (ROA)	Dependent	Measures profitability relative to the bank's total assets.
Loan-to-Deposit Ratio (LDR)	Dependent	Indicates how much of the bank's deposits are being used for lending.
Credit Growth	Dependent	Measures the rate of increase in the bank's loan portfolio.
Non-Performing Loans (NPL)	Dependent	Measures the proportion of loans that are in default or close to default.
Capital Adequacy Ratio (CAR)	Dependent	Indicates the bank's capital strength relative to risk-weighted assets.
Risk-Weighted Assets (RWA)	Dependent	Reflects the total value of assets, weighted for their respective credit risks.
Total Assets (TA)	Dependent	Represents the total assets of the bank.

Table 1.
Variable Descriptions (Continued)

VARIABLES	TYPE	DEFINITIONS
AI Levels	Independent	The variable uses a binary scale from zero to three to measure banking operation AI adoption. Pre-adoption has zero value but post-adoption levels progress through Basic AI (1) to Moderate AI (2) and Advanced AI (3).
GDP Growth	Control	Measures the rate of economic growth in Indonesia.
Inflation	Control	Represents the inflation rate in Indonesia.
Interest Rate	Control	The prevailing interest rate in Indonesia.

In this study, data were collected on total assets to determine bank size, as well as on GDP growth, inflation, and interest rates as indicators of macroeconomic control. The data-gathering strategies in this study follow the guidelines used in all literature reviews that analyse the financial effect of AI on performance. The study variables are in line with existing research on the impact of technological adoption in banking, particularly regarding the performance ratios of cost-to-income, non-performing loans, and capital adequacy.

Figure 1.
General Trends

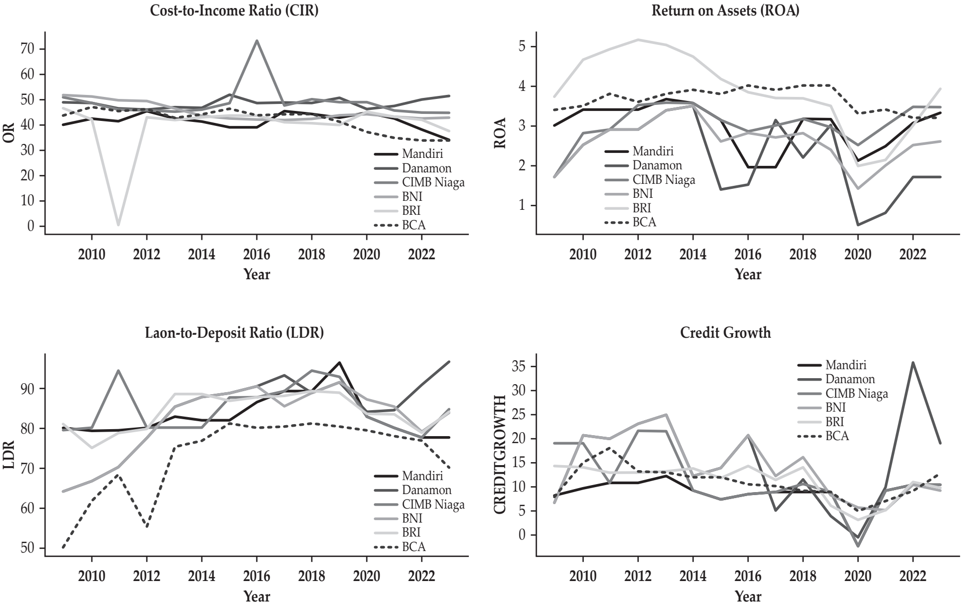
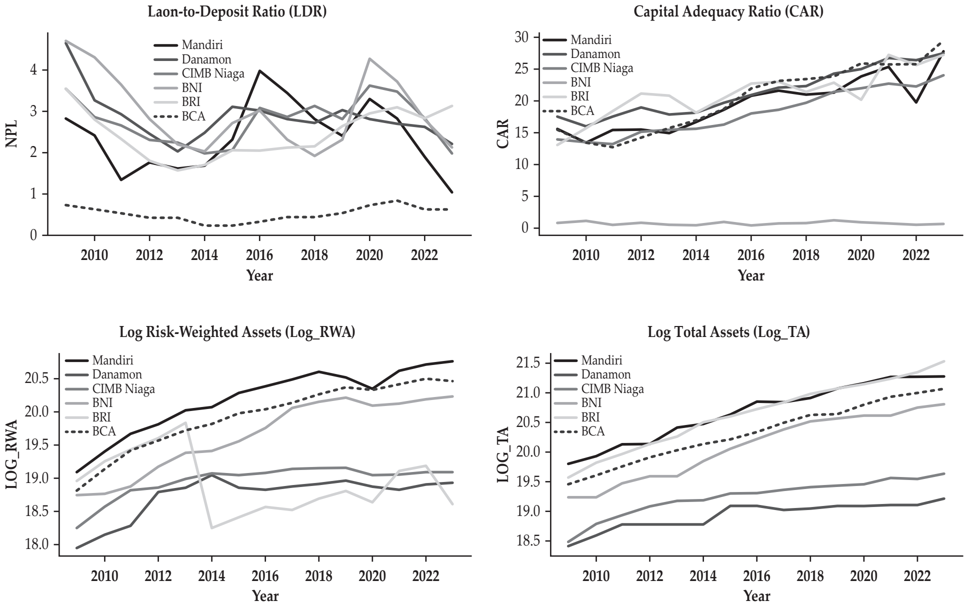


Figure 1.
General Trends (Continued)



Source: Data Proceed

The financial information used in the research highlights the major trends in banking performance over the period under study. The CIR is fluctuating amid efficiency gains and cost pressures, whereas the ROA is decreasing across most banks, indicating profitability difficulties, especially after 2015. The LDR is increasing in a similar direction, indicating that more and more banks are relying on deposits to issue loans. However, Credit Growth is volatile, with a sharp fall in the years starting in 2020 and a strong recovery in 2022, suggesting that some banks have been impacted by economic shocks.

