EXPLORING THE IMPACT OF AI ADOPTION ON THE FINANCIAL PERFORMANCE OF THE BANKING INDUSTRY IN MALAYSIA

BY

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(1) This undergraduate research project is the end result of my own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

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LIST OF ABBREVIATIONS

ACBT – AI Chatbot

AI – Artificial Intelligence

CAR – Capital Adequacy Ratio

DOI - Diffusion of Innovation

e-KYC - electronic Know-Your-Customer (e-KYC)

GDPG – Gross Domestic Product Growth Rate

ML – Machine Learning

NPL – Non-Performing Loan

RBV – Resource-Based View

ROA – Return on Assets

RPA – Robotic Process Automation

Preface

The purpose of this study is to investigate the impact of artificial intelligence (AI) adoption on the financial performance of Malaysian commercial banks. In addition, it aims to provide practical recommendations and implications for bank managers and policymakers based on the research findings.

In this research, panel data analysis is used to examine the models. The data covers a total of ten largest commercial banks in Malaysia over ten years from 2015 to 2024, in the form of panel series data. Moreover, the fixed effects model is considered the most suitable and effective model for presenting the relationship between AI adoption and bank financial performance.

Abstract

In recent years, the application of artificial intelligence (AI) has been continuously reshaping the global banking landscape by enhancing operational efficiency, strengthening risk management, and optimizing customer service. This trend has prompted banks to invest in technologies such as machine learning, AI chatbots, and robotic process automation to improve operational effectiveness. While numerous studies have examined the impact of AI adoption in developed countries, empirical evidence remains scarce in emerging markets like Malaysia. This study aims to fill this gap by examining the relationship between AI adoption and the financial performance of Malaysian commercial banks. Employing panel data analysis, the research samples Malaysia's ten major banks from 2015 to 2024. Financial performance is assessed by measuring banks' return on assets (ROA). AI adoption is determined by the application of machine learning, AI-powered chatbots, and robotic process automation. The main findings indicate that AI adoption has mixed effects on bank performance. Machine learning shows a positive impact on profitability after an adjustment period, while AI chatbots do not exhibit a consistent relationship with financial performance. Robotic process automation initially has a negative effect due to implementation costs but contributes positively in the long run. Overall, the results suggest that AI adoption in Malaysia’s banking sector remains at an early stage, with financial benefits becoming more evident over time. This study provides useful insights for bank managers and policymakers regarding the effective adoption of AI technologies in the Malaysian banking industry.

Keywords: AI adoption, Machine Learning, AI chatbot, Robotic Process Automation, Financial Performance, Malaysian Banks, Panel Series Data.

CHAPTER 1: INTRODUCTION

1.0 Research Background

In recent years, artificial intelligence (AI) has emerged as one of the most revolutionary technological advancements. Since new technical advancements have gained widespread acceptance and their applications are currently being investigated in a variety of commercial sectors, the field of AI has grown at a never-before-seen pace (Kumar et al., 2024). This fast-paced development of AI has transformed numerous industries, including financial services. According to Phapale (2025), the size of AI applications in the Middle East financial services market is expected to grow from $625 million in 2023 to $4.704 billion in 2032, which fully demonstrates the rapid development of AI in this field. The convergence of AI technologies such as machine learning, AI-powered chatbots, and robotic process automation (RPA) has enabled banks to improve operational efficiency, enhance customer experience, and develop innovative financial products. Among these technologies, AI stands out as a powerful tool with wide-ranging applications, from virtual assistants and robo-advisory services to real-time fraud prevention and credit risk modelling (Bughin et al., 2018).

In Malaysia, the banking industry plays a crucial role in supporting national economic growth and financial inclusion. Over the past decade, Malaysian banks have adopted various digital transformation strategies in response to evolving customer expectations and regulatory developments. The Malaysia Digital Economy Blueprint (MyDIGITAL) and Bank Negara Malaysia's Financial Sector Blueprint 2022-2026 both prioritize the use of sophisticated technologies like AI to improve innovation, resilience, and efficiency in the financial sector. (Economic Planning Unit, 2021; Bank Negara Malaysia, 2022). According to Zahid (2024), stated that over 80% of banks have implemented at least one AI-related project; in Malaysia, the most popular use cases are fraud detection, customer analytics, and electronic Know-Your-Customer (e-KYC). Leading local banks such as Maybank,

CIMB, and RHB have actively integrated AI into various aspects of their operations.

For instance, in 2020, RHB Banking Group introduced the RHB Financing (SME) Mobile App, marking it as the first artificial intelligence (AI)-powered "customer self-initiated" SME financing mobile application in Malaysia. This innovative application enables small and medium enterprises to access fast-term loan offers without the need for collateral. Also, it has help to streamlines the customer onboarding process by leveraging AI technology in which bringing a new level of automation and digitalisation to the SME financing application experience (Thevamanohar, 2020). Similarly, Maybank, one of the largest banks in Malaysia, is using AI and machine learning tools to improve productivity by automatically detecting financial crime through enhanced fraud and compliance processes. In addition, the bank is also automating collections through conversational AI, thereby reducing the need for dedicated resources (*Maybank - Digital Transformation Strategies*, 2024). Also, AI chatbots and virtual assistants are transforming customer service operations in Malaysian banks, significantly enhancing efficiency and user experience. These technologies offer multilingual financial assistance, enabling better access to banking services for Malay, Tamil, and Mandarin-speaking communities (Liew, 2025). In 2024, AmBank has emerged as the first major Malaysian financial institution to integrate Voice AI automation into its operational ecosystem through a strategic collaboration with AI Rudder. This initiative highlights AmBank's commitment to leveraging cutting-edge AI technologies to enhance both customer experience and the efficiency of its digitally evolving workforce (*AmBank pioneers voice AI automation in Malaysia with AI Rudder*, 2024).

By streamlining interactions and delivering personalized, real-time engagement, AI not only improves customer satisfaction but also helps optimize operational costs. Banks recognize AI's transformative potential, particularly in driving productivity, enhancing service quality, fostering business growth, and accelerating operational speed. Notably, generative AI alone is projected to contribute between $200 billion and $340 billion in annual revenue to the global banking industry, which represents an estimated 9% to 15% of total operating profits (Devanesan, 2024). For instance, according to Nair (2025), leading banks such as JPMorgan Chase leverage AI

models that have reduced payment verification errors by 20%, contributing to lower fraud and operational costs. Employee productivity also might rise by 30% and revenue could improve by up to 6% in three years if GenAI is successfully adopted and scaled (The Association of Banks in Malaysia, 2024). In Malaysia, banks are following suit. Hong Leong Bank Bhd, for instance, expects AI integration to significantly improve cost management and reduce its cost-to-income ratio (CIR) beyond initial expectations (Lai & Yap, 2025). In order to stay competitive and spur previously unheard-of innovation in the financial sector, Malaysian banks can further unlock new avenues for innovation, efficiency, and customer satisfaction by embracing GenAI's advanced capabilities in data analysis, predictive modeling, natural language processing, and more.

However, despite AI being promoted as a transformative tool, its actual impact on the financial performance of Malaysian banks is still unclear. Globally, many studies have reported that AI contributes positively to return on equity (ROE) and return on assets (ROA), but few empirical studies have examined these results specifically in the context of the Malaysian banking industry. As AI adoption becomes more widespread, it is important to assess whether it leads to measurable improvements in financial performance or whether its expected benefits are merely theoretical or context dependent.

1.1 Problem Statement

Previous research has largely focused on the impact of artificial intelligence (AI) on financial performance (Cherish, et.al, 2025; Bharadwaj, et.al,2024 and Sattar, 2025). However, there are only a few studies are available to examine the impact of AI on financial performance in banking industry in Malaysia. Although research on AI and financial performance has been done, it has mostly been conducted worldwide, which includes Jordan bank (Shiyyab, et.al, 2024), Indian bank (Singh, 2021) and across 20 countries (Gyau, et.al, 2024). Therefore, it may not be applicable to Malaysia in general, given that the benefits of AI application in the Malaysian banking sector are still in the early stages of adoption in many institutions.

Despite the significant attention garnered by artificial intelligence (AI), many banks remain cautious about a full rollout, fearing that the financial benefits may not outweigh the costs and operational challenges. Industry analysis shows that numerous AI projects at banks remain in isolated proof-of-concept stages due to factors such as fragmented data systems, compliance issues, and internal resistance. This not only delays wider deployment but also limits their measurable financial impact. This hesitation is also reflected in financial markets. For example, JPMorgan Chase's stock price fell sharply after it announced a significant increase in spending, which was partly due to increased investment in AI, highlighting investor concerns about the short-term cost pressures of AI spending. These developments suggest that while AI promises to improve productivity, banks often only implement it on a large scale after seeing clear and sustainable financial returns (Gauchat & Srinivas, 2025).

According to Spinelli (2025), approximately 30% of early adopters in the banking sector face significant challenges due to the high costs associated with building and maintaining AI systems, which often require substantial investment in infrastructure, data management, and specialized talent. These financial burdens can outweigh short-term benefits, especially for mid-sized or digitally immature banks. Additionally, around 29% of early adopters reported the absence of clear success metrics, making it difficult to evaluate the effectiveness of AI initiatives. Many banks struggle to establish performance indicators or return-on-investment benchmarks, which leads to uncertainty in assessing whether AI deployments are truly delivering value. Without measurable outcomes, banks may hesitate to scale their AI systems or allocate further resources, thereby stalling innovation. These concerns underscore the need for more structured implementation strategies, clearer performance frameworks, and cost-effective solutions to support sustainable AI integration in Malaysia’s banking industry.

Understanding the financial impact of artificial intelligence is critical for bank executives, investors, regulators, and policymakers. Without empirical evidence on how AI applications affect financial performance, decision makers may overestimate their value or overlook key factors that influence their effectiveness. This gap limits banks’ ability to assess the return on AI investments, strategically

allocate resources, or mitigate the risks associated with implementation. From a theoretical perspective, the lack of localized empirical research also limits the development of AI performance models relevant to emerging economies such as Malaysia. Therefore, there is an urgent need for research that explores the direct relationship between AI applications and key financial performance indicators of Malaysian banks.

Given the growing importance of AI in the banking industry and the limited evidence on its financial outcomes in Malaysia, this study aims to explore the extent to which AI applications affect the financial performance of Malaysian banks. This study aims to fill a critical research gap by evaluating measurable financial indicators and determining whether banks that invest in AI see tangible improvements. By focusing on this underexplored area, the study will contribute to academic understanding and practical decision-making in the field of fintech and digital banking transformation.

1.2 Research Questions

The research questions are as follows:

i. Does the adoption of Artificial Intelligence (AI) technologies like Machine Learning, AI chatbot, and Robotic Process Automation (RPA) impact commercial banks' financial performance in Malaysia?

ii. What is the relationship between machine learning, AI chatbots, and robotic process automation (RPA), and commercial banks' financial performance in Malaysia?

iii. How long do the financial benefits derived from AI adoption last for commercial banks in Malaysia?

1.3 Research Objectives

The research objectives are shown as follows:

i. To examine the impact of Artificial Intelligence (AI) adoption on commercial banks' financial performance in Malaysia.

ii. To analyze the relationship between individual AI technologies and commercial banks' financial performance in Malaysia.

iii. To determine the duration over which AI adoption continues to generate financial performance benefits for commercial banks in Malaysia.

1.4 Hypothesis of the Study

H1: There is a significant positive relationship between AI adoption and ROA of Malaysian commercial banks.

H2: Machine Learning (ML) adoption is positively associated with the financial performance (ROA) of commercial banks in Malaysia.

H3: AI Chatbot (ACBT) adoption is positively associated with the financial performance (ROA) of commercial banks in Malaysia.

H4: There is a significant relationship between Robotic Process Automation (RPA) adoption and the financial performance (ROA) of commercial banks in Malaysia.

H5: The financial benefits derived from AI adoption (ML, ACBT, RPA) in commercial banks are realized over different time periods.

1.5 Significance of the Study

The significance of this study lies in its timely argument on the adoption of artificial intelligence (AI) and its economic value to the Malaysian commercial banking sector. In recent years, the rapid development of AI technology has spurred banks around the world to rethink their business models, with many banks choosing to utilize AI to improve customer service provision, automate decision-making processes, enhance risk detection, and streamline internal processes. Malaysia is no exception, with more than 80% of domestic banks allegedly having introduced at least one AI initiative according to reports. However, while the technical potential of AI is widely reported, much empirical research still needs to ascertain the actual extent of its contribution to financial performance, especially in emerging markets such as Malaysia. This study aims to fill this gap with its emphasis on AI adoption within Malaysian business banks and their profitability in terms of financial performance measures such as return on assets (ROA). With this, the research has a greater understanding of how digital transformation initiatives are realized as quantifiable business value.

Another salient aspect of this study is that it takes into account Malaysia's listed domestic commercial banks, who possess the majority of the country's total banking assets. Commercial banks are at the forefront in the implementation of AI and are also the most willing to reveal data reporting, making them suitable to quantify the financial effects of tech spending. This study aims at this sector to deliver methodologically rigorous results which are relevant to the real-world application of AI in Malaysia's financial sector. Second, the analysis moves beyond a simplistic comparison of AI uptake and performance metrics to examine a more extensive range of contextual determinants of profitability. These factors consist of macroeconomic trends, credit quality, and institutional capital strength, all of which are important in determining whether AI brings financial returns on its own or with other structural elements.

Furthermore, this research aims to specialize in the time dynamics of investments in AI, as the financial effect of AI does not come about instantly. Integrating AI systems involves considerable initial investment, system integration, staff training,

and regulatory coordination. Hence, its benefits may be realized in the future. Including time lags in the analysis, this study provides a more real-world and holistic portrayal of the returns on AI investment in banking. The longitudinal approach enhances the pragmatic value of the findings, especially for bank decision-makers who are tasked with justifying enormous amount of technology spend to stakeholders.

More broadly, the evidence of this study can inform policymakers and regulators wanting to know how AI can contribute to making the financial sector more robust and efficient. As Bank Negara Malaysia continues to advance digital revolution and fintech growth, empirical evidence on the impact of AI can help develop policy regulations, technology regulation, and performance levels. This research can also complement bank CEOs' strategic planning activities by pointing to the most promising areas of AI applications that are most likely to bring about financial gains. For researchers and scholars, this research contributes to the emerging literature on digital banking, with empirical findings from Malaysia that can be used in comparative studies across regions. In general, this study not only contributes to theoretical knowledge, but also facilitates real-world decision-making in a rapidly expanding data-driven and innovation-driven bank setting.

1.6 Outline of the Study

This final year project report is organized into five chapters as follows:

The chapter 1 presents an overview of the expanding use of artificial intelligence (AI) in global and Malaysian finance. It provides background information for the study, outlines the research problem, aims, and questions, and highlights the importance, scope, and constraints of the research.

This chapter follows Chapter 2 and introduces the theories that support the study. It will also analyze relevant academic literature on artificial intelligence adoption and its impact on bank financial performance. It analyzes the definitions and characteristics of AI in the financial setting, identifies key performance measures such as Return on Assets (ROA), and summarizes previous empirical findings. The

chapter will also introduce theoretical frameworks and highlights gaps in previous research.

Furthermore, Chapter 3 describes the research design, data collection methods, and sampling approach. The chapter defines the dependent variable, such as ROA, the independent variable, such as AI adoption, and control variables, which are GDP growth rate, nonperforming loans, and capital adequacy ratio. It also outlines the model specification, and the statistical techniques used for data analysis.

Chapter 4 presents the results of the analysis, including descriptive statistics, correlation analysis, and regression outputs. It interprets the impact of AI adoption on financial performance indicators among Malaysian banks. The findings are discussed about the research objectives and existing literature.

This study concludes with Chapter 5, which summarizes the key findings of the study, discusses their implications for policymakers, banking institutions, and technology adopters, and highlights limitations encountered during the research. The chapter concludes with suggestions for future research directions in the area of AI and banking performance.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter reviews existing literature on the adoption of Artificial Intelligence (AI) in the banking sector and its effect on financial performance. It provides definitions, theoretical underpinnings, and empirical studies focusing on these variables.

2.1 Theoretical Frameworks

2.1.1 Resource-Based View

The Resource-Based View (RBV) is the first theoretical lens applied in this study. RBV posits that a firm's success is fundamentally driven by its internal resources, economic advantages, and capabilities. According to Barney (1991), firms can obtain long-term competitive advantage and superior performance by using resources that are valuable, rare, inimitable, and non-substitutable. These strategic assets create value and are difficult for competitors to replicate, thereby enhancing long-term performance (Bag et al., 2021). Innovation in AI technology is becoming more widely acknowledged as a strategic resource in the banking industry. Two examples of how artificial intelligence may improve risk management, accelerate processes, and customize customer experiences are chatbots used for customer service and machine learning used for credit risk assessment. Financial performance measures like return on equity (ROE) and return on assets (ROA) can be directly impacted by these improvements. Furthermore, the RBV framework supports the premise that a synergistic combination of complementary resources can yield more value than the sum of separate components (Mikalef et al., 2021). This can be a strong reason that reinforces the strategic importance of integrated AI capabilities.

2.1.2 Diffusion of Innovation Theory (DoI)

The second theoretical framework employed in this study is the Diffusion of Innovation (DOI) theory. This theory, originally developed by Rogers, posits that the adoption of innovation follows a predictable trajectory beginning with innovators and early adopters, and gradually diffusing through the early majority, late majority, and laggards (Rogers et al., 2014). DOI provides a valuable lens for examining how AI technology innovations are adopted and diffused within the banking sector, and how this process influences financial performance. By using DOI, this study could explore the factors that drive or hinder the banks' adoption of AI innovations, the rate at which these technologies spread across institutions, and the implications for key financial metrics. Understanding these adoption processes is essential for determining how rapidly AI capabilities like predictive analytics, automated decision-making, and intelligent customer interfaces may improve profitability, operational efficiency, and other performance indicators.

2.2 AI Adoption Trend in Banking

Technological innovation has long served as a driver of transformation in the banking sector. Historically, the implementation of IT has come through the bounds of transformation in the banking industry. For example, Oluwatolani et al. (2011) noted that the IT facilities fundamentally altered the nature and quality of services in the Nigerian banking sector, thus transforming the business models. The trajectory of this trend is being followed by the new wave of AI adoption, where emerging technologies similarly alter the operations of banks. The global research community has mirrored this growing attention. According to Lülök & Sebestyén (2025), the number of AI-related publications has risen sharply since 2019 and will peak in 2024, indicating that AI has become a strategic technology in the banking industry. These trends indicate that financial institutions are increasingly relying on machine learning and natural language processing to optimize business decisions, risk management, and customer relationships.

Malaysia reflects this international trend, as there is growing appetite in Malaysia for AI adoption, which is gaining further momentum, particularly after the COVID-19 pandemic triggered banks and fintech companies to digitize at a much higher pace to meet lockdown limitations as well as customer behavior changes (Kok & Siripipatthanakul, 2023). Consequently, numerous Malaysian banks implemented AI-based chatbots to provide customer support, introduced automated loan sanctioning through AI-based credit scoring, and made use of predictive data analytics in enhancing risk management practices.

Beyond this efficiency in operations, this adoption has implications in more general issues such as financial inclusion. Under this Industry 4.0 lens, AI meets issues of risk detection, information asymmetry, fraud deterrence, and security, while enabling more convenient customer care by virtue of chatbots and virtual assistants. In Malaysia, such benefits translate into lower costs of operations, better fraud detection, higher customer satisfaction, and even support of digital smart contracts, which do not necessarily need paper-based means without sacrificing anything in terms of authenticity. Beyond this, AI-based predictive analytics also enable deeper customer loyalty analysis, so that management can align strategies in terms of further customer retention (Mhlanga, 2020; Svoboda, 2023; Rahman et al., 2021). While, as George & Baskar (2024) suggest, AI is also building up towards much more highly customized banking services, this also opens up prospects towards Industry 5.0, in which automation is coupled with human insight in crafting customer-centric financial services.

2.3 Financial Performance Indicator

Return on Assets (ROA) is one of the most widely used and reliable indicators of bank financial performance, as it measures the efficiency with which a bank utilizes its total assets to generate profits. A higher ROA reflects stronger managerial effectiveness, better asset quality, and more productive utilization of resources, making it a key benchmark in evaluating profitability across banks of different sizes

(Demirguc-Kunt & Huizinga, 1999). Prior empirical studies consistently emphasize ROA as a central performance metric in the banking sector. For example, Berger and Humphrey (1997) highlight that ROA is particularly useful in assessing operational efficiency because it captures the outcome of both revenue generation and cost management strategies. Similarly, Athanasoglou et al (2008) state that ROA is a robust measure for understanding internal factors influencing profitability, including risk management and cost structures. Kosmidou (2008) further reinforces that ROA is essential in comparative performance analysis because it effectively reflects how well a bank converts its assets into net income. Given its reliability and widespread acceptance, ROA remains the primary indicator for evaluating the financial performance of banks in this study.

2.4 AI in the banking sector

2.4.1 Machine Learning

Machine learning is the process by which computers change their settings or algorithms to new knowledge without requiring manual retraining. Rahmani et.al (2021) stress that Machine Learning (ML) is a subset of AI. The key advantage of machine learning is that it is capable of making discoveries that otherwise might never have happened, as it can process more data than a human being and use the data to train itself by unearthing patterns difficult for human beings to recognize. Such capabilities make Machine learning (ML) algorithms perfectly suitable for addressing the different kinds of risks that banks face (Heß & Damásio, 2025). In this regard, the Financial Stability Board (2017) further demonstrates the growing use of AI and machine learning by financial institutions in a variety of financial system applications, such as pricing, selling insurance contracts, evaluating credit quality, and automating client interactions. These technologies are also utilised for capital optimization, model back-testing, and evaluating the market impact of sizable transactions. Overall, the adoption of machine learning has been motivated by the immense potential for cost reductions, along with increased productivity and better risk management. It is the machine learning process by which computers keep changing their settings or algorithms when confronted with new information.

2.4.2 AI Chatbots

A chatbot is a service provider driven by algorithms that interacts with customers through voice or text in a natural, human-like way. It employs natural language processing (NLP) to interact with users either orally or in writing (Adamopoulou & Moussiades, 2007). In the banking context, AI chatbots have offered significant benefits for both institutions and customers. For example, they enable advanced communication by allowing customers to obtain account information, perform transactions, and resolve queries without visiting a branch, thereby helping the bank to save a lot of time and reducing operational costs. Chatbots also provide 24/7 accessibility that allows assisting the users with common issues such as password recovery, transaction guidance, or branch information outside business hours. In addition, they can also enhance the speed of transactions, eliminating long queues and delays associated with traditional banking services. By quickly solving customer needs, AI chatbots contribute to improved customer satisfaction, fostering trust and loyalty (Cimpeanu et al., 2023). Furthermore, AI chatbot systems have reduced lineups at call centers and relationship centers, allowing human attendants to answer tough inquiries, hence improving service efficiency. Consequently, AI-powered chatbots contribute to gains and higher levels of operational and organizational efficiency within the banking industry (De Andrade& Tumelero, 2022).

2.4.3 Robotic Process Automation (RPA)

Robotic Process Automation (RPA) is a software-based technology that mimics human activities in digital systems to automate repetitive and rule-driven processes. One of the primary drivers behind the adoption of RPA in banking is the need for cost reduction and operational efficiency. Thompson (2018) emphasizes that by automating labor-intensive processes, banks can significantly reduce operational costs and improve processing times. For instance, bots can handle high volumes of transactions and data processing tasks without the fatigue or errors that typically accompany manual work. This leads to quicker turnaround times and enhanced customer experiences. Empirical evidence further supports these benefits, with

studies showing that RPA adoption can lower banking costs by 30% to 70%, and while simultaneously improving accuracy and enabling 24/7 operations (Vijai et al., 2020). However, Robotic Process Automation (RPA) can create short-term negative effects on ROA because banks must absorb several upfront costs before efficiency gains materialize. Development costs such as planning, process redesign, training, and bot testing are substantial one-time expenses that reduce profitability early on. Banks also face investment costs, including software licences, infrastructure, and hardware, especially when scaling RPA or adding cognitive tools like OCR or NLP. In addition, ongoing operation costs for system maintenance, licence renewals, governance, and IT support continue throughout the automation lifecycle. In the early adoption stage, these combined costs often exceed the immediate benefits, leading to a temporary decline in financial performance (Axmann et al., 2021).

2.5 Impact of AI on Banks' Financial Performance

The effect of artificial intelligence (AI) on financial performance in the banking industry has been the subject of numerous studies. Empirical evidence consistently indicates that organizations integrating AI into their operations experience measurable improvements in financial outcomes (Davenport & Ronanki, 2018; Alsheibani et al., 2018). Similarly, Brynjolfsson and McAfee (2016) have discovered that businesses that use AI technologies experienced notable increases in profitability since AI helps identify inefficiencies, minimize waste, and allocate resources more effectively.

Recent banking-focused studies provide further empirical support for these arguments. Shiyyab et al. (2023), examining Jordanian banks over the period 2014–2021, documented a gradual increase in AI-related disclosures, reflecting an early stage of technological adoption across the sector. Despite relatively low disclosure intensity among certain banks, their findings demonstrate a positive association between AI-related disclosures and financial performance, particularly return on assets (ROA), alongside a reduction in operating expenses. These results suggest that AI adoption can simultaneously enhance revenue generation and cost efficiency within banking institutions.

According to Cherish et al. (2025), it examined the distinctions between AI adopters and non-adopters by comparing 161 businesses from a variety of industries between 2018 and 2022. Their findings showed that the use of AI significantly increased revenue growth, profitability, and operational effectiveness. In particular, AI-adopting firms recorded higher sales volumes and improved gross profit margins, indicating that AI contributes to overall organisational competitiveness and financial success.

However, the financial impact of AI investment is not uniformly positive across all contexts. In the Nigerian environment, specifically for the eleven-year period among the Nigerian deposit money banks analyzed by Adejola (2024), the results indicated that the effects on financial performance were mixed. Although the spending on software did not have an effect on ROA and ROE, the impact of the book value of software spending was found to be negatively related to the two financial ratios. However, the net effect on bank performance was still significant. This means that the efficiency of AI is dependent on its application.

Cross-country analyses further highlight the role of contextual factors. Gyau et al. (2024) examined the dynamic relationship between AI innovation and financial performance across 20 countries from 2010 to 2020. These findings stated that AI innovation positively impacts ROA, particularly in environments characterised by strong economic growth. Their mediation analysis revealed that information and communication technology (ICT) development plays a critical role in converting AI innovation into financial gains. Furthermore, the study found that while initial innovation surges are associated with greater financial success, however, prolonged exposure leads to diminishing returns. It also included lagged impacts. They also emphasize how non-performing loans have a detrimental effect on financial performance. Government restrictions had a negative effect on performance, but regulatory capital and economic growth had a positive relationship.

Otsupius and Inuwa (2024) studied how supply chain technology and artificial intelligence affected the financial performance of eight listed ICT companies in Nigeria over fifteen years, from 2009 to 2023. Using secondary data from the firms' published annual reports and accounts, their findings revealed that, while both artificial intelligence and supply chain technology improved financial performance,

artificial intelligence had a statistically significant impact, whereas supply chain technology had no significant. This study highlights the crucial role AI plays in improving financial results, showing that increased use of AI technology can result in quantifiable gains in performance and profitability.

Finkenwirth (2021) examined the influence of artificial intelligence on financial performance in the financial services industry in Germany, employing a content-oriented quantitative methodology. As AI represents a key technological pillar of the industry 4.0 agenda, the study assessed whether the extent of AI-related discussion in corporate disclosures reflects firm-level financial performance. The study targeted financially serviced companies listed on the German stock market, permitting the investigation of the development status of AI implementation. Using data from 323 annual reports submitted by 84 companies over a period of four consecutive years, the analysis revealed a consistent upward trend in AI-related reporting, signalling increased strategic attention toward AI technologies. However, as AI implementation remains at an early stage, its financial benefits appear to materialize gradually. The study further concludes that references to AI alone provide limited explanatory power in predicting financial performance, although some evidence suggests a potential positive association.

Building on this perspective, Gunawan and Sustaningrum (2024) investigated the relationship between AI utilisation and financial performance in Indonesia's conventional banking sector, incorporating sustainability practices as a moderating variable. Using return on assets (ROA) and return on equity (ROE) as performance indicators, the study examined data from the ten largest banks listed on the Indonesian Stock Exchange during the 2022–2023 period. The empirical results show that AI utilisation does not significantly influence ROA once sustainability considerations are introduced into the model. In contrast, banks that combined AI adoption with a moderate level of sustainability engagement demonstrated a statistically significant improvement in ROE. These findings suggest that the financial effectiveness of AI initiatives is enhanced when supported by complementary sustainability strategies.

In summary, the existing literature presents mixed yet generally supportive evidence regarding the relationship between artificial intelligence (AI) and financial

performance in the banking and financial services sectors. Many studies report that AI integration enhances profitability, improves return on assets (ROA), and strengthens operational efficiency by optimizing resource allocation and reducing costs. However, several studies also highlight challenges in capturing the immediate financial returns of AI investments, particularly during early adoption stages, where implementation costs and learning effects may offset short-term gains. Furthermore, external factors such as regulatory frameworks, asset quality, and macroeconomic conditions restrict the usefulness of artificial intelligence in driving financial results. Banks that strategically integrate AI within a supportive economic and regulatory environment are more likely to achieve sustained improvements in financial performance.

2.6 Research Gap

Despite the global literature consistently attributing the transformative banking performance impact of AI, empirical evidence for Malaysia is sparse. The vast majority of the associated literature concerns the developed economies where the maturity and support for the AI are more established and the associated maturity and support for the regulations (Shiyyab et al., 2023; Cherish et al., 2025). In the Malaysian context, literature such as that of Kok and Siripipatthanakul (2023) cited the outbreak of COVID-19 for the development of the AI-based financial technologies; however, such literature concerns the associated technological adoption or the digital transformation or customer experience outcome and not the associated performance of the financial performance of the banking firms. Main performance indicators such as the return on the asset (ROA), are under-researched for the Malaysian banking context.

Furthermore, the overwhelming number of prior studies relies on cross-sectional data, therefore hindering them from capturing the short-term, dynamic effect of embracing AI. The latent, delayed effect of AI which investment expenditure on new technology taking a few years before it emerges as measurable financial performance is simply unrepresented throughout the literature. In the same manner, where some foreign studies acknowledged the moderating effect of the

macroeconomic and institutional factors such as economic growth, asset quality, and capital adequacy that influence the success of embracing AI (Gyau et al., 2024), the moderating effect itself is not systematically analysed within the Malaysian context.

Filling the above gaps, the present work undertakes a longitudinal event study spanning nine years (from 2015 to 2024) and covers commercial banking entities within Malaysia exclusively. In distinction from previous literature, it estimates financial performance with the help of ROA as the mainstay dependent variable and considers moderating roles of economic growth, NPL ratio, and CAR too. It also considers the possibility of realizing the advantages of the adoption of AI with a latent (lagged) impact. In doing all this, the research will supply fresh empirical contributions toward the existing literature on banking and the applications of AI, and it offers context-specific observations pertinent for Malaysia's banking scenario.

CHAPTER 3: METHODOLOGY

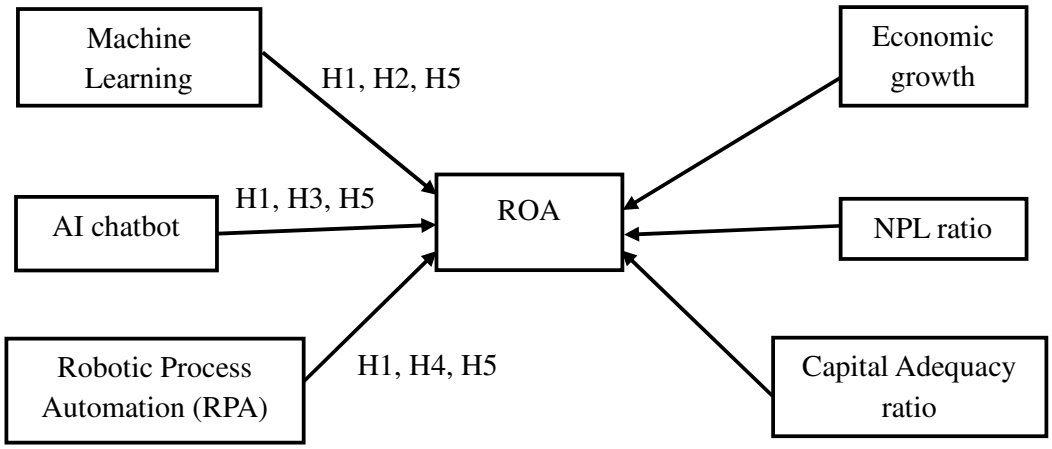
3.0 Introduction

This chapter outlines the research methodology used to investigate the impact of Artificial Intelligence (AI) adoption on the financial performance of Malaysian commercial banks. A quantitative research design is applied, using secondary panel data for ten largest banks in Malaysia over the period 2015–2024. These banks were selected because their larger capital reserves and asset base enable them to invest more aggressively in costly and complex AI technologies, making them representative of the industry. Panel data regression analysis is used as the primary statistical technique, supported by lagged effect modeling to capture delayed impacts.

3.1 Conceptual Framework

The conceptual framework of this study aims to illustrate how the adoption of artificial intelligence (AI) impacts the financial performance of Malaysian commercial banks, and how this relationship is influenced by economic and financial factors. AI adoption is treated as the core independent variable, operationalized through a binary indicator capturing whether banks adopted AI-related technologies such as machine learning, AI chatbots, and RPA between 2015 and 2024. The dependent variable “financial performance” is measured by Return on Assets (ROA), a widely recognized metric in banking performance studies reflecting a bank's ability to generate profits relative to its assets. Beyond the direct impact of AI adoption on ROA, the framework incorporates three control variables, including economic growth that proxied by GDP growth rate, GDPG, which is expected to strengthen the positive association, non-performing loan ratio (NPL), which is expected to weaken the positive association, and capital adequacy ratio (CAR), which is expected to reinforce the positive link between AI adoption and bank performance. Additionally, the framework also accounts for the possibility of lag effects, assuming that the financial benefits of AI applications may not materialize immediately but become more pronounced in subsequent periods. The

theoretical foundation of this framework draws from the Resource-Based View (RBV), which treats AI as a strategic resource capable of generating competitive advantage, and the Diffusion of Innovations (DoI) theory, which elucidates the adoption process of new technologies within organizations. Together, these theories construct a structured analytical perspective for systematically examining the impact of AI adoption on Malaysian commercial banks.



3.2 Model Specification

In order to determine the impact of AI adoption on the annual financial performance of Malaysia's 10 largest banks between 2015 and 2024, this study uses panel data analysis. According to its definition, a panel dataset is a cross-sectional time series dataset that often offers such measurements in several variables throughout time on observed units, such as a group of individuals, businesses, or nations, among others (Tae et al., 2007). The regression model estimates the direct relationship between AI adoption of machine learning, AI chatbot and Robotic Process Automation (RPA) and financial performance, measured by Return on Assets (ROA), while controlling for macroeconomic and bank-specific factors.

3.2.1 Hausman Test

Figure 3.1: Hausman Test result

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

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	17.410051	6	0.0079

The Hausman test will be employed to build the panel data model, determining whether the fixed effect model or the random effect model is more appropriate and effective. When applying panel analysis in research, the Hausman test distinguishes between random-effects and fixed-effects models (Hausman, 1978). The null hypothesis posits that the random-effects model is more valid. However, the alternate hypothesis suggests that the fixed effect model is preferable. As shown in Figure 4.2, the p-value of 0.0079 provides sufficient evidence to reject the null hypothesis. Therefore, we conclude that the fixed-effects model is more appropriate and effective.

3.2.2 Redundant Fixed Effect Test

Figure 3.2: Redundant Fixed Effect Test result

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

Effects Test	Statistic	d.f.	Prob.
Cross-section F	2.990048	(9,84)	0.0039
Cross-section Chi-square	27.790615	9	0.0010

The redundant fixed effects test was employed to determine whether the pooled OLS model or the fixed effects model was more appropriate for this study. As shown in Figure 3.2, the p-value for the cross-sectional F-test was 0.0039, and the p-value for the chi-square test was 0.0010. Both results were statistically significant at the 5% level. There is sufficient evidence to reject the null hypothesis. Therefore, we conclude that the fixed-effects model is more appropriate than the pooled OLS specification in this study.

The model is specified in Equation (1) as follows:

i. Baseline model

$$ROA_{it} = \beta_0 + \beta_1 ML_{it} + \beta_2 ACBT_{it} + \beta_3 RPA_{it} + \beta_4 GDPG_{it} + \beta_5 NPL_{it} + \beta_6 CAR_{it} + \varepsilon_{it} \quad (1)$$

In this specification, the indices i and t denote banks and years, respectively, for each observation. ML_{it} , $ACBT_{it}$, and RPA_{it} stands for AI adoption of machine learning, AI chatbot, and Robotic Process Automation (RPA) of a commercial bank. While $GDPG_{it}$ was the first control variable, which describes the economic growth rate. NPL_{it} were the second control variables that consisted of non-performing loans of the bank. While CAR_{it} represents the capital adequacy ratio of each bank. The symbol $\beta 0$ represents the constant term and ε_{it} represents the error term.

Furthermore, to examine the lagged impact of AI adoption on financial performance in the banking industry and test Hypothesis 5, this study includes AI adoption levels from the first to fifth lag periods as independent variables in equation (1), yielding equation (2) as shown below:

ii. Lagged effect model

$$ROA_{it} = \beta_0 + \beta_1 ML_{it-k} + \beta_2 ACBT_{it-k} + \beta_3 RPA_{it-k} + \beta_4 GDPG_{it} + \beta_5 NPL_{it} + \beta_6 CAR_{it} + \varepsilon_{it} \quad (2)$$

$k = 1, 2, 3, 4, 5$

Here, $k = 1, 2, 3, 4, 5$ *denotes* the lagged periods, while all other variables remain the same.

3.3 Dependent variable

The dependent variable in this study is bank's financial performance, measured by Return on Assets (ROA), expressed as a percentage after tax and collected from Refinitiv data stream. ROA reflects management's ability to efficiently utilize bank assets to generate profits and is widely used as an indicator of profitability in banking studies (Kusuma, 2021). In this study, ROA is used as the key outcome

variable to analyze the influence of AI technology deployment on bank financial performance, in line with previous empirical research (Haibo & Manu, 2022).

3.4 Independent variable

The key independent variables in this study are AI adoption, operationalized through three key components, which are machine learning, AI chatbots, and robotic process automation (RPA). Each component is measured using a binary dummy variable. The choice of a binary measure is appropriate because data on the scale or intensity of AI investment by Malaysian banks is not publicly available. Prior studies on technology adoption in banking and other industries have frequently employed binary coding to capture whether or not an institution has adopted a particular innovation (Shiyyab et al., 2023; Cherish et al., 2025). Following this approach, the AI adoption takes the value of 1 if the commercial bank has adopted each of the AI technologies of machine learning, AI chatbot, and Robotic Process Automation (RPA) from 2015 to 2024, and 0 for the commercial banks that have not adopted the AI technology. Evidence of adoption will be identified from the ten largest banks' annual reports, sustainability reports that highlighting the initiatives. This operationalization allows for capturing the formal implementation of AI initiatives rather than informal or experimental applications, ensuring consistency across the sample.

0 = Not adopted AI technology

1 = Adopted AI technology

3.5 Control Variables

To prevent other variables that will affect the financial performance, in this study, three control variables will be tested, which are the microeconomic impact of economic growth, bank measurement of non-performing loans, and capital ratio.

Each of the variables' data will be collected from Refinitiv DataStream, and the annual report for the data that is not available in the Refinitiv database.

3.5.1 Economic growth

GDP growth represents overall economic expansion and captures the macroeconomic environment in which banks function. It is included as a control variable to account for external economic factors that may influence banks' financial performance (Hakimi et al., 2023). A stable economy indicates rising incomes, which in turn increase the returns on bank loans and, consequently, improve bank performance (Purwohandoko & Iriani, 2021). This variable has been utilized in numerous studies and found that there is a positive and significant relationship between ROA and GDP growth (Siniţîn & Socol, 2020; Samhan & AL-Khatib).

3.5.2 Non-performing loans

The non-performing loan (NPL) ratio is included as an indicator of asset quality because it represents the proportion of loans that are in default or near default. A high NPL ratio typically reduces profitability and thus must be controlled for when analyzing AI's impact. Several studies have used these variables to measure the financial performance and found that there is a negative effect of the nonperforming loans ratio on return on assets (Isinta & Muniraju, 2025; Kingu, 2018; Linh, 2020).

3.5.3 Capital Adequacy

The third control variable in this study is the capital adequacy ratio. The capital adequacy ratio serves to measure a bank's ability to raise funds for business development and the risk of losses that may arise from its operations. These control variables are critical because they ensure that any observed relationship between AI adoption and financial performance is not confounded by macroeconomic or bank-

level risk factors. Numerous studies suggest that he higher the capital adequacy ratio, the better the bank's capital position and thus influence on the increase in profits shown by ROA (Purwohandoko & Iriani, 2021; Arsew, 2020).

3.6 Summary Data and Source

The table below presents the summary data and sources that will be employed in this study.

Table 3.1: Summary of Data and Sources

Variable	Unit	Type	Sources
Return on Asset (ROA)	%	Dependent	Refinitiv DataStream
Machine Learning Adoption	Binary	Independent	Annual Report
AI Chatbot Adoption	Binary	Independent	Annual Report
Robotic Process Automation (RPA) Adoption	Binary	Independent	Annual Report
GDP Growth rate	%	Control	Refinitiv DataStream
NPL ratio	%	Control	Refinitiv DataStream, annual report
Capital Adequacy ratio	%	Control	Refinitiv DataStream, annual report

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This section presents and discusses the analysis results, providing interpretations and insights linked to the research objectives.

4.1 Descriptive statistics

In Table 4.1 that attached below, presents the descriptive statistics of all variables covering a total of 10 largest commercial banks in Malaysia, over a 10-year sample period from 2015 to 2024, in the form of panel series data.

Table 4.1: Descriptive statistics

	ROA	***ML***	***ACBT***	***RPA***	***GDPG***	***NPL***	***CAR***
Mean	0.9245	0.4700	0.5100	0.6100	3.9999	1.7711	17.8666
Median	0.9700	0	1	1	4.6464	1.7800	17.8825
Minimum	-2.19	0	0	0	-5.4569	0.31	13.16
Maximum	1.53	1	1	1	8.8618	4.50	23.31
Std. Dev.	0.4165	0.5016	0.5024	0.4902	3.4893	0.8827	1.7659
Skewness	-4.3584	0.1202	-0.0400	-0.4511	-1.7248	0.5011	0.2269
Observations	100	100	100	100	100	100	100

Note: *ROA* represents Return on Asset, *ML* represents Machine Learning, *ACBT* represents AI chatbot, *RPA* represents Robotic Process Automation, *GDPG* represents Gross Domestic Product Growth rate, *NPL* represents Non-performing Loans, *CAR* represents Capital Adequacy Ratio.

Table 4.1 above provides a comprehensive overview of the characteristics of banks in the sample over the period from 2015 to 2024, including their financial performance, risk management, macroeconomic conditions, and use of technology. Return on Assets (ROA) is a leading measure of profitability, with an average of 0.9245 and a median of 0.97 that ranges from –2.19 to 1.53. Its strong negative skewness of –4.3584 reflects the fact that most banks remained profitable during these ten years, while a few banks experienced substantial losses, which may be due to periods of economic stress or operational problems.

Regarding AI technology adoption, machine learning (ML), AI chatbots (ACBT), and robotic process automation (RPA) are dummy variables indicating whether banks implemented these digital solutions. ML shows a mean of 0.47, meaning that roughly 47% of banks had adopted machine learning during ten years, while ACBT and RPA adoption rates are higher, at 51% and 61%, respectively. The skewness values indicate that ML adoption is slightly concentrated in a few banks, whereas ACBT and RPA adoption are more evenly distributed, reflecting a gradual increase in digital technology integration over the years. The higher adoption of chatbots and RPA likely reflects their relative ease of implementation and immediate operational benefits, while ML adoption may be slower due to higher technical requirements and investment needs.

Control variables also show notable trends. GDP growth (GDPG) has an average of approximately 4%, with high variability of 3.4893 and negative skewness at -1.72, which shows that over the 2015–2024 period, there was very low or negative growth in a few years that might have impacted banking operations. Non-performing loans (NPL) average of 1.7711 with a slight positive skew of 0.5011, reflecting that in most periods, banks could maintain comparatively low credit risk, though a few suffered higher loan defaults during this period. Capital Adequacy Ratio (CAR) averages 17.8666 with slight positive skewness of 0.2269, showing that banks generally have maintained strong capital buffers over the decade.

Overall, these descriptive statistics illustrate that while the banking sector with moderate profitability and strong capital adequacy between 2015 and 2024, the adoption of digital technologies varied across institutions. The increasing convergence of machine learning, AI chatbots, and robotic process automation (RPA) underscores the banking industry's shift towards technology-driven efficiency improvements and operational enhancements. The time span of this dataset provides context for understanding trends in performance and risk management, as well as the evolving role of digital technologies in shaping the banking landscape. These insights provide an important foundation for subsequent panel data analysis focused on the relationship between the adoption of AI technology, financial performance, and risk over time.

4.2 Correlations Test

Table 4.2: Correlation test result

Variables	*ROA*	*ML*	*ACBT*	*RPA*	*GDPG*	*NPL*	*CAR*
ROA	1						
ML	0.1226	1					
ACBT	-0.0954	0.5222	1				
RPA	-0.0677	0.7530	0.5697	1			
GDPG	0.1696	-0.1930	-0.1234	-0.0905	1		
NPL	-0.3460	-0.0055	0.2228	0.0297	-0.0615	1	
CAR	-0.0111	0.2998	0.0463	0.3110	-0.1173	0.2643	1

Note: *ROA* represents Return on Asset, *ML* represents Machine Learning, *ACBT* represents AI chatbot, *RPA* represents Robotic Process Automation, *GDPG* represents Gross Domestic Product Growth rate, *NPL* represents Non-performing Loans, *CAR* represents Capital Adequacy Ratio.

Based on Table 4.2, the correlation result of ROA shows a weak positive correlation to ML at 0.1226 and GDPG at 0.1696, suggesting that higher machine learning adoption and stronger economic growth are associated with slightly improved bank profitability. While it is negatively correlated with ACBT at –0.0954, RPA at –0.0677, NPL at –0.3460, and CAR at –0.0111, with the strongest negative relationship observed for NPL, indicating that higher credit risk reduces profitability. Among the independent variables, ML and RPA exhibited a strong positive correlation at 0.7530, and ML and ACBT were moderately positively correlated at 0.5222, and likewise for RPA and ACBT at 0.5697, suggesting that banks often consider several AI technologies at the same time. The control variables show generally weak correlations with ROA, indicating that GDP growth, NPL, and CAR influence profitability but do not move together strongly with ROA in the correlation matrix alone. Although the correlation between ML and RPA is moderately high, it remains below the commonly cited multicollinearity concern threshold of 0.8–0.9, suggesting that multicollinearity is unlikely to severely affect the regression results. Overall, the correlation analysis highlights that ML adoption may slightly enhance ROA, NPL strongly lowers ROA, and co-adoption patterns exist among AI technologies, which will be further examined in the regression models.

4.3 Diagnostic Tests

4.4.1 Multicollinearity Test

Table 4.3: Variance Inflation Factor Test result

Variable	VIF	1/VIF
ML	2.55	0.392258
ACBT	1.79	0.559866
RPA	2.72	0.367525
GDPG	1.06	0.944601
NPL	1.22	0.819363
CAR	1.32	0.756147
Mean VIF=1.78		

Table 4.3 presents the Variance Inflation Factor (VIF) results used to assess multicollinearity among the independent variables. Multicollinearity occurs when independent variables are highly correlated, making it difficult to assess each variable's individual effect and potentially leading to misleading estimates (Harrison et al., 2021). If all VIF values are below the common thresholds of 5 or 10, we do not reject the null hypothesis that multicollinearity is not a concern. In this study, VIFs range from 1.06 to 2.72, well below these thresholds, indicating no multicollinearity problem. The highest VIF value is that of RPA with a VIF value of 2.72, followed by ML and ACBT with a VIF value of 2.55 and 1.79, respectively, which are still within an acceptable range and thus do not indicate harmful correlation among predictors. The control variables GDPG, NPL, and CAR also exhibit low VIF values, thus implying that these variables do not appreciably overlap with other variables in explaining ROA. The mean VIF of 1.78 also supports the argument that the model does not suffer from multicollinearity problems.

4.4.2 Heteroscedasticity and Serial Correlation Tests

Table 4.4: Heteroscedasticity and Serial Correlation tests result

Test	F-Statistic	Prob.
Heteroscedasticity (Breusch Pagan test)	75.97	0.0000
Serial Correlation (Wooldridge test)	3.819	0.0824

The results of the diagnostic tests are necessary to ensure the reliability of the panel regression model. Heteroscedasticity refers to a situation in regression models where the variance of the error terms is not constant across observations. The null hypothesis of homoscedasticity is rejected if a test, such as Breusch-Pagan, yields p-value lower than 0.05, showing that heteroskedasticity exists (Astivia, 2019). As shown in Table 4.6, the Breusch-Pagan test shows a highly significant p-value of 0.0000, indicating that the null hypothesis of homoscedasticity errors is rejected. This suggests the presence of heteroskedasticity in the model, implying that the error variances are not constant across banks and over time.

While serial correlation, also known as autocorrelation, refers to the correlation of residuals over time, which violates the independence assumption and may affect estimated coefficients (Drukker, 2003). In panel data, the Wooldridge test checks for first-order serial correlation, where if p-value is lower than 0.05 indicates the rejection of null hypothesis of no serial correlation. In this study, the Wooldridge test yields a p-value of 0.0824 which is greater than the significance level of 5%. Hence, the null hypothesis cannot be rejected, indicating that the model does not suffer from autocorrelation.

4.4 Output Estimation

4.4.1 Fixed Effect Model

Table 4.5: Fixed Effect Model result

Variables	Coefficient	Std. err.	t	p-value
ML	0.2178**	0.1169298	1.86	0.0660
ACBT	0.0915	0.116685	0.78	0.4350
RPA	-0.4105***	0.1276146	-3.22	0.0018
GDPG	0.0249**	0.0102785	2.42	0.0175
NPL	-0.0854	0.0896732	-0.95	0.3434
CAR	0.0600*	0.0306936	1.96	0.0539
Constant	0.0261	0.4986185	0.05	0.9584

Observations: 100
R-squared: 0.4181
F-statistic: 2.68
Prob > F: 0.0199

Note: *ML* represents Machine Learning, *ACBT* represents AI chatbot, *RPA* represents Robotic Process Automation, *GDPG* represents Gross Domestic Product Growth rate, *NPL* represents Non-performing Loans, *CAR* represents Capital Adequacy Ratio. Significance at the 1% (***), 5% (**) and 10% (*) levels, respectively.

Based on the outcome that is presented in Table 4.1, machine learning (ML) shows a positive and statistically significant relationship with ROA ($\beta = 0.2178$, $p = 0.0660$). For an additional unit increase in the ML, the ROA is estimated to increase by 0.2178 units. This result may suggest that banks using machine learning tend to achieve higher profitability. Its ability allows the banking firms to handle large amounts of data, improve decision-making, and risk management capabilities which directly contribute to improvement in financial performance. In this regard, the findings are consolidated and tally with Cherish et al. (2025), who reported that ML and wider AI adoption significantly contributes to better profitability as it improves efficiency and mitigates financial and operational risks.

In contrast, the AI chatbot (ACBT), which is presumably another AI-related technology, has a positive but insignificant effect on ROA ($\beta = 0.0915$, $p = 0.4350$). For an additional unit increase in the ACBT, the ROA is estimated to increase by 0.0915 units. This indicates that although AI chatbot adoption may support customer service efficiency and reduce workloads, its financial impact may not yet

be strong enough to influence profitability. The insignificant result may reflect limited deployment scales or the early stage of chatbot usage among several banks. This may align with De Andrade & Tumelero (2022), who note that chatbots reduce call-centre traffic and enhance service speed. However, these improvements may take time to translate into measurable financial gains, especially if usage levels remain low. Moreover, the positive effect is smaller compared to Machine Learning (ML), which may be because chatbots primarily improve service efficiency rather than directly contributing to profitability.

Meanwhile, robotic process automation (RPA) exhibits a significant negative relationship with ROA ($\beta = -0.4105$, $p = 0.0018$). For an additional unit of increase in RPA, the ROA is estimated to decrease by 0.4105. The reason for this result may be the high upfront costs and challenges associated with early-stage RPA implementation. Banks often need to invest in software licenses, infrastructure, process redesign, training, and bot testing before efficiency gains are realised. These initial costs can reduce profitability in the short term. Additionally, temporary disruptions during integration and the limited scale of deployment may further constrain immediate financial benefits. The result is consistent with Axmann et al. (2021) and Adejola (2024), who found that early adoption of automation and AI technologies may negatively affect short-term profitability before delivering long-term efficiency and cost savings.

4.4.2 Lagged Effect Model

Table 4.6: Lagged effect result

Variables	lag 1 ROA	lag 2 ROA	lag 3 ROA	lag 4 ROA	lag 5 ROA
ML	0.1386	0.1948	0.2916**	0.1080	-0.005831
	(0.2629)	(0.2166)	(0.0671)	(0.5875)	(0.9838)
ACBT	-0.0905	-0.1317	-0.2670**	-0.0215	0.0387
	(0.3953)	(0.2361)	(0.0327)	(0.8778)	(0.8325)
RPA	0.04641	0.0649	0.1491	0.2967	0.4361**
	(0.7131)	(0.6532)	(0.3287)	(0.1185)	(0.0309)
GDPG	0.01733**	0.0111	0.0090	0.0013	0.0030
	(0.1170)	(0.4037)	(0.4699)	(0.9326)	(0.8407)
NPL	-0.1443***	-0.1545***	-0.1675***	-0.1969***	-0.2087**
	(0.0056)	(0.0037)	(0.0041)	(0.0043)	(0.0164)
CAR	0.0136	0.0154	0.0149	0.0502	0.0851**
	(0.6351)	(0.6077)	(0.6383)	(0.1603)	(0.0783)
Constant	0.8390**	0.8391	0.8672	0.2041	-0.4555
	(0.0995)	(0.1258)	(0.1341)	(0.7517)	(0.5995)
Observations	90	80	70	60	50
R-squared	0.1742	0.1814	0.2476	0.2164	0.2556

Note: () is the probability. *ROA* represents Return on Asset, *ML* represents Machine Learning, *ACBT* represents AI chatbot, *RPA* represents Robotic Process Automation, *GDPG* represents Gross Domestic Product Growth rate, *NPL* represents Non-performing Loans, *CAR* represents Capital Adequacy Ratio. Significance at the 1% (***), 5% (**) and 10% (*) levels, respectively.

Table 4.2 provides insight into AI adoption on bank profitability over five lag periods. Machine learning (ML) shows a positive coefficient across all lags except lag 5. However, statistical significance is observed only at the 3-year lag ($\beta = 0.2916$, $p = 0.0671$). This suggests that ML adoption contributes to improved profitability, but the benefits will materialise after a medium-term period of approximately three years. This can be said to be in correlation with prior evidence where ML systems do take their time in the accumulation of data, calibration of algorithms, integration of core banking systems, and upskilling of staff. The reduction to an insignificant

and near-zero coefficient at lag 5 (β = –0.0058) indicates that the impact does not extend into the long term. Therefore, ML adoption can help to enhance profitability in the medium term, but it does not guarantee sustained long-term advantages.

AI chatbots (ACBT) has a slightly negative coefficient at almost all lags, but with significant findings at lag 3 (β = -0.2670, p = 0.0327). The result shows that AI chatbots tend to negatively impact profitability on a medium-term perspective, perhaps because of costs associated with implementation and customer acceptance of services. The influence is still negative but insignificant within a short period-lags 1–2-suggesting that a limited contribution is made to profitability. Interestingly, it becomes slightly positive at lag 5 but is still insignificant (β = 0.0387, p = 0.8325), suggesting that it might offer some benefits in a very long-term perspective. This may be due to an implementation lag that might make it more familiar and acceptable. Overall, ACBT appears to impose a medium-term financial burden before any potential long-term benefit.

Robotic process automation (RPA) coefficients are positive across all lags. However, the emergence of significance is only at lag 5, with a β value of 0.4361 and $p < 0.05$. This indicates a very different pattern than that from ML and ACBT. The findings suggest that RPA contributes to profitability only in the long run. Lack of significance in lags 1–3 indicates that initial implementation and integration costs may delay financial benefits. However, by the fifth year, process optimization, decreased operational errors, cost savings, and scale efficiencies begin to yield measurable improvement in ROA. Alternatively, RPA has a strong payoff over the long term, though its benefit requires sustained adoption and operational maturity, with align with the findings of Axmann et al. (2021).

Overall, the findings indicate that AI technologies do not instantly influence financial performance which supported by the research of Gyau et al. (2024). Instead, their impact unfolds gradually and unevenly across technologies where ML produces medium-term gains, chatbots reveal short-term drawbacks, and RPA delivers long-term benefits. These results highlight that AI adoption in banking is most effective when paired with strong risk management and sufficient capital buffers.

4.5 Robustness Test

To strengthen the validity of the findings, a robustness check was performed by comparing results from the early AI adoption period with the post AI adoption period. The year 2020 is chosen as the breakpoint because it marks a major structural shift in the banking industry. During the early adoption period, AI technologies were implemented on a limited scale and were still in the experimental stage, as banks gradually explored how this could be used on the customer service end, in risk management, and for operational efficiency. Post-2020, rapid adoption began as the COVID-19 pandemic accelerated this along with the wider digital transformation of the world, resulting in deeper integration of AI into core banking operations, enhanced online services, and improved customer engagement (Dutta et al., 2025). By using 2020 as a breakpoint, the analysis can capture how AI adoption impacts bank performance across different stages of implementation and structural transformation.

4.5.1 Early AI adoption period (2018-2020)

Table 4.7: Early adoption period result

Variables	Baseline ROA	lag 1 ROA
ML	-0.0112	0.0100
	(0.8721)	(0.9131)
ACBT	0.0850	0.0754
	(0.1174)	(0.2040)
RPA	-0.0412	-0.0292
	(0.4967)	(0.5944)
GDPG	0.0252	0.0259
	(0.0004)	(0.0002)
NPL	-0.2323	-0.2249
	(0.0000)	(0.0000)
CAR	0.0063	0.0040
	(0.6871)	(0.8121)
Constant	1.2026	1.2274
	(0.0003)	(0.0004)
Observations	30	30
R-squared	0.8570	0.8340

Note: () is the probability. *ROA* represents Return on Asset, *ML* represents Machine Learning, *ACBT* represents AI chatbot, *RPA* represents Robotic Process Automation, *GDPG* represents Gross Domestic Product Growth rate, *NPL* represents Non-performing Loans, *CAR* represents Capital Adequacy Ratio. Significance at the 1% (***), 5% (**) and 10% (*) levels, respectively.

During the early AI adoption period from 2018 to 2020, it can be seen that for both the baseline and lag-1 models, there are no significant effects on the financial performance of Malaysian banks. In the baseline model, machine learning (ML) records a small negative coefficient of 0.0112 with a high p-value of 0.8721, indicating that early ML usage did not translate into measurable performance gains. However, after introducing a one-year lag, the ML coefficient becomes slightly positive at 0.0100, though still statistically insignificant (p = 0.9131). This suggests

that ML required more time to mature and may not have been effectively integrated into banking operations during the early implementation stage. Similarly, AI chatbots (ACBT) show a positive effect in both models, where 0.0850 in baseline and 0.0754 in lag-1, but these results remain insignificant, implying that customer-facing automation alone was insufficient to influence bank profitability within the short period. Robotic process automation (RPA) is also negative in both baseline (–0.0412) and lag-1 (–0.0292) models, indicating that early automation may have imposed adjustment costs or operational disruptions, although its insignificance means the negative effect cannot be meaningful. The results clearly indicate that AI in its early stages of adoption had not yet generated measurable performance benefits, likely due to limited maturity, small-scale implementation, or insufficient integration into core banking systems.

4.5.2 Post AI adoption period (2020-2024)

Table 4.8: Post AI adoption period result

Variables	lag 1 ROA	lag 2 ROA	lag 3 ROA	lag 4 ROA	lag 5 ROA
ML	0.2825 (0.1691)	0.3530* (0.0973)	0.3103 (0.1020)	0.0768 (0.7185)	-0.0058 (0.9838)
ACBT	0.0884 (0.5998)	0.0012 (0.9938)	-0.1841 (0.2470)	0.0536 (0.7240)	0.0387 (0.8325)
RPA	0.4895** (0.0493)	0.3154 (0.1390)	0.3365* (0.0975)	0.4234** (0.0517)	0.4361** (0.0309)
GDPG	-0.0084 (0.5501)	-0.0131 (0.4718)	-0.0056 (0.7280)	-0.0095 (0.5712)	0.0030 (0.8407)
NPL	-0.1598** (0.0307)	-0.1744** (0.0195)	-0.1959** (0.0117)	- 0.2124*** (0.0071)	- 0.2087** (0.0164)
CAR	0.0754 (0.1200)	0.0546 (0.2551)	0.0415 (0.3683)	0.0734* (0.0900)	0.0851* (0.0783)
Constant	-0.8914 (0.3314)	-0.2184 (0.8062)	0.2431 (0.7744)	-0.2887 (0.7128)	-0.4555 (0.5995)
Observations	50	50	50	50	50
R-squared	0.3333	0.3179	0.3177	0.2718	0.2333

Note: () is the probability. *ROA* represents Return on Asset, *ML* represents Machine Learning, *ACBT* represents AI chatbot, *RPA* represents Robotic Process Automation, *GDPG* represents Gross Domestic Product Growth rate, *NPL* represents Non-performing Loans, *CAR* represents Capital Adequacy Ratio. Significance at the 1% (***), 5% (**) and 10% (*) levels, respectively.

Table 4.8 above represents the results for the post-adoption period from 2020 to 2024. During the post-adoption period, the impact of AI adoption on the profitability of Malaysian banks shows clear variation across technologies and contrasts with the early adoption period. The post-adoption period reveals stronger and more differentiated effects, with the machine learning (ML) exhibiting generally positive coefficients where there is significance at lag 2 ($\beta = 0.3530$, $p = 0.0973$), reflecting the fact that medium-term benefits emerge when algorithms are calibrated, staff are trained, and ML becomes fully integrated into core banking

functions. AI chatbots (ACBT) remain largely insignificant across all lags, which could imply that automating customer interfacing alone still does not directly improve profitability. Conversely, robotic process automation (RPA) shows consistent positive and significant effects across multiple lags (lag 1, 3, 4, and 5), indicating that automation starts to yield measurable efficiency dividends in cost reduction once adopted at scale.

Comparing the two periods, backend-oriented AI technologies such as ML and RPA evolve from insignificant or negligible effects in the early adoption phase to meaningful contributors to profitability in the post-adoption period, whereas customer-facing AI like ACBT remains a minimal impact. Overall, the comparison suggests that AI adoption demands adequate time, scale, and operational integration to impact financial performance and underlines the importance of post-implementation maturity and experience in leveraging the benefits of AI in banking.

CHAPTER 5: CONCLUSION AND IMPLICATIONS

5.0 Introduction

This chapter presents the summary of the key findings, practical implications, limitations, and recommendations for future research, linking them to the main themes discussed in the previous chapter. It provides insights for policymakers and practitioners while outlining directions for future studies.

5.1 Summary of Statistical Analyses and Major Findings

In this study, panel data analysis is used to examine the relationship between AI adoption, such as machine learning (ML), AI chatbot (ACBT), and robotic process automation (RPA) to the financial performance as measured by return on asset (ROA) of the banking industry in Malaysia from 2015 to 2024. Furthermore, to prevent additional variables that may affect financial performance, our research controls the gross domestic product growth rate (GDPG), non-performing loans (NPL), and capital adequacy ratio (CAR). This study estimates four model specifications, including the fixed effect model, lagged effect models, and sub-sample analyses as robustness check, to comprehensively examine the impact of AI adoption on bank profitability. The results show that ML has a significant positive impact on ROA in the medium term, suggesting that profitability gains emerge after sufficient integration and learning. In contrast, ACBT does not exhibit a consistent positive relationship with ROA and shows a medium-term negative effect, implying limited direct profitability benefits from customer-facing AI. Meanwhile, RPA demonstrates a short-term negative impact but a significant positive long-term effect on ROA, indicating that automation generates efficiency gains only after initial implementation costs are absorbed. Among the three technologies, RPA delivers the strongest long-term profitability effect, while ACBT shