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Artificial Intelligence Adoption and Financial Stability under Geopolitical Pressure: Evidence from Indonesia's Digital Banking Sector

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ABSTRACT

Research Aims: This study investigates how Artificial Intelligence (AI) adoption and Geopolitical Risk Index (GPR) influence the financial stability of Indonesia's digital banking sector, focusing on profitability (ROA) and credit risk (NPL).

Design/methodology/approach: Using annual panel data from 2021–2024 and employing regression and scenario-based simulations to evaluates both structural effects and conditional responses to varying GPR levels.

Research Findings: The findings reveal that higher AI adoption generally enhances profitability and reduces credit risk under low to moderate geopolitical risk. However, AI's influence remains statistically insignificant, while GPR significantly decreases NPL, indicating conservative lending behaviorduring uncertainty. Operational efficiency and capital adequacy are identified as key internal factors influencing profitability.

Theoretical Contribution/Originality: This study contributes to the understanding of digital banking resilience by integrating econometric and simulation techniques, providing policy insights that emphasize adaptive credit risk frameworks, AI-driven risk management, and capital buffer adjustments amid geopolitical volatility.

Research limitation and implication: These findings imply that digital banks should prioritize strengthening operational efficiency and capital buffers, while leveraging AI adoption and GPR monitoring as supportive tools to mitigate potential pressures on profitability and credit quality. This research model can be recalibrated using GPR data to predict NPL spikes and ROA decline.

***Keywords**:* Artificial Intelligence, Geopolitical Risk, Financial Stability, Digital Banking, Sensitivity Analysis

JEL Classifications: G21, G32, E44, F52, O33

INTRODUCTION

Global geopolitical pressures have led to various consequences and disruptions across multiple sectors, including the financial industry. Global geopolitical uncertainty triggers financial sector instability, such as exchange rate depreciation and panic-induced capital inflows and outflows, and even disrupts monetary stability (Bekaert et al., 2012). Global geopolitical pressures also impact Indonesia, which is involved in various international activities (Caldara & Iacoviello, 2018). This statement is supported by data from the Global Geopolitical Risk (GPR) Index, which shows that although Indonesia's geopolitical pressure remains relatively low, ranging from 0.01 to 0.07, this figure spiked in the first quarter of 2022 (0.065) during Russia's invasion of Ukraine. Furthermore, data from Indonesia's Economic Policy Uncertainty (EPU) Index also shows fluctuations between 100 and 300, peaking during the pandemic and leading up to the elections (Baker et al., 2016).

Amidst these uncertainties, Indonesia's digital banking sector undoubtedly faces significant challenges, particularly the need to maintain stability, resilience, and profitability amidst global uncertainty (World Bank, 2014). The digital banking sector deserves special attention, given its technology-based and automated operations, which make it more sensitive to external shocks. Geopolitical pressures can trigger tight liquidity, payment system disruptions, and even a decline in customer trust (Bussmann et al., 2021). In such conditions, systems and technologies that are more adaptive and responsive to risk and uncertainty, such as Artificial Intelligence (AI) (Akter et al., 2019), are needed.

AI offers various advantages that benefit digital banking operations in Indonesia, including increased operational system efficiency, strengthened risk resilience, and improved overall service quality (Mikalef et al., 2020). In practice, AI can be applied in various aspects, including as an automated answering machine (AI Customer Service), as machine learning for credit scoring, and even to detect potential defaults in prospective financing customers (Lee & Shin, 2018). Furthermore, in the long term, AI can also be used in macro analysis, which can strengthen resilience to various external pressures and risks, such as geopolitical pressures (Caldara & Iacoviello, 2018). This statement is supported by research by Mikalef et al. (2018), which shows that the use of big data analytics and AI can improve and strengthen a company's capabilities in facing external environmental uncertainty (Mikalef et al., 2020).

Several digital banks in Indonesia have begun adopting AI as a step to modernize and automate their operational systems and to increase their long-term competitiveness (Thabhawee, 2025). However, the level of AI utilization by digital banks in Indonesia still varies. For example, Bank Jago and SeaBank have integrated AI into their operational systems and services, while others are still in the early stages of implementation (OJK, 2023). Investment in AI technology is also uneven, with the adoption of advanced features like AI-based underwriting or integration with technology startups still limited. This is due to differing readiness levels among digital banks. This statement is supported by research by Ferdosi & Tarek (2019), which shows a gap in readiness among digital banks in adopting AI. However, to support the successful implementation of a strategy, digital readiness, infrastructure, and the ability to adapt to new technologies are necessary (Deng & Karia, 2025).

In addition to increasing the effectiveness and automation of digital bank operations, the use of AI has a positive impact on bank financial performance, particularly on profitability and stability ratios. Simply put, through automation with AI, banks' Return on Assets (ROA) will increase due to reduced operational costs due as the replacement of several functions will be replaced by AI (Brynjolfsson & McElheran, 2016). At the same time, in terms of stability, AI can reduce NPLs by improving the accuracy of credit risk evaluations and early fraud detection (Agustiawan, 2024).

In conditions of high geopolitical tension, AI capabilities can assist in risk management and mitigation by providing adaptive responses to maintain the stability and financial performance of digital banks (Öztürk & Kula, 2021). Several previous studies have shown that optimal use of AI can increase the resilience and competitiveness of financial institutions (Akter et al., 2019). Furthermore, research by Wang & Choi (2023) Additionally, it shows that integrating AI into credit decision-making can reduce subjective bias and significantly enhance the accuracy of risk evaluations. Bughin et al. (2017) Also emphasized the importance of machine learning in detecting financial fraud and strengthening banks' early warning systems. Meanwhile, on the service side, research by Shaban & Al-Hawatmah (2024) shows that AI not only increases cost efficiency but also improves the quality of customer relationships through personalized digital services.

However, empirical studies integrating political pressure and AI adoption into the financial performance and resilience indicators of digital banks in Indonesia are still relatively limited (Feyen et al., 2021). Therefore, this study aims to fill this gap by analyzing the relationship between AI adoption, geopolitical pressure (GPR Index), and performance variables such as ROA and NPL. More specifically, the objectives of this study are: (1) to identify the level of AI adoption in digital banks in Indonesia; (2) to analyze the impact of AI adoption and geopolitical pressure on digital bank performance using panel data regression analysis; and (3) to simulate the sensitivity of digital bank performance to variations in geopolitical pressure and AI readiness levels using a sensitivity analysis approach.

Using a sensitivity simulation approach and panel data regression, this study aims to explore various scenarios of geopolitical change and technology adoption dynamically, thereby enhancing the understanding of the financial sector's resilience to external shocks (Saltelli et al., 2010). Thus, for policymakers such as the Financial Services Authority (OJK), the results of this study can be used to develop a risk-based financial technology supervisory framework, develop a data-driven and performance-impact-driven banking digitalization roadmap, and design risk mitigation schemes that are more adaptive to external pressures.

LITERATURE REVIEW

Dynamic Capabilities Theory

Dynamic Capabilities Theory (DCT) was developed by Shuen (2017) As an extension of the Resource-Based View (RBV). This theory focuses on an organization's ability to dynamically create, expand, or modify internal resources and capabilities in response to rapid and uncertain environmental changes. In the context of digital banking, external pressures such as geopolitical tensions, technological disruption, and market volatility are important drivers of the need for high adaptive capabilities (Saputra & Hardjono, 2024). Alonso & Kok (2018) divide dynamic capabilities into three main components: (1) Sensing: The organization's ability to identify opportunities and threats from the environment, such as AI adoption or geopolitical risks. (2) Seizing: The ability to capture opportunities through investment and organizational restructuring. (3) Transforming: The ability to overhaul internal assets and processes to remain competitive and efficient.