NPLs exhibit cyclical characteristics in financial risk, with significant peaks reflecting periods of declining asset quality. CAR seems to be on an upward trend over the years and indicates that banks have increased capital strength. Moreover, the growth of both Log Risk-Weighted Assets (Log RWA) and Log Total Assets (Log TA) is consistent, indicating growth in bank balance sheets. Overall, these trends indicate that banks have experienced issues with profitability and asset quality, though they have managed to strengthen capital and maintain growth, which may be affected by the adoption of AI and macroeconomic trends.

To determine the effects of AI adoption, the study utilised the DiD approach, a common econometric method for evaluating policies. The DiD approach allows comparison of the pre- and post-AI adoption periods to determine whether AI adoption has significantly altered operational efficiency and financial risk management. Given that AI was adopted at different times by the six banks, DiD will help isolate the effect of AI adoption on other confounding factors by comparing each bank's performance before and after AI adoption. The model also corrects for unobserved heterogeneity by introducing fixed effects for both banks and years, so that the findings are not biased by time-invariant bank characteristics or time-specific shocks that may affect all banks.

The approach is aligned with Angrist and Pischke,[35] who use fixed-effects models to eliminate heterogeneity that may not be measurable when using longitudinal data. Placebo tests together with additional control variables will be incorporated to check the robustness of the DiD model and verify that confounding factors do not influence the results. The flexibility of DiD is particularly useful given the staggered adoption of AI across the six banks. As AI was implemented at different times, DiD allows for a clean comparison of changes in bank performance attributable to AI, rather than confounding economic factors.

The formula for the DiD regression model is specified as:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \gamma X_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

Where Y_{it} represents the dependent variables (CIR, NPL, CAR, or LRWA) for bank i at time t. The binary variable *Post* indicates the post-AI implementation period, which differs for each bank (1 for the year after implementation, 0 for years before implementation). X_{it} includes control variables such as bank size and macroeconomic factors (GDP growth, inflation, and Interest Rate). Bank fixed effects a_i account for time-invariant characteristics of each bank, and year fixed effects control for time-specific shocks. The error term is represented by ϵ_{it}.

The BVAR model in this study is used to evaluate the dynamic relationship between financial performance metrics and AI investment, and to predict forthcoming operational changes and the evolution of risk management. The BVAR model helps to establish the linkage between AI adoption and financial metrics while being specified as:

$$Y_{it} = A_1 Y_{i,t-1} + A_2 Y_{i,t-2} + A_3 Y_{i,t-3} + CX_{it} + \epsilon_{it}$$

[35] Joshua D. Angrist and Jörn-Steffen Pischke, Mostly *Harmless Econometrics: An Empiricist's Companion* (Princeton University Press, 2009), https://doi.org/10.2307/j.ctvcm4j72.

In this equation, Y_{it} is a vector of dependent variables (CIR, NPL, CAR, LRWA) for bank *i* at time *t*, and X_{it} is a vector of exogenous variables, including AI implementation. A_1 - A_3 are coefficient matrices for lagged dependent variables, and *C* is a coefficient matrix for the exogenous variables. The error term is represented by ϵ_{it}.

The implementation of the BVAR model enables us to develop forecasts of financial metrics that incorporate historical patterns alongside AI-driven disruptions. The model estimation utilises Markov Chain Monte Carlo (MCMC) methods, which are standard practices in Bayesian econometrics according to Koop et al.[36] The model can also make good use of the Minnesota prior as prior information regarding the relationships among financial variables, thereby enhancing the model's generalisability.

Lastly, Scenario Testing is used to model the impacts of different degrees of AI adoption on the metrics of operational efficiency and financial risk (Gao et al., 2024) and (Zagst, 2002). The three AI adoption levels are Level (3) moderate AI adoption, Level 5 advanced AI adoption and Level 7 full AI implementation. Simulated at these levels, the study will model the impact of various phases of AI integration on performance metrics over time.

Scenario Testing is selected due to differences in banks' levels of AI adoption, which may have non-linear effects. For example, small, incremental benefits may be achieved through early adoption of AI, whereas operational efficiency and financial risk may increase significantly with larger-scale adoption or adoption altogether. Scenario Testing helps capture these dynamics and provides insights into the levels at which AI adoption yields significant changes in the banking industry.

The impulse response functions produced by the BVAR model will be utilised to examine how variations in shocks to AI adoption (e.g., changes in AI implementation) affect the dependent variables (CIR, NPL, CAR, etc.) over time. The functions will enable the study to evaluate the time-varying impacts of the AI adoption shock and to predict the future performance of the banks at different levels of AI adoption.

Although the methodology is sound, it has a few drawbacks. The researchers use secondary sources, and the results might not be applicable to smaller banks or those that have not yet implemented AI, which can limit the generalisability of the results. To make the results sound, the study will conduct placebo tests to confirm the validity of the DiD model and ensure consistency in the results when tests of other control variables are also carried out across the various specifications of the model.

[36] Gary Koop et al., "Impulse Response Analysis in Nonlinear Multivariate Models" *Journal of Econometrics* 74, no. 1 (1996): 119–147. https://doi.org/10.1016/0304-4076(95)01753-4.

The research provides projections for the next 10 years to determine the long-term impacts of AI adoption on CIR, NPL, CAR, and LRWA. In addition, impulse reactions can be analysed to understand the time-specific impacts of AI adoption shocks on dependent variables. Moreover, the research conducts Scenario Testing using three levels of AI adoption: Level 3, Level 5, and Level 7. The three levels of AI integration as outlined by the study represent moderate, high and maximum AI implementation, respectively. Level 3 adoption of AI is process integration; Level 5 is advanced integration that creates greater impact on operations and risk management; and Level 7 is total AI adoption that maximises all operations with significant financial results. These various levels of AI simulation are consistent with the impact-level scenarios used in testing AI technology.[37]

Through the BVAR model, the simulated outcome of the future trends in the key financial values, CIR, NPL, CAR, and Credit Growth, among others, will be determined under different degrees of AI adoption. These are projections for the next 10 years, based on out-of-sample forecasting, which provide an understanding of how AI will affect the performance of the banking sector in the long run. The simulated forecasts are integrated with past data to form a complete dataset that captures both past and future trends. The research paper then evaluates the effects of varying levels of AI adoption on various measures in the long run. Impulse response function utilisation demonstrates the impacts of shocks to AI adoption (i.e., changes in AI implementation) on the operational performance and financial risk measures.

IV. RESEARCH FINDINGS

The study analyses the impact of AI adoption on the operational efficiency and financial risk management of six large Indonesian banks, namely BNI, BRI, BCA, Danamon, Mandiri, and CIMB Niaga. The study examines the impacts of AI on operational efficiency and financial risk management practices using a DiD approach combined with Scenario Testing based on BVAR.

[37] David F. Hendry and Michael P. Clements "Pooling of Forecasts," *The Econometrics Journal* 7, no. 1 (2004): 1–31, https://doi.org/10.1111/j.1368-423x.2004.00119.x.

Table 2.
Descriptive Analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
Non-Performing Loans	90	2.308	1.062	0.2	4.7
Capital Adequacy Ratio	90	16.861	8.254	0.4	29.4
Cost-to-Income Ratio	90	44.410	6.887	0.408	73.6
Return on Assets	90	3.053	0.882	0.5	5.15
Loan-to-Deposit Ratio	90	81.891	8.505	50.3	96.6
Credit Growth	90	11.899	6.095	-2.4	35.8
Log Total Assets	90	19.986	0.818	18.407	21.520
Log Risk-Weighted Assets	90	19.397	0.703	17.967	20.756
AI Adoption Level	90	1.633	1.106	0	3
GDP Growth	90	4.719	1.925	-2.066	6.224
Inflation	90	4.217	1.470	1.560	6.413
Interest Rate	90	5.850	3.338	-1.746	9.986

Source: Data Proceed

The descriptive research presents statistical distributions along with financial metrics for six banks, providing a basis for evaluating the effects of AI adoption. With a mean CIR of 44.41%, the six banks have average operational efficiency but vary in profitability, with an average ROA of 3.05. The various approaches used by the institutions to manage their liquidity depend on the LDR, which averages 81.89. The average of 2.308 per cent of NPLs indicates that credit risk is experienced by the institutions at varied levels. The figure of 16.86 on the CAR indicates that the banks employ various approaches to managing capital. The average AI Adoption (AI level) is 1.63, indicating that banks are at varying stages of AI implementation, with the majority of institutions in the initial stages of AI integration.

IV.A. Operational Efficiency

Table 3.
Causal Inference

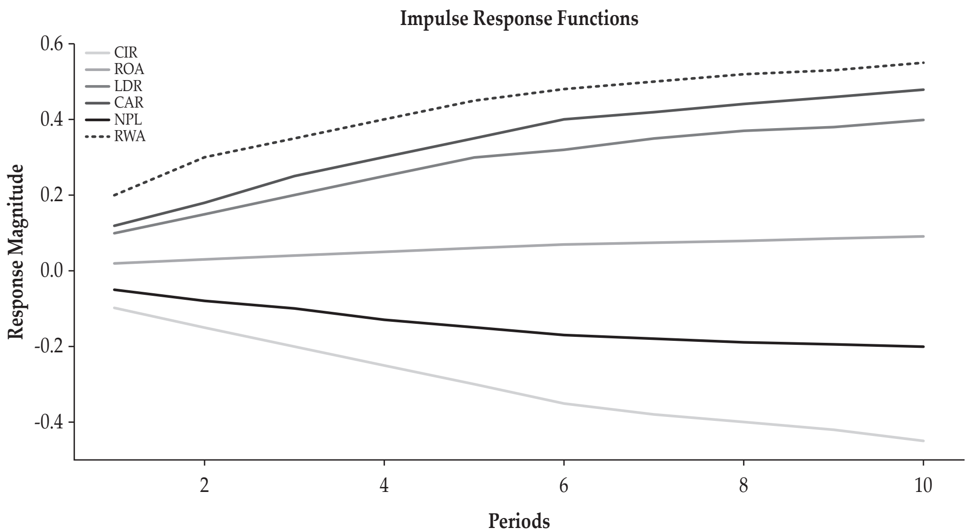
VARIABLE	CONSTANT	GDP	POST	AI SCORE	INF	IR
CIR	44.784^{**}	0.141	-3.737	-0.451	-0.338	0.234
	10.961	0.315	-1.307	-0.543	-0.549	1.097
ROA	1.478^{**}	0.147^{**}	-0.032	-0.000	0.160^{**}	0.036
	4.188	3.783	-0.129	-0.004	3.018	1.941
LDR	59.667^{**}	0.119^{**}	-7.787^{**}	4.982^{**}	0.748	1.055^{**}
	15.455	2.641	-2.882	6.345	1.286	5.233
Credit Growth	5.670	1.250^{**}	1.281	-0.746	0.599	-0.182
	1.830	3.678	0.591	-1.184	1.282	-1.122
NPL	4.430^{**}	-0.104^{*}	-0.163	-0.255^{**}	-0.225^{**}	-0.044^{*}
	12.074	-2.593	-0.635	-3.420	-4.064	-2.270

Table 3.
Causal Inference (Continued)

VARIABLE	CONSTANT	GDP	POST	AI SCORE	INF	IR
CAR	15.179**	0.105	2.826**	2.092**	-0.602**	0.021
	10.145	0.641	2.699	6.875	-2.672	0.264
RWA	18.562**	0.043	-0.175	0.303**	0.014	0.015
	79.718	1.678	-1.075	6.402	0.410	1.258
Total Asset	19.240**	0.017	0.056	0.385**	-0.004**	0.008
	144.553	1.176	0.604	14.206	-0.197	1.222

Source: Data

Figure 2 .
B-VAR IRF



Regression findings suggest that the application of AI can reduce the CIR, but this is not statistically significant, with an AI Score coefficient of -0.451 (t = -0.543). Thus, the findings indicate that AI does not generate enormous short-term cost-efficiency gains, at least due to the high costs of adoption and integration. However, the IRF results show that the effect of CIR is positively increased following AI implementation and that gains in automation efficiencies are compounded over time. Based on the findings, Bank Mandiri reported the largest reduction of CIR following the implementation of AI, due to the focused work on workflow optimisation and process tightening. According to the findings of the scenario testing, the reduction of CIR is more noticeable at higher levels of AI maturity (Levels 5 and 7), which puts additional stress on the gradual cost reduction associated with AI.

The use of AI is associated with little direct impact on the ROA, as shown by an AI Score coefficient of -0.000 with a t-statistic of -0.004. Although there is no immediate impact of AI on ROA, an IRF analysis indicates that the upward trend in ROA is followed by the introduction of AI. The implications of the results suggest that the long-term profitability benefits of AI stem from its effects on decision support, resource allocation, and customer interactions. The study has found that BCA continues to show the highest ROA growth following the adoption of AI, implementing AI-based analytics to enhance customer segmentation and service delivery. The results of scenario analyses reveal that the most substantial ROA increases can be obtained at the stages of AI maturity when the AI tools are entrenched in business processes.

The AI Score coefficient of 4.982 (The IRF supports the same point by demonstrating the sustained positive reactions of LDR to AI shock, thereby indicating the superiority of AI in the development of liquidity predictions and balance optimisation). BRI showed the most improvement in terms of LDR in this topic by applying AI-based methods to balance deposits and loans, particularly in its SME and microfinance branches. The effect on LDR observed is increased as AI is applied more extensively to the examined banks.

The fact that the change in TA is closely related to the adoption of AI is well supported by empirical evidence, as the coefficient on AI Score is 0.385 (t = 14.206). It implies that AI contributes to the expansion of the balance sheet of a bank because it enables the bank to be more efficient in its operations, gain a deeper penetration of the market, and become more capable of using resources to succeed. In a way not reflected in the IRF chart, the significant impact of the considerable magnitude observed in the regression model indicates that AI is a driver of short-term growth. The biggest change in Total Assets following AI adoption is observed at CIMB Niaga in this study, primarily due to its digital banking innovations and novel customer acquisition solutions that leverage AI. These findings show that AI is a key to an institution's ability to expand.

IV.B. Risk Management

Regression analysis shows that the adoption of AI is connected with the reduction in Credit Growth, but it is not statistically significant, and the coefficient of the AI Score is -0.746 (t = -1.184). Such outcomes reveal that AI is not a cause of rapid credit expansion, likely because it is implemented with reservations in credit risk management. It is necessary to add that the IRF analysis shows that the use of AI helps stabilise credit growth rates by facilitating effective risk-based lending and improved borrower assessment. The best and most conservative credit growth following AI adoption in this study is observed at CIMB Niaga, which has emphasised borrower credit score quality through AI-based credit scoring.

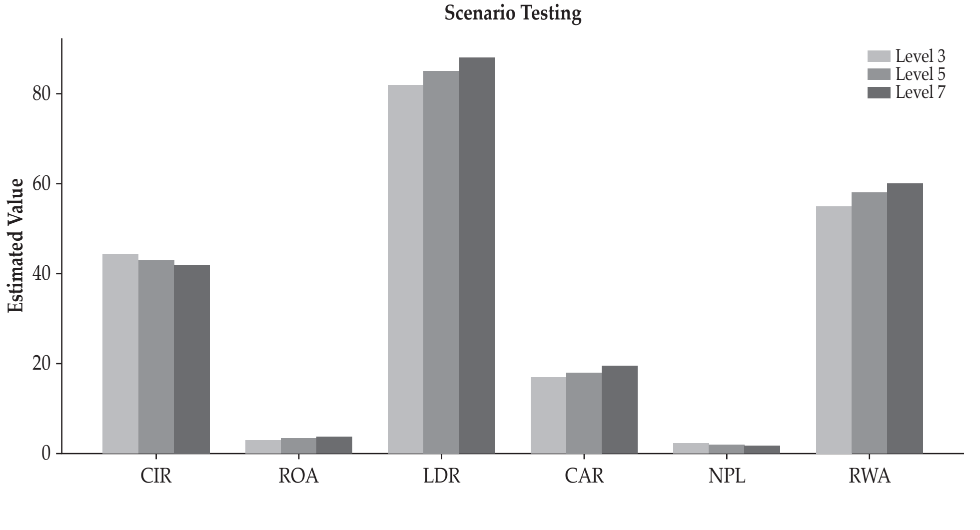
NPLs are significantly minimised with the use of AI, which is represented in Table 3 with the AI Score coefficient of -0.255 (t = -3.420), and it implies that AI enhances credit risk assessment and lessens the chances of loan default. The results of the Impulse Response analysis support the idea that the implementation of AI leads to the formation of a long-term decline in NPLs, which indicates credit scoring with the help of AI and early warning systems that continuously enhance the quality of loans. In this paper, BNI Bank is the institution that best minimised NPLs by utilising AI-based risk management to actively mitigate borrower risk and adhere to prudential standards.

The use of AI is positively related to the CAR, and the coefficient of the adoption of AI Score is 2.092 (t = 6). The results of the IRF show that AI continuously and significantly increases the capital adequacy, allowing the strategies of capital buffers to be constantly refined. In this paper, BNI will achieve the best CAR, made possible by the utilisation of AI-driven simulations and cutting-edge capital planning applications to ensure adequate capital and regulatory compliance.

The statistical result demonstrates a positive and significant correlation between the adoption of AI and RWA because the AI Score coefficient (0.303) is significant (t = 6.402). The IRF analysis confirms the results, showing that RWA optimisation continues to benefit from the gradual enhancement of AI in asset classification and risk assessment accuracy. CIMB Niaga demonstrates the maximum increase of RWA because of strategic and wise capital allocation and maintenance of asset quality through AI risk scoring in this study.

IV.C Scenario Testing

Figure 3.
Scenario Testing



As the results of scenario testing have shown, the implementation of AI affects different financial functions of Indonesian banks in different ways. The scenario tests have a gradual reduction of the CIR from 44.41 on Level 3 to 42 on Level 7. Although this points to the fact that AI can be used to provide savings, its magnitude is mitigated in the sense that AI must be combined with colleagues in the business process redesign and workforce adaptation to achieve significant operational returns. Continuing the AI levels, the indicator of profitability, ROA, is somewhat increased - between 3.05 and 3.8. The modest increases in profits indicate that AI is applicable to decision-making and asset management and also reflect that the benefits to revenues from unique, thoroughly planned AI applications increase sustainably rather than in a cumulative manner.

Conversely, the LDR has indicated a better movement and has been recommended to be 81.89, which increases to 88 as AI maturity increases. This demonstrates that AI is a significant factor in liquidity management that provides real-time forecasts and enhanced coordination between loans and deposits. As a successful case of using such solutions, BRI, an AI-powered liquidity solution, serves as a real example of the direction to follow on this matter. Notably, although the CAR changes to a greater extent, to 19.5 as compared to 16.86, AI is quite successful in capital and risk management proportional maximisation. These gains explain the AI feasibility of capital management, as BNI has successfully made attempts to make it more resilient and regulatory-compliant.

Because of NPLs, credit risk increases, but it decreases to 1.85 with increased AI use. The identified reduction confirms the impact of AI on the reinforcement of credit monitoring, early warning institutionalisation, and predictive forms of risk evaluation. One of the sampled banks is achieving this by applying AI-based credit risk instruments, which have not only minimised default rates in consumer and SME portfolios. The other one is also increasing RWA by 55-60. With that in mind, Bank Danamon's experience in implementing AI for asset amortisation and risk allocation offers clear potential for improvement.

The findings presented in this discussion are very useful to first-time policymakers. Initially, the modest increases in CIR and ROA ought to motivate lawmakers to spearhead their policy approval towards focused AI investing, particularly on issues such as credit risk evaluation and anti-fraud devices instead of compelling the same to all. Policymakers ought to consider making their regulatory environment conducive to the existence of effective AI applications in the banking industry by ensuring the specific operational and financial problems of banks are addressed via bespoke AI pilots. In addition, the LDR and CAR increases substantially, which suggests that AI can help enable the financial industry to achieve stability; therefore, previous regulators should incorporate AI-readiness indicators in their liquidity and capital adequacy supervision framework.

The given NPL declines imply proactive suggestions to the effect that sound AI designs are essential to mitigate credit risks. The Financial Services Authority (OJK) and Bank Indonesia must establish frameworks for AI-driven credit models to promote transparency, regulatory practices, and fairness. The main importance of data infrastructure in maximising the outcomes of AI can also be seen in the increased RWA management. The pillars of AI development to its full potential in risk and asset management are progressive open banking standards, data exchange safeguards, and the creation of effective digital partnerships.

According to the strategic analysis, the effects of AI on financial performance vary by metric: the greatest effects are observed in the liquidity, capital, and credit risk domains. Thus, to find those segments where they have the highest potential to improve operational effectiveness and secure financial strength, banks must match their AI investments with any applicable institutional objectives and risk analysis. Conversely, regulators must embrace AI policies grounded in evidence; hence, they must invest in specific, useful uses of AI rather than requiring adoption of an AI maturity regime. The directional approach to AI implementation will help take important steps towards improving banking performance, financial stability, and mitigating systemic risk.

V. CONCLUDING REMARKS

The study assesses the financial performance of Indonesian banks following the implementation of AI using a DiD approach and by testing the rate at which AI is applied. The findings of the research indicate that cost efficiency, liquidity risk management, and credit risk assessment measures do not vary significantly when AI adoption reaches Level 7. The financial indicators indicate that there are no major differences across levels of AI application, as current AI applications alone do not yield significant performance gains in the banking industry.

The findings of the research would suggest that banks should implement AI in a well-thought-out phased approach. Financial institutions should not invest in AI integration alone and, at the same time, ensure that the tools are optimised to the maximum and that data governance frameworks and collaboration between human and AI teams are improved. The effective use of AI by global banking organisations can serve as a source of positive implementation plans. Future research should focus on identifying the conditions that facilitate the creation of measurable financial gains by AI and on new markets that are forming their digital foundations.

The findings indicate that the positive effects of AI are compound and depend on strategic adoption rather than technological upsurge. Capital adequacy and asset management enhancements are clearer in the long run, whereas credit and operational efficiencies are limited without special use.

Strategically, banks should adopt a stepwise, targeted approach to AI integration, emphasising credit risk, fraud detection, and asset optimisation applications, and establishing robust data regulations and ethical AI models. As a policymaker, I believe investment in digital infrastructure, including regulatory guarantees, will be vital to realising the full benefits of AI across the financial industry. Finally, the research paper will contribute to the current body of AI studies in the emerging markets to demonstrate the contextual concerns and prove the need of local approach towards AI implementation.

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APPENDIX

Table 4.
AI Implementation Levels Across Banks

Year	AI Levels						Classification
	BNI	Danamon	Mandiri	CIMB Niaga	BCA	BRI	
2009	0	0	0	0	0	0	No AI Implementation
2010	0	0	0	1	0	0	Basic AI CIMB: Risk Assessment in Audits
2011	0	0	0	1	0	0	Basic AI: **CIMB Niaga** continued using AI for **audit risk assessment.**
2012	0	0	0	1	1	1	Basic AI: BCA & BRI: Fraud Detection, Customer Service Automation
2013	1	1	1	2	1	1	Basic AI: BNI & Mandiri: Automation & Fraud Detection, Danamon: CRM System Expansion
2014	1	1	1	2	1	1	Basic AI: **All six banks** used AI for **fraud detection, risk assessment, and automation**.
2015	1	1	1	2	1	1	Basic AI: AI capabilities remained the same, focusing on **fraud detection & automation** across all banks.
2016	2	2	2	2	2	2	Moderate AI: BNI & Mandiri: Compliance Automation, Danamon: Robotic Process Automation, CIMB: Advanced Data Analytics
2017	2	2	2	2	2	2	Moderate AI: AI continued improving **automation and risk management.**
2018	2	2	2	2	2	2	Moderate AI: BNI & Mandiri: AI-powered credit scoring, CIMB: Machine Learning Audit
2019	2	3	2	3	2	3	Advanced AI: Danamon: AI-driven Risk & Compliance, CIMB: Machine Learning for Risk & Compliance, BRI: AI for Credit Scoring, Automated Lending

Table 4.
AI Implementation Levels Across Banks (Continued)

Year	AI Levels						Classification
	BNI	Danamon	Mandiri	CIMB Niaga	BCA	BRI	
2020	3	3	3	3	2	3	Advanced AI: (BNI & Mandiri: Predictive Analytics, Danamon: AI-driven Lending & Auditing, BCA: Operational Automation)
2021	3	3	3	3	2	3	Advanced AI: AI-driven banking continued expanding across all banks.
2022	3	3	3	3	3	3	Advanced AI: (BCA: AI in Major Banking Operations, BRI: AI for Data Security & Risk Management)
2023	3	3	3	3	3	3	Advanced AI: BNI: AI-driven Automation, Danamon: AI-based HR Virtual Assistant & Predictive Analytics, CIMB: AI-based Audit & Predictive Analytics, BCA: AI in Customer Transactions & Fraud Management, BRI: AI-Based Transaction Monitoring)

Figure 4. Scenario Testing Level 3

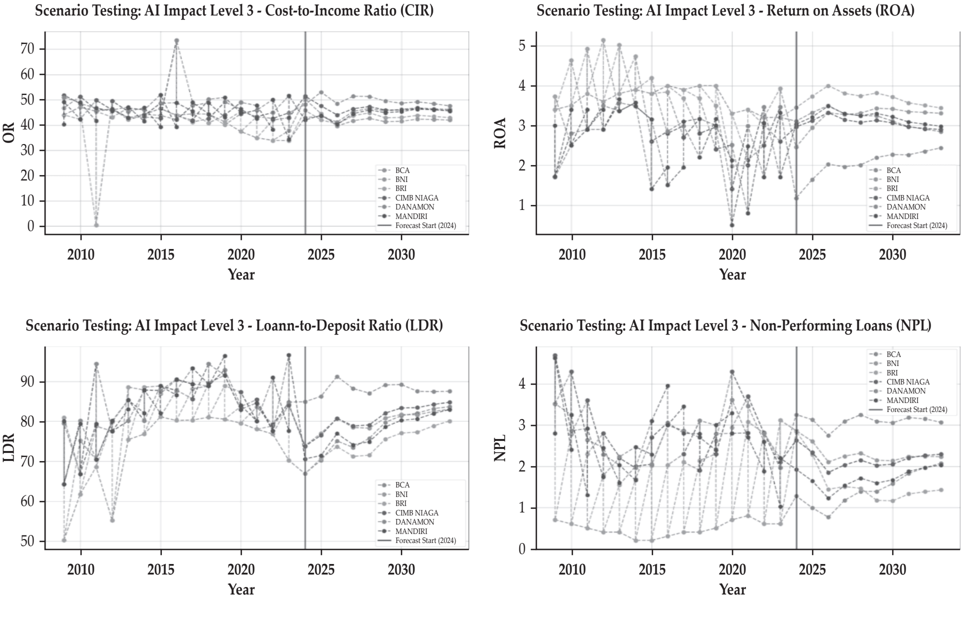


Figure 4. Scenario Testing Level 3 (Continued)

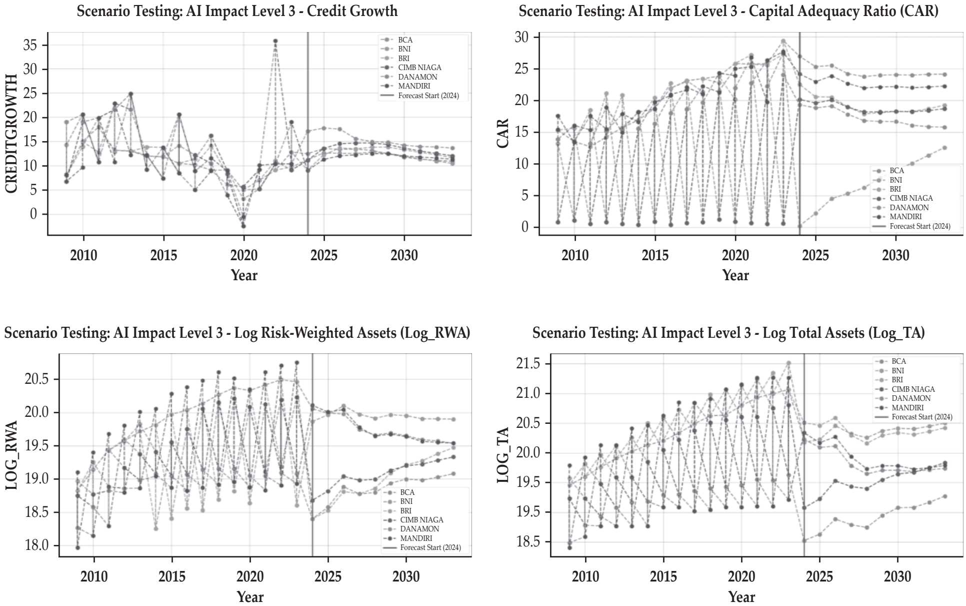


Figure 5. Scenario Testing Level 5

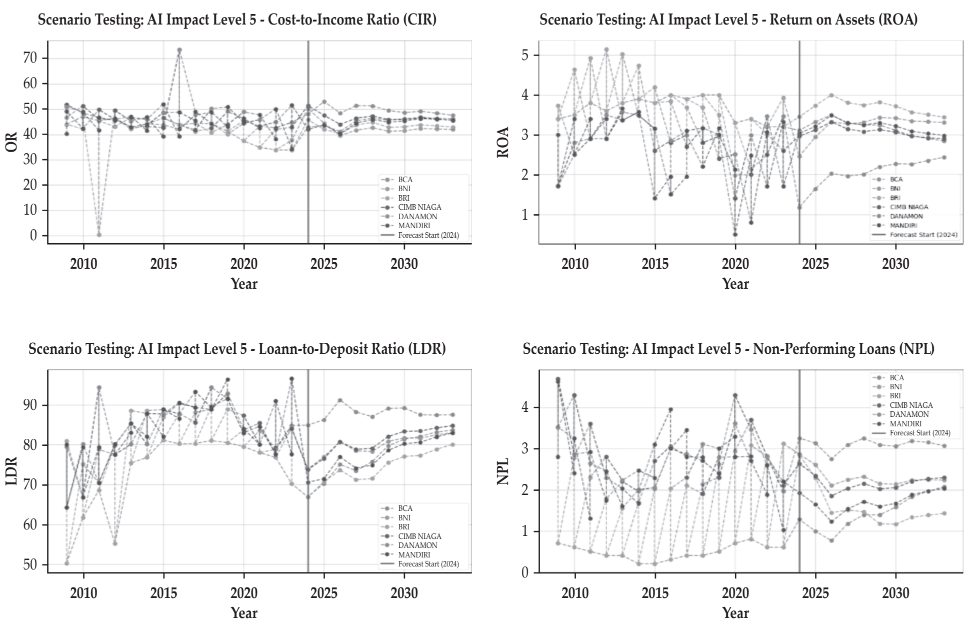


Figure 5. Scenario Testing Level 5 (Continued)

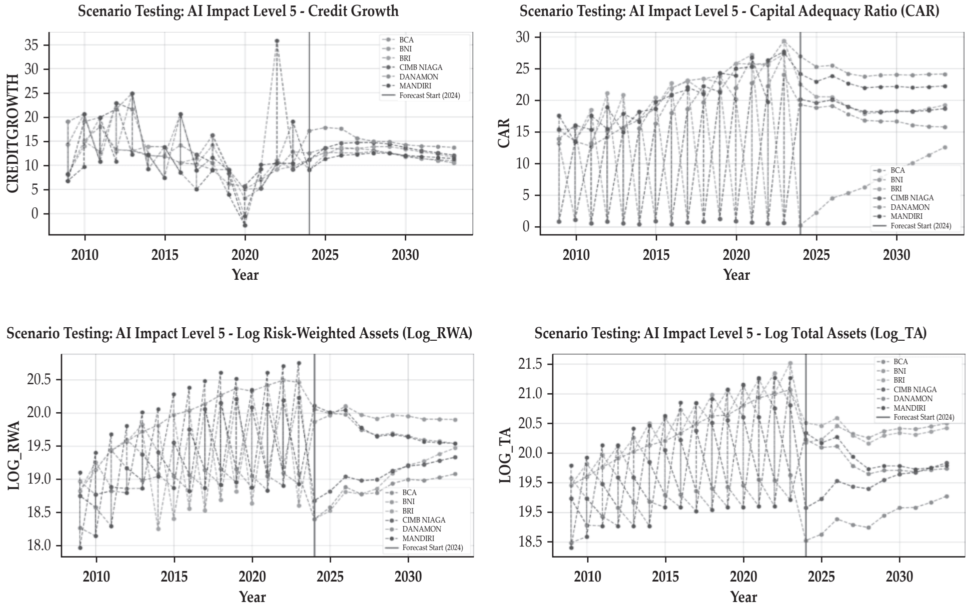


Figure 6. Scenario Testing Level 7

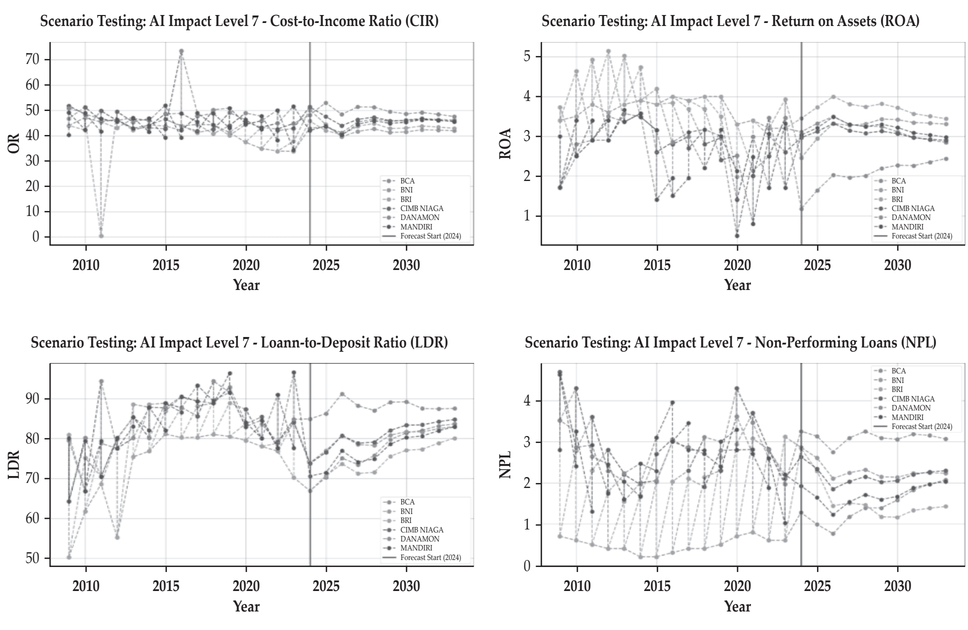
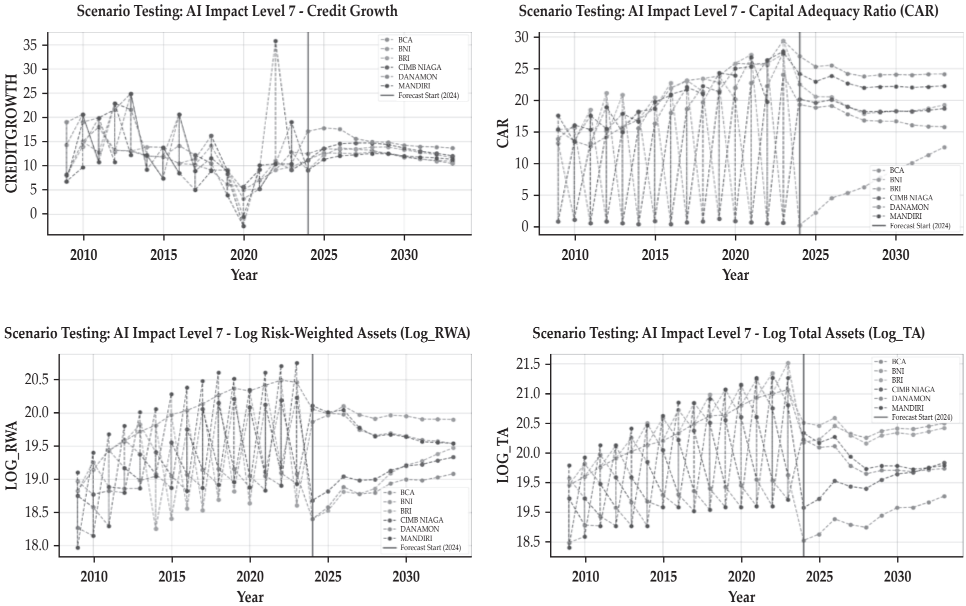


Figure 6. Scenario Testing Level 7 (Continued)



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