In the digital banking industry, the adoption of Artificial Intelligence (AI) technology is a form of dynamic capability because it enables banks to respond efficiently to external pressures. AI plays a role in automating decision-making, improving operational efficiency, and strengthening resilience against risks such as non-performing loans (NPL) and declining profitability (ROA). A study by Hossain et al. (2022) states that banks that are able to develop sensing and seizing capabilities through AI have better resilience in facing external pressures. Additionally, research by Gomez & Heredero (2020) shows that digital banks that build AI-enabled capabilities can enhance adaptability to crises and maintain financial performance stability.

TOE (Technology-Organization-Environment) Framework

The Technology-Organization-Environment (TOE) Framework was introduced by Eveland & Tornatzky (1990) as a theoretical approach at the organizational level to explain the adoption of new technology. The TOE Framework is considered an effective organizational theory in describing how unique organizational context characteristics influence the process of adopting and implementing innovation (Li, 2020). The TOE Framework was introduced by Tornatzky (1990) has three main complementary dimensions: technology, organization, and external environment. These three dimensions form an analytical framework for understanding the factors that influence organizational decisions in adopting technological innovations such as Artificial Intelligence (AI), particularly in the digital banking sector (Khatib, 2023).

The TOE Framework is widely used in technological innovation studies due to its ability to integrate internal and external perspectives into a single integrative model (Baker et al., 2016). In the digital banking sector, AI adoption is significantly influenced by digital infrastructure readiness (technology), management support and budget allocation for innovation (organization), as well as global geopolitical tensions and financial regulations (environment). As stated by Sheriffdeen (2024) external pressures, such as geopolitics, can drive banks to strengthen their digital resilience through the implementation of AI-based technologies. The TOE Framework provides a comprehensive foundation for understanding variations in AI adoption levels among digital banking institutions, which ultimately impact financial performance differences, including profitability efficiency through Return on Assets (ROA) and the effectiveness of credit risk management reflected in the Non-Performing Loan (NPL) ratio (Ali et al., 2021).

Theory Integration

In this study, the integration between Dynamic Capabilities Theory (DCT) and the TOE Framework is carried out by positioning TOE as a contextual framework that explains the determinants of AI adoption, while DCT is used to understand the internal strategic capabilities of organizations in effectively utilizing this technology. The TOE Framework explains how organizations adopt technology based on technological, organizational, and external environmental factors (Eveland & Tornatzky, 1990; Oliveira et al., 2014). On the other hand, DCT explains why organizations require dynamic capabilities to absorb, adapt, and optimize technologies like AI as a source of competitive advantage in the face of uncertain environmental changes (Shuen, n.d.; Teece, 2018). The integration of these two approaches provides a more comprehensive understanding of how an organization's contextual readiness (TOE) and internal strategic capacity (DCT) interact in determining the success of AI-based technology adoption and implementation in the digital banking sector (Heredero et al., 2020; Khatib, 2023).

The combination of these two studies provides a more complete understanding of the mechanisms of AI adoption and its impact on bank performance indicators such as Return on Assets (ROA) and Non-Performing Loans (NPL). In situations of high geopolitical pressure, banks with strong sensing and seizing capabilities, supported by technological readiness, flexible organizational structures, and regulatory resilience, will be able to maintain financial stability and operational efficiency (Kou et al., 2019; Sheriffdeen, 2024).

The Development of Artificial Intelligence (AI)

The development of digital technology drives systemic transformation in banking, including the increasing demand for fast, secure, and adaptive services. One of the widely adopted strategic technologies is Artificial Intelligence (AI), which mimics human intelligence in recognizing patterns, making decisions, and solving problems automatically (Sulistyowati et al., 2023).

Based on the findings in the McKinsey & Company working paper, the adoption of Artificial Intelligence (AI) in the banking sector yields four main strategic benefits, namely increased profitability, large-scale personalization, tapping into the omnichannel market (online shopping), and enhancing innovation within the company (Kamalnath et al., 2023). The study also revealed that nearly 60% of large-scale banking institutions have integrated AI into their banking business processes. Most of the banking industry, including digital banking, utilizes AI for virtual assistant services (robotic customer service) as a tool for fraud detection and real-time risk monitoring (OJK, 2022). AI is adopted by the financial sector at various levels.

The implementation of AI can start from the most basic level, such as the use of chatbots or AI customer service to assist customers. At a higher level, AI implementation can involve the use of machine learning in credit scoring or risk modeling in banking (Arner et al., 2017; Lee & Shin, 2018). The commitment of the financial sector to implement AI is also evident from collaborations or partnerships with AI startups or AI-based Fintech, allocation of capital expenditures specifically for AI, and even the establishment of special AI or Data Science units (Arner et al., 2017; Thabhawee, 2025). The combination of these indicators provides a comprehensive picture of the organization's commitment and readiness to integrate AI as part of the digital transformation (Jöhnk et al., 2021). The implementation of AI also supports the transformation of services towards a faster, more personalized, and flexible accessible digital format through various channels such as mobile banking, internet banking, and other digital platforms (Bhaskaran & Sudhir, 2018).

However, this progress also poses challenges such as data security risks, privacy, and digital inequality (Vardalachakis et al., 2024). In the global context, AI has the potential to strengthen the resilience of financial systems, especially in developed countries. However, its impact varies depending on the level of technological readiness and the economic structure of each country (Omri, 2020). This study views AI not only as an operational technology but also as a determining factor in simulating financial resilience measured through ROA and NPL indicators, as well as sensitivity to geopolitical pressures.

Hypothesis Development

Artificial Intelligence (AI) Adoption and Return on Assets (ROA)

The adoption of Artificial Intelligence (AI) by the banking sector has been an important catalyst in strengthening the competitiveness and operational efficiency of digital banks (Öztürk & Kula, 2021). AI enables banks to process big data in real time, accelerating decision-making that directly impacts profitability (Manukyan & Parsyan, 2024). Research in the United States shows that the acquisition of FinTech companies and AI patent ownership by large banks significantly increases Return on Assets (ROA) (Boyrie & Pavlova, 2025). In the Middle East, AI has proven to be a positive moderator between financial leverage and bank performance measured through ROA (Shaban & Al-Hawatmah, 2024).

Studies in Indonesia also found that digital banking, including AI, has a significant positive impact on ROA, especially in large-scale banks (Setiawan & Prakoso, 2024). Similar results were also found in India, where internet banking as a form of AI application was proven to increase overall bank ROA (Karimzadeh & Sasouli, 2013). Thus, the higher the level of AI adoption in digital banks, the greater the potential for these banks to increase their profitability through Return on Assets (ROA) (Rauf & Qiang, 2014).

H1: The adoption of Artificial Intelligence (AI) has a positive effect on Return on Assets (ROA) in Digital Banks in Indonesia from 2021 to 2024.

Artificial Intelligence (AI) Adoption and Non-Performing Loan (NPL)

The adoption of Artificial Intelligence (AI) in the banking sector provides more sophisticated and accurate credit data analysis capabilities, reducing the risk of errors in lending *(Öztürk & Kula, 2021)*. The implementation of machine learning and AI-based early detection systems enables banks to identify patterns of customer behavior that could potentially lead to credit problems *(Manukyan & Parsyan, 2024)*. AI also supports more objective credit scoring systems that can be adjusted in real-time, reducing the likelihood of granting loans to high-risk customers *(Boyrie & Pavlova, 2025)*.

Empirical studies show that banks that are more digital and adopt AI technology have lower Non-Performing Loan (NPL) rates compared to conventional banks *(Setiawan & Prakoso, 2024)*. Additionally, AI enables continuous tracking and evaluation of loan performance, allowing for corrective actions before defaults occur *(Rauf & Qiang, 2014)*. AI can also be used in faster, data-driven loan restructuring decision-making systems, accelerating the recovery of problematic loans *(Karimzadeh & Sasouli, 2013)*. Thus, the application of AI in credit risk management has been proven to contribute to a significant reduction in NPL rates in various global banking systems *(Rauf & Qiang, 2014)*.

H2: The adoption of Artificial Intelligence (AI) has a negative effect on Non-Performing Loan (NPL) at Digital Banks in Indonesia in 2021-2024.

Geopolitical Pressure and Return on Assets (ROA)

Geopolitical Risk (GPR) creates high economic uncertainty, which can hamper banking sector activity and reduce profitability, such as ROA (Yildirim & Sanyal, 2022). When geopolitical risk increases, financial intermediation costs tend to rise due to increased risk premiums and investor caution (Trinh & Tran, 2023). A decline in investment flows and increased market risk due to geopolitical conflicts can reduce banks' revenue growth potential, thereby pressuring ROA (Boungou & Urom, 2025). Long-term studies indicate that GPR has a significant negative impact on bank profitability ratios, including Return on Assets, particularly in developed countries (Behn et al., 2025). Research by (Banna et al., 2023) shows that increased geopolitical tensions are significantly negatively correlated with ROA, especially in financial institutions with global exposure or digital business models. This occurs because GPR increases funding costs and market uncertainty, thereby reducing the effectiveness of asset allocation and bank expansion strategies (Yildirim & Sanyal, 2022).

In the context of developing countries, such as the Middle East and Africa, bank's sensitivity to geopolitical risk is even higher, and ROA is vulnerable to such external pressures (Adel & Naili, 2024). Geopolitical uncertainty has been shown to erode bank stability by reducing profit margins and worsening capital structure (Phan et al., 2022). Overall, geopolitical tensions systematically hurt ROA by reducing operational efficiency and the quality of digital bank assets (Nguyen & Thuy, 2024).

H3: The GPR Index has a negative effect on Return on Assets (ROA) at Digital Banks in Indonesia from 2021 to 2024

Geopolitical Pressure and Non-Performing Loan (NPL)

Geopolitical pressures increase macroeconomic uncertainty, causing income and liquidity volatility for customers, thereby increasing the risk of loan defaults (Yildirim & Sanyal, 2022). Unstable geopolitical conditions, such as war or economic sanctions, often result in a decline in debtors' repayment capacity, directly contributing to an increase in the Non-Performing Loan (NPL) ratio (Bhowmik & Sarker, 2024). Cross-country studies show that spikes in the geopolitical risk index impact bank solvency and increase problem loans through the transmission of fiscal and monetary uncertainty (Phan et al., 2022). In the context of developing countries, political risk also exacerbates domestic economic conditions, weakens payment systems, and triggers a surge in NPLs in the banking sector (Adel & Naili, 2024).

A high Geopolitical Risk Index (GPR) also hinders foreign investment and worsens the business climate, negatively impacting companies' ability to repay bank loans (Choudhury, 2025). Other research shows that geopolitical shocks directly increase credit risk exposure, particularly for digital banks with technology-based loan portfolios lacking strong physical collateral (Behn et al., 2025). In general, the higher the geopolitical tension, the greater the NPL risk borne by the banking sector due to declining public confidence and payment capacity toward the financial system (Boungou & Urom, 2025).

H4: The GPR Index has a positive effect on Non-Performing Loans (NPL) at Digital Banks in Indonesia from 2021 to 2024.

RESEARCH METHOD

This study uses a quantitative approach that combines sensitivity analysis and panel data regression analysis. As a first step, this study will conduct a scenario-based sensitivity analysis to explore the impact of the adoption of Artificial Intelligence (AI) technology and geopolitical pressures on the resilience of the digital banking sector in Indonesia. This approach is relevant for mapping the influence of changes in input variables on outcomes, particularly in the context of external uncertainties such as global geopolitical volatility and digital transformation of the financial sector (Saltelli et al., 2010). Sensitivity analysis is also considered more flexible than conventional regression in simulating strategic policy scenarios and analyzing various possible outcomes (Pianosi et al., 2016).

In the face of increasing global uncertainty, sensitivity simulation is a superior analytical approach for evaluating the extent to which variations in external variables and technology such as geopolitical risk (GPR) and artificial intelligence (AI) adoption, can impact the financial resilience of digital banks, particularly regarding the Return on Assets (ROA) and Non-Performing Loans (NPL) indicators. Additionally, this method enables the systematic exploration of various hypothetical scenarios, providing a more realistic picture of the potential impacts and adaptive responses of the banking sector to both technological pressures and innovations (Saltelli et al., 2010). After conducting a sensitivity analysis, this study also uses panel data regression analysis to strengthen the validation of findings by analyzing the relationships between variables.

Data

The data used in this study is panel data from 10 (ten) digital banks in the period 2021–2024. The data was collected from various sources, including annual reports published by digital banks on their respective websites, publications from the Financial Services Authority (OJK) and Bank Indonesia (BI), as well as data from the Geopolitical Risk Index (GPR Index) from Matteo Iacoviello's official website (https://www.matteoiacoviello.com/gpr.htm). The inclusion criteria for the sample in this study are digital banks officially registered with the OJK, namely Bank Jago, SeaBank, Allo Bank, Bank Aladin Syariah, Blu by BCA, Neo Bank, TMRW by UOB, Digibank, Motion Bank, and Jenius. Additionally, supporting literature was obtained from studies by institutions such as McKinsey, the IMF, and academic publications related to the impact of AI and geopolitical risks on the financial sector (Caldara & Iacoviello, 2018).

In general, this study has three variables, namely the dependent variable, the main independent variable, and other independent variables as control variables. The dependent variables in this study consist of two variables that reflect financial resilience and sustainability, namely Non-Performing Loans (NPL) and Return on Assets (ROA). The use of these two dependent variables is based on the possibility that the use of Artificial Intelligence (AI) does not directly impact the reduction of NPL in the short term, but rather first impacts the profitability of digital banks. ROA is defined as net income after tax divided by total bank assets (ROA = Net Income / Total Assets), while NPL is calculated as total problem loans divided by total loans granted (NPL = Non-Performing Loans / Total Loans). Both variables are measured in percentage form and obtained from each bank's annual financial statements.

In addition, The main independent variables in this study consist of two variables. First, the level of AI adoption, which is classified into three categories: Low (0–2), Medium (3–5), and High (6–7), as assessed in Table 1. AI adoption is measured using a cumulative proxy score derived from six indicators adopted from prior studies. Since the analysis uses annual panel data from 2021–2024, the AI score is recalculated for each bank year by examining that year's disclosures, including annual reports, digital banking reports, and public statements. Each indicator is coded based on its presence or absence in that specific year, allowing the score to vary dynamically over time. This approach captures the progression or regression of technological integration within each digital bank and produces a comparable annual AI adoption score across the four years.

Table 1. Artificial Intelligence (AI) Adoption Score

Indicator	Score	References
Chatbot AI/ AI Customer Service	Yes = +1; No= 0	Lee & Shin (2018); Arner et al. (2020)
AI Credit Scoring/ AI Risk Modelling	Yes= +2; No= 0	Zhang et al. (2022); Lee & Shin (2018)
AI Start-up Partnership	Yes= +1; No= 0	Arner et al. (2020)
IT/AI Capital Expenditure	Yes= +1; No= 0	Zhang et al. (2022) Arner et al. (2020)
Specific AI Unit/Data Science	Yes= +1; No= 0	Zhang et al. (2022)
Mention AI in the report >3 times	Yes= +1; No= 0	Zhang et al. (2022)

The data indicate that most institutions started with very low adoption levels in 2021 (scores between 0 and 5), followed by a sharp technological escalation in 2022 as they introduced AI-enabled credit scoring, automated customer service, and data-driven risk management tools. By 2023–2024, almost all banks converged at the highest score range (6–7), reflecting a sector-wide shift toward mature AI integration. This uniform acceleration demonstrates not only the diffusion of AI capabilities but also a competitive pressure among digital banks to upgrade their technological infrastructure within a relatively short period.

The second independent variable is the GPR (Geopolitical Risk Index) as a representation of global geopolitical pressure. GPR data was obtained from Matteo Iacoviello's official website (www.matteoiacoviello.com/gpr.htm) for the period 2021–2024. GPR values are categorized into three simulated scales: Low (0–90), Medium (91–150), and High (>150), with these ranges determined based on the historical distribution of global GPR values. Optional control variables include the Capital Adequacy Ratio (CAR), which is the ratio of capital to risk-weighted assets (CAR = Capital / Risk-Weighted Assets); BOPO, which is the ratio of operational expenses to operational income; Total Assets, as a measure of bank scale; and Digital Investment, measured as the percentage of capital expenditure (CAPEX) for digitalization relative to total assets or total capital expenditure, depending on the availability of data in each bank's annual report.

Analysis Technique

The analysis in this study was conducted using three approaches. First, semi-regression linear modeling based on coefficient parameters assumed from the literature for each AI and GPR scenario. Second, visualization of simulation results in the form of heatmaps to illustrate the sensitivity of changes in ROA and NPL to input variations. Calculations and visualizations were performed using Python software, employing libraries such as NumPy, pandas, and seaborn for data computation and mapping through the Visual Code Studio application. This approach was chosen for its ability to explain results intuitively, even for non-technical decision-makers (Hunter, 2007).

Third, as a complement to the sensitivity analysis, this study also implemented panel data regression analysis with STATA 17 to test the significant effect of AI adoption levels and the GPR index on digital bank performance. The regression model was used to detect the empirical linear relationship between independent and dependent variables, thereby providing statistical justification for the scenario simulations constructed (Wooldridge, 2010). Panel data regression analysis was conducted using model specification tests to determine the best estimation technique, namely the Chow Test and the Hausman Test/Lagrange Multiplier Test. Based on the results of the Chow Test and Hausman Test conducted, the Random Effect Model (REM) is the most appropriate estimation technique for this study.

RESULTS AND DISCUSSIONS

The main objective of this study is to analyze the impact of Artificial Intelligence (AI) adoption and geopolitical pressure (Geopolitical Risk Index/GPR) on the performance and resilience of digital banks in Indonesia, specifically through two main indicators, namely Return on Assets (ROA) and Non-Performing Loans (NPL). The analysis was conducted using two approaches, namely Sensitivity Analysis and panel data regression analysis. Thus, the discussion results will be presented in five (5) subsections, namely: 1) Descriptive Statistics; 2) Descriptive Correlation Analysis using a Heatmap; 3) Panel Data Regression Analysis Results; 4) Scenario-Based Sensitivity Simulation, which will be divided into two parts, namely its impact on ROA and NPL; and 5) interpretation of the strategic implications of empirical findings. This approach aims to comprehensively describe the dynamics of interaction between technological factors and external risks on the stability of the digital banking sector. The findings in this section are expected not only to contribute academically but also to provide practical relevance for regulators and policymakers in developing technology-based financial transformation strategies.

Descriptive Analysis

Tabel 2. Statistic Descriptive

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	40	-0.88225	4.267547	-13.71	4.76
NPL	40	0.8675	0.99943	0	3
AdopsiAI	40	5.8	2.138775	0	7
GPR_int	40	125.24	17.30842	105.35	142.28
LN_TA	40	16.42732	2.483626	9.30919	19.30072
CAR	40	63.3285	73.18875	9	390.5
BOPO	40	111.977	71.26455	52.38	428.4
LN_DIG	40	10.79137	2.835872	0	14.84838
DIG_TA	40	6.054577	20.28277	0	117.7643

Source: Data Processed, Stata 17 (2025)

Although the panel consists of 40 observations, the dataset reflects the entire population of licensed digital banks in Indonesia, rather than a sampled subset. Therefore, the purpose of the econometric analysis is not statistical generalization to a wider universe, but analytical generalization within the specific industry context. In small population settings, panel data estimation remains valid because the identification relies on within-entity and across-time variation rather than sample size asymptotics. Furthermore, the structure of the data (balanced panel, complete coverage of all digital banks, and meaningful year-to-year variation in the key variables) provides sufficient information to estimate the coefficients reliably. Therefore, the findings should be interpreted as population-level insights for Indonesia's digital banking sector, not as broad cross-country generalizations.

Descriptive statistics in Table 2 of this research data show that the average Return on Assets (ROA) of banks in the sample is -0.88 percent with a standard deviation of 4.27 percent. This negative average value indicates that, in general, many banks experienced operational losses during the observation period, and the variation among these banks was quite high. The level of Artificial Intelligence (AI) adoption is quite high, with an average value of 5.8 on a scale of 0 to 7, meaning that most banks have implemented most of the AI aspects measured in this study. However, variation is still evident, with a standard deviation of 2.14.

The Government Policy Response Index (GPR_int) has an average value of 125.24 with a relatively narrow spread, namely a standard deviation of 17.31, indicating that government policies in responding to macroeconomic dynamics are active but tend to be stable during the study period. In terms of company size, the log total assets (LN_TA) shows that the banks studied have a very diverse scale, with log values ranging from 9.31 to 19.30 and an average of 16.43, indicating diversity in operational scale among banks.

The Capital Adequacy Ratio (CAR) shows very high and scattered values, with an average of 63.33 percent and a standard deviation of 73.19 percent. This could be due to the presence of highly overcapitalized banks, possibly small banks with large capital relative to their total assets, or the presence of unprocessed outliers. The BOPO ratio (operating expenses to operating income) averaged 111.98 percent, meaning that operating expenses generally exceeded operating income. This indicates low operational efficiency in many banks during the study period. The spread is also high, with a standard deviation of 71.27 percent.

In terms of credit risk, Non-Performing Loans (NPL) averaged 5.13 percent with a standard deviation of 10.23 percent. This figure indicates that some banks still face relatively high levels of non-performing loans, with some banks having extremely high NPLs of nearly 95 percent. This could be a strong signal of weak risk management and credit quality in certain banks.

Meanwhile, the digitalization index measured through LN_DIG shows an average value of 10.79, with moderate dispersion (standard deviation of 2.84), indicating that the level of digitalization among banks is uneven—some banks are highly advanced in digitalization, while others are still lagging. Finally, the DIG_TA ratio, or total digitalization budget to total assets, shows an average of 6.05 percent with a very high dispersion (standard deviation of 20.28 percent). This indicates that there are banks that allocate a significant amount of their budget to digitalization, even up to more than 100 percent of total assets, which is likely due to the very small scale of assets or outliers in the data.

Overall, the results of this descriptive statistical analysis show that there is considerable heterogeneity among banks in terms of financial performance, operational efficiency, credit quality, and AI technology adoption. Therefore, further panel regression analysis is needed to gain a deeper understanding of how factors such as AI adoption, credit risk, and government policies impact bank profitability in Indonesia.

Descriptive Analysis: Heatmap Correlation

To understand the complex interactions between artificial intelligence (AI) adoption and geopolitical pressures (GPR Index) on digital bank performance, researchers used visual methods such as heatmaps, which are considered superior in analyzing multivariate scenarios. Wilkinson & Friendly (2009) stated that heatmaps not only display the strength of correlations between variables but also depict sensitivity patterns in a visual format that is easier to understand and analyze.

In the context of this study, researchers used a heatmap to simulate how the combination of AI adoption scores and geopolitical risk levels (GPR index) impacts two key indicators of banking stability: Return on Assets (ROA) and Non-Performing Loans (NPL).

This approach allows for visual mapping of outliers and optimal zones, providing a strategic overview for risk-based policymaking and digital readiness(Ferdosi & Tarek, 2019). Furthermore, this analysis aligns with the systemic approach, which emphasizes the importance of data-driven scenario planning in macroprudential supervision, particularly when the financial system is under high external pressure (Cerra et al., 2021).

Based on the results of the data analysis and visualization, Figure 1 shows a heatmap of the correlation between variables in this study. The colors shown in the heatmap in Figure 1 have several meanings: 1) Red or bright orange indicates a high positive correlation between two variables; 2) Blue or dark colors indicate a high negative correlation; and 3) White or neutral colors indicate no significant correlation between two variables.

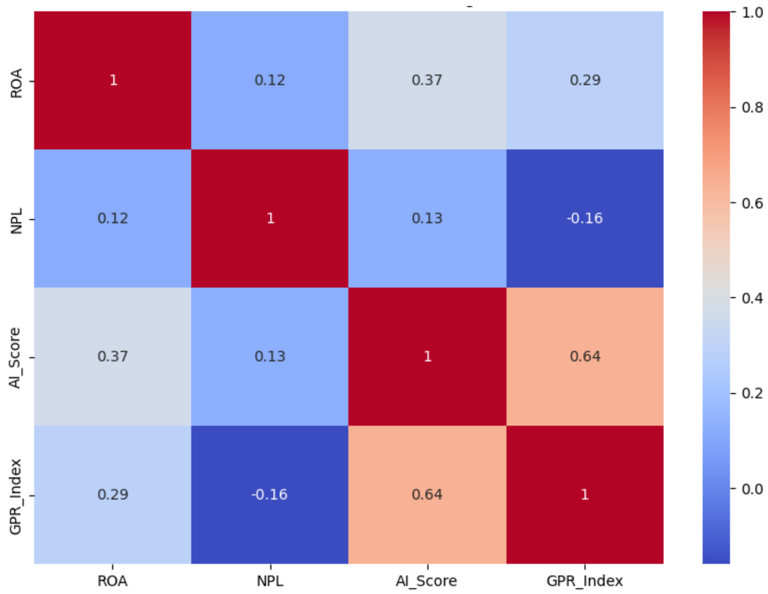

Figure 1. Heatmap Correlation

Source: Data Processed, Phyton (2025)

The relationship between ROA and other variables shows some variation. First, ROA and AI Score show a moderate positive correlation (0.37). This visualization indicates that AI adoption contributes to a moderate increase in profitability through the operational efficiency of AI-based services already implemented by digital banks in Indonesia. This finding aligns with Kou et al. (2022), who stated that the adoption of intelligent technology in the financial system improves financial performance. This is certainly possible because AI plays a role in automating operational processes, accelerating services, and reducing costs, thereby increasing the efficiency and profits of digital banks (Brynjolfsson & McElheran, 2016). Other studies also show that the application of AI in financial decision-making, such as calculating credit scores, can accelerate workflow processes, reduce the risk of human error, and support predictive analytics for profit optimization (Bughin et al., 2017).

Therefore, this correlation confirms the strategic role of AI in boosting the competitiveness of digital banks through profitability.

Second, ROA and the GPR Index show a weak positive correlation (0.29). This could indicate that under certain conditions, rising GPR is actually responded to with aggressive strategies that positively impact ROA. In other words, in conditions of immediate geopolitical tension, digital banks respond more adaptively and aggressively, thereby increasing ROA. In the literature, this condition is known as the 'strategic resilience' effect, where organizations are able to maintain or even improve financial performance in an uncertain external environment (Deng & Karia, 2025). Furthermore, digital technologies such as AI are considered to act as a buffering mechanism that mitigates the negative impact of geopolitics on profitability through efficiency, automation, and strengthening data-driven decision-making systems (Agustiawan, 2024).

Third, ROA and NPL show a weak positive correlation (0.12). This means that changes in ROA are not significantly followed by changes in NPL, and vice versa. In the context of this sample, the low correlation value indicates that the two indicators are influenced by structurally different factors. Profitability (ROA) may be more affected by internal dynamics and operational efficiencies related to technology (such as AI). Meanwhile, NPL is more sensitive to external pressures such as geopolitical fluctuations.

A study by Sarazin et al. (2019) shows that the correlation between ROA and NPL can be very low during crises or macroeconomic uncertainty, because ROA reflects broader and more dynamic financial performance results, while NPL reflects more stable or slower-changing asset quality. Furthermore, Thabhawee (2025), in a study in the European region, found that a low correlation between NPL and ROA often occurs in banks with diversified revenue sources or strong credit reserves. This phenomenon suggests that profitability-enhancing strategies do not always have a direct impact on reducing credit risk. Therefore, separate interventions and monitoring are required for each indicator.

On the other hand, researchers also found a variable relationship between NPL and the AI adoption and GPR Index variables. First, NPL and AI Score showed a very weak positive correlation (0.13). This indicates that AI adoption has not had a significant impact on reducing the NPL ratio. This is likely due to the early stages of AI implementation in several digital banks in Indonesia, where technology utilization is still limited to basic functions such as chatbots and has not been fully implemented in more complex credit risk assessment processes (Alt et al., 2018). Furthermore, a study by Bussmann et al. (2021) showed that the effectiveness of AI in risk mitigation will only be seen when the integration of machine learning for credit scoring and credit portfolio monitoring has reached system maturity (Yuniarti et al., 2024). Therefore, this correlation score emphasizes the need for increased technology investment and the development of data-driven decision-making capacity so that AI can contribute significantly to sustainable NPL reduction.

Second, the NPL and GPR Index show a weak negative correlation (-0.16). This weak negative correlation contradicts the theory that geopolitical pressures will worsen credit quality. However, this finding can be explained by the relatively small size of digital banks in Indonesia, with low exposure to high-risk sectors or cross-border activities vulnerable to geopolitical pressures (Yuniarti et al., 2024). Furthermore, some digital banks are still in their early stages of growth with conservative loan portfolios, so their impact on NPLs has not yet been fully reflected (Behn et al., 2025). This negative correlation may also indicate that geopolitical uncertainty tends to encourage digital banks to tighten lending policies, thus reducing the potential for non-performing loans. Therefore, these results suggest that digital banks' risk mitigation strategies in the face of global pressures require further study through a longitudinal approach or more specific portfolio segmentation.

Interestingly, the correlation between the AI Score and the GPR Index shows a strong positive correlation (0.64). This indicates that as global geopolitical pressures increase, digital banks are tending to increase their adoption of AI. This phenomenon can be interpreted as a strategic response to an uncertain external environment, where technology is used as an adaptive tool to strengthen operational and financial resilience (Akter et al., 2019). A study by Wang & Choi, (2023) also emphasized that AI is a crucial instrument in addressing geopolitical uncertainty through predictive analytics capabilities and automated decision-making (Phan et al., 2022). However, this relationship could also be a temporal coincidence, given that the post-COVID-19 pandemic period and Russia-Ukraine tensions simultaneously fueled the push for banking digitalization and AI adoption across various sectors.

Regression Analysis Results

This study uses panel data regression analysis to examine the effect of Artificial Intelligence (AI) adoption, geopolitical pressure (GPR Index), and financial variables on profitability and credit risk in digital banking in Indonesia on Return on Assets (ROA) and Non-Performing Loans (NPL). The analysis was conducted systematically through the stages of model selection testing, classical assumption testing, and regression result interpretation.

For the model with ROA as the dependent variable, the Chow test results showed a p-value of 0.0011, indicating that the fixed effect (FE) model is superior to the pooled OLS model. However, the Hausman test results showed a p-value of 0.9753, so the selected model was the random effect model because it was more statistically efficient and consistent with the RE assumptions that were not violated. For the model with NPL as the dependent variable, the Chow test results produced a p-value of 0.000, indicating that the fixed effect model was more appropriate than pooled OLS. However, the Hausman test result of 0.3105 indicates that the random effect model is the best estimation technique for this model. Thus, both models in this study use the random effect approach. Furthermore, Table 3 shows the results of panel data regression analysis for the dependent variables ROA and NPL, which are influenced by AI adoption and geopolitical pressure (GPR_int) and other financial variables.

Tabel 3. Panel Data Regression Analysis Result

Variabel	ROA (RE Model)	NPL (RE Model)
AdopsiAI	0,270	0,0112
	(0,330)	(0,0935)
GPR_int	-0,008	-0,0239**
	(0,035)	(0,00989)
LN_TA	-0,280	0,104
	(0,278)	(0,0787)
CAR	0,031***	-0,00912***
	(0,011)	(0,00305)
BOPO	-0.066***	0,00347
	(0,010)	(0,00274)
DIG_TA	-0,015	-0,00855
	(0,037)	(0,0104)
Constant	8,636	2,335
	(6,951)	(1,971)
Observations	40	40
R-squared	0,631	0,459

Standard errors in parentheses
*** p<0,01, ** p<0,05, * p<0,1

Source: Data Processed, Stata 17 (2025)

Table 3 shows that the ROA model has an R-squared value of 0.631, which means that approximately 63.1% of the variation in ROA can be explained by the independent variables. The analysis results indicate that the Capital Adequacy Ratio (CAR) has a significant positive effect on ROA (coefficient 0.031; $p < 0.01$), indicating that as the level of capital adequacy increases, bank profitability tends to rise. Conversely, BOPO has a significant negative effect on ROA (coefficient -0.066; $p < 0.01$), indicating that the higher the operational costs relative to operational income, the lower the bank's profitability.

Other variables such as AI Adoption, GPR_int, LN_TA, and DIG_TA are not statistically significant, although they are still theoretically relevant in influencing ROA. The insignificance of AI Adoption's effect on ROA may be due to several factors. First, the adoption of AI by banks may still be in the early stages of implementation, so its impact on profitability is not yet optimal. AI technology requires time for effective integration into operational systems and decision-making processes. This aligns with the findings of Li (2020), who state that the impact of AI on bank profitability will only become significant in the long term after the technology is strategically and uniformly adopted across all operational lines of the bank.

Meanwhile, geopolitical pressure (GPR_int), which represents the international policy response of governments to global crises or changes, also does not have a significant impact on the ROA of digital banks. This can be explained because this index is macro and general in nature, so it may not have a direct impact on micro banking financial performance. A study by Boug et al. (2023) shows that macro policies such as fiscal and monetary stimulus only have a significant impact if they are translated into direct interventions in specific industries, including the banking sector. Thus, GPR_int may reflect broader external conditions and is not detailed enough to explain variations in bank profitability specifically.

Some coefficients in the model do not reach statistical significance, which can be attributed to the limited number of observations and the relatively large set of explanatory variables that reduce the degrees of freedom. Nevertheless, the direction and magnitude of the coefficients remain theoretically consistent and aligned with previous empirical studies on small-N panel settings (Anderson & Hsiao, 1981; Baltagi, 2008). Therefore, despite statistical constraints, the regression results still offer meaningful insights into the relationship among variables within the Indonesian digital banking context.

The NPL model showed an R-squared value of 0.4034, indicating that 40.34% of the variation in NPL can be explained by the independent variables in the model. The regression results show that the GPR_int variable has a significant negative effect on NPL (coefficient -0.020; $p < 0.01$). In the context of this research, this indicates that when geopolitical pressures increase, the level of non-performing loans in the Indonesian digital banking sector decreases. This finding is interesting, as the digital banking sector is generally more adaptive and responsive to changing global conditions, including geopolitical pressures. Digital banks operating with technology-based systems and infrastructure tend to implement risk management more quickly because they are cloud-based. This enables digital banks to anticipate potential increases in NPLs amid global uncertainty. This argument is supported by research conducted by Demma et al. (2024) which shows that banks with high levels of digitalization demonstrate greater resilience because they are more flexible in credit allocation and risk portfolio management.

This phenomenon can be explained through two approaches. First, when global geopolitical uncertainty increases, domestic monetary and fiscal authorities tend to respond with protective policies or stimulus to maintain the stability of the national financial system. This can certainly reduce credit risk in the banking sector, as explained by Caldara & Iacoviello (2018). They found that an increase in the geopolitical index makes regulators more focused on maintaining financial system stability. Second, in an uncertain geopolitical situation, households and companies are considered more cautious in borrowing, which indirectly reduces the potential for non-performing loans.

This rationale can be understood through exploration of data obtained by researchers. For example, PT Bank Jago Tbk and PT Bank Neo Commerce, known for their real-time technology-based risk monitoring systems, are certainly able to respond more quickly to changes in risk exposure, including those triggered by global tensions. These digital banks also tend to minimize aggressive credit expansion during times of uncertainty, thereby reducing the likelihood of an increase in NPLs. This statement is reinforced by reports from DailySocial.id (2023) dan Kompas.com (2023), which state that Bank Jago and Bank Neo Commerce are actively developing AI-based risk modeling and analytics to maintain the quality of their loan portfolios during periods of global uncertainty. A study by Rolando & Mulyono (2024) also supports these findings, showing that digital banks in Indonesia have adaptive internal mechanisms for data-driven risk management. Thus, digital banks in Indonesia have the potential to avoid credit exposure as a negative impact of global uncertainty.

Conversely, the variables AI Adoption, Total Assets (LN_TA), Capital Adequacy Ratio (CAR), Operational Expense to Operational Efficiency Ratio (BOPO), and Digital Investment to Total Assets (DIG_TA) did not have a significant effect on NPL. The insignificance of AI Adoption in reducing NPLs may reflect that this technology has not been optimally utilized for credit risk management, such as in credit scoring or fraud detection processes. Research by Chen & Siklos (2022) also reveals that the effectiveness of AI in reducing credit risk is highly dependent on the integration of AI into the core functions of bank risk management, which may not yet be widely implemented in the context of banks in Indonesia.

In general, the regression analysis results in this study indicate that operational efficiency and capital adequacy are the factors that most consistently influence digital banks' profitability performance. Meanwhile, global geopolitical pressures play a significant role in reducing credit risk. This finding strengthens the argument that digital banks' resilience to macroeconomic and geopolitical conditions can be a key competitive advantage, especially when supported by technology and adaptive risk management. On the other hand, the role of technology and digitalization, such as AI, has not yet demonstrated a statistically significant impact on profitability or credit risk. This analysis indicates that technology optimization in this sector still requires time and a more comprehensive approach.

Sensitivity Simulation of AI and GPR on ROA & NPL

In policy research, scenario-based sensitivity simulations can provide a more specific and tested picture of the marginal effects of each variable (Sarazin et al., 2019). Furthermore, sensitivity simulations allow readers to compare the relative impacts of each analyzed change scenario (Hendry & Pretis, 2023). Therefore, the results of this research can help regulators develop more structured, simulation-based risk mitigation strategies and planning (Saltelli et al., 2010). Figure 2 shows the sensitivity simulation results to project how the combination of AI adoption levels and geopolitical pressure (GPR) affects ROA levels.

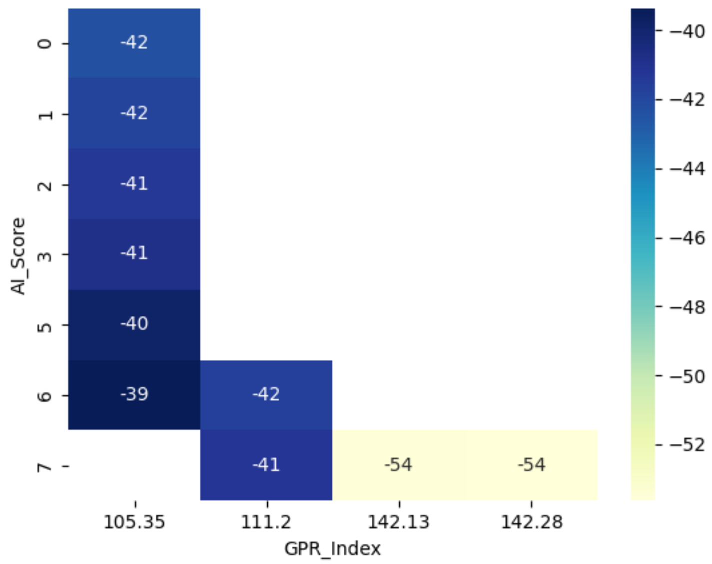

Figure 2. ROA simulation based on AI adoption and GPR Index

Source: Data processed, Phyton (2025)

There are three scenarios to examine how the combination of AI adoption levels (AI Score) in digital banks and geopolitical pressure (GPR Index) affects ROA. First, in the scenario of low AI adoption (score 0-2) and a low GPR Index. In this scenario, financial performance remains negative, with ROA ranging from -42 to -41. This figure reflects suboptimal operational processes and asset management. Despite stable external conditions (low GPR), banks are deemed unable to translate this stability into profitability. One of the main causes is the low adoption of AI, which also results in suboptimal operational efficiency. Furthermore, portfolio optimization and risk prediction are not yet automated and adaptive. As stated by Brynjolfsson & McElheran (2016), AI has significant potential to improve business process efficiency and productivity in the financial sector through process automation and predictive analytics. Without the support of intelligent technology, financial institutions still rely on manual or semi-digital processes, which are slow, expensive, and inaccurate. This worsens profit margins and causes performance to remain weak despite minimal external pressure.

Second, ROA in the moderate AI adoption scenario (3-5) has begun to contribute to improved financial performance. This is reflected in the ROA value improving from -42 to -39. This data indicates increased operational efficiency and improved analytical capabilities in asset management and risk prediction. However, moderate external pressures (GPR Index 111.2) remain a barrier to achieving positive profitability. Therefore, despite promising initial results from AI, geopolitical uncertainty remains a major limiting factor in profit growth.

The third scenario involves high levels of AI adoption (score 6-7) and high geopolitical pressure. These conditions play a significant role in reducing banking profits, resulting in ROA falling to -54. Although AI technology has been implemented at a high level (score 6-7), its sophistication is insufficient to withstand the impact of increasing global macroeconomic uncertainty. This indicates that when geopolitical tensions reach extremes, the impact on the financial sector is systemic and difficult to mitigate through technological innovation alone. A study by Jacobs (2004) shows that a surge in geopolitical risk can lead to excessive caution in investment, an increase in risk premiums, and a decline in credit and consumption growth. Furthermore, Choudhury (2025) emphasized that exposure to systemic shocks, such as geopolitical crises, can spread rapidly within the global financial network. This condition can worsen profitability even with technological mitigation instruments. Therefore, synergy between technological sophistication and adaptive macro policy strategies is essential in addressing such global pressures.

Furthermore, Figure 3 shows the results of NPL sensitivity simulations based on the adoption of AI and the GPR Index.

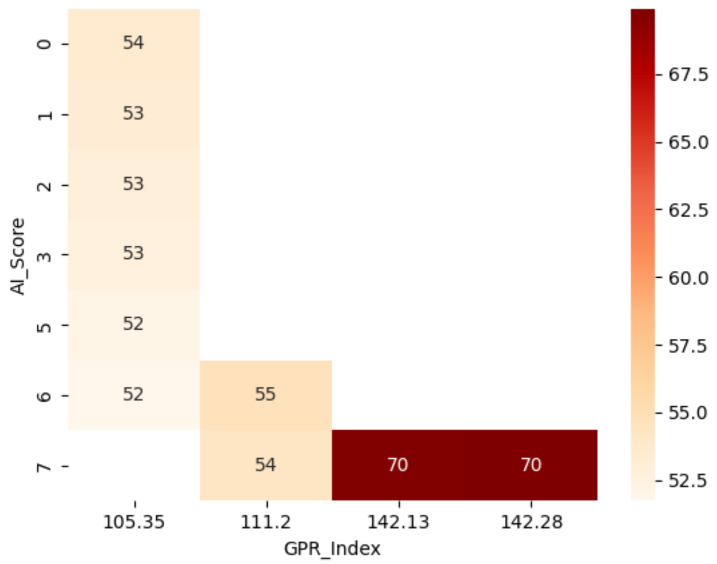

Figure 3. NPL simulation based on AI adoption and GPR Indeks

Source: Data Processed, Phyton (2025)

Sensitivity simulation scenarios for NPLs were also conducted in three scenarios: low, moderate, and high. First, under conditions of low AI adoption (score 0–2) and a low GPR Index. Under stable geopolitical conditions, reflected by a low GPR index (105.35), the financial system exhibits relatively good stability, with NPLs in the range of 53–54. This indicates that in a calm macroeconomic environment with minimal external disruption, financial institutions have the ability to maintain credit quality. The still-minimal use of AI also indicates that technology has not yet made a significant contribution to risk management. However, stability is maintained due to conducive external factors. According to research by Chen & Siklos (2022), macroeconomic stability tends to have a greater impact on banking asset quality than technological intervention in the early stages of implementation. Therefore, in this scenario, the financial system is in a moderate and controlled condition without the need for a major technological boost.

Second, at a moderate level of AI adoption (score 3–5) and a moderate GPR Index (111.2), there was an increase in NPLs from 53–54 to 55. This indicates that the use of AI has not been fully effective in offsetting the increase in external risks. At this stage, the technology is still undergoing integration and adaptation, so its contribution to credit risk management is still limited. Furthermore, the increase in GPR reflects global uncertainties such as geopolitical conflicts, trade tensions, or aggressive foreign policies, which can trigger an increased risk of default. In other words, while AI can help project risk, it is not yet fully capable of containing external pressures arising from geopolitical fluctuations (Li, 2020).

Third, at a high level of AI adoption (score 6–7) and a high GPR index. In conditions of very high geopolitical instability, as reflected by a spike in the GPR Index to 142.13–142.28, this situation will give rise to significant systemic pressure on the financial sector. Although the AI score is at the highest level (7), indicating the use of advanced technology in risk management, the drastic increase in NPLs to 70 indicates that technological sophistication is not sufficient to offset the exogenous impacts of global political tensions. This is in line with the findings of Jacobs (2004) who showed that escalating geopolitical risks can disrupt financial market stability despite a strong technological foundation. Furthermore, Choudhury (2025) emphasized that crises stemming from uncertain investor expectations and macroeconomic shocks are very difficult to mitigate with conventional or technology-based risk management tools. In this scenario, AI is not a strong enough damper to mitigate extreme global uncertainty, resulting in a significant spike in the non-performing loan ratio.

Comparative Sensitivity Interpretation

This sensitivity simulation shows that both the adoption of Artificial Intelligence (AI) technology and geopolitical pressures, reflected in the Geopolitical Risk (GPR) index, play a significant role in determining the stability of credit risk (NPL) and financial performance (ROA) of financial institutions, particularly digital banks in this context. In the low GPR and low AI (weak scenario), the financial system appears stable in terms of credit risk, with NPL values within the safe range (53–54), although profitability (ROA) remains negative. This situation indicates that external stability has not been sufficiently leveraged to drive internal efficiency, which is typically achieved through technology adoption. Low AI results in suboptimal operational efficiency and risk prediction.

Meanwhile, in the moderate GPR and moderate AI scenarios (moderate scenario), AI's contribution to performance improvement began to be evident. NPLs only experienced a small increase. This indicates that technology is starting to play a role in maintaining asset quality despite increasing geopolitical pressures. Meanwhile, ROA improved from -42 to -39, also indicating increased efficiency and risk management. However, AI capabilities did not fully mitigate external impacts. Conversely, in the high GPR and high AI scenarios (extreme scenario), very high geopolitical pressure triggered a significant spike in NPLs to 70 and a drastic drop in ROA to -54. This demonstrates that no matter how robust a technological system, the systemic impact of geopolitical risk cannot be fully mitigated by technological approaches alone. Technology remains vulnerable to global-scale external shocks, as evidenced by the study by Arner et al. (2017).

CONCLUSION AND RECOMMENDATION

This study comprehensively combines scenario-based sensitivity analysis and panel data regression analysis. This combined research method aims to evaluate the impact of

Artificial Intelligence (AI) adoption and the geopolitical risk index (GPR) on profitability (ROA) and credit quality (NPL). Sensitivity simulation results indicate that increased AI adoption generally correlates with increased ROA and decreased NPL, particularly in low to moderate geopolitical risk scenarios. However, this correlation tends to weaken at high GPR levels, indicating that external risks can hinder the effectiveness of technology if not supported by adequate organizational readiness and risk mitigation systems. Meanwhile, the results of panel regression analysis reinforce that, to date, the adoption of AI has not shown a statistically significant effect on ROA and NPL. This can be understood in the context of ongoing digital transformation, particularly as the strategic use of AI is still limited and uneven across the banking sector. Nevertheless, empirical evidence from several digital banks in Indonesia that have achieved the maximum AI score (7) demonstrates the significant potential of AI in enhancing efficiency and strengthening banking resilience. On the other hand, the GPR index has been proven to have a negative and significant impact on NPL, paradoxically indicating that banks tend to tighten their credit policies when geopolitical uncertainty increases. Adaptive AI-based risk management strategies enable digital banks to react more quickly to these external dynamics.

Overall, these findings indicate that although AI and GPR have not yet had a significant direct impact on short-term quantitative data, both are strategic factors that need to be integrated into long-term banking sector policies. The adoption of AI needs to be developed comprehensively and systematically, supported by adequate regulations, human resources, and digital infrastructure. Meanwhile, macro risk management needs to actively anticipate and respond to GPR dynamics to maintain financial sector stability amid increasing global uncertainty. This research provides a strong foundation for policymakers, banking authorities, and industry players to formulate adaptive digital transformation strategies and contextual prudential policies based on data and scenarios.

Based on the results of this study, the following are several related policy recommendations, 1) Strengthening AI technology and governance strategies by formulating adaptive and dynamic regulations in the financial sector. For example, accommodating innovations such as machine learning for credit scoring, robotic process automation (RPA), and real-time detection, 2) Systemic stabilization against geopolitical pressures, such as increasing credit portfolio diversification by sector or geography to minimize risk concentration. In addition, digital banks can implement an AI-based Early Warning System (EWS) to detect macroeconomic and geopolitical turmoil. This research model can be recalibrated using GPR data to predict NPL spikes and ROA declines, 3) Enhancing institutional capacity and human resources by conducting specialized AI training for risk management, particularly in default techniques, stress-testing measurements, and capital optimization for risk analysts and portfolio managers. Additionally, digital banks can collaborate with AI start-ups or fintech companies to accelerate real-time technology transfer and risk innovation, 4) Enhance AI integration in macroeconomic and financial policies, namely by increasing the use of AI by financial regulators or central banks to detect systemic risk accumulation and design predictive data-based policies, including simulations of the impact of GPR on the financial system. 5) Optimizing AI implementation, namely by developing an AI Maturity Framework for the financial sector that measures AI integration not only from an infrastructure perspective, but also in terms of business functionality and governance, 6) Use a crisis-response strategy based on Geopolitical Risk Intelligence (GPI), namely by opening up opportunities to use the global GPR index as an early warning signal in credit risk management, especially for highly adaptive digital banks. In addition, regulators need to encourage digital banks to develop credit portfolio policies that are responsive and adaptive to the GPR Index, for example through adjusted risk-weighting or capital buffers calibrated to global GPR volatility.

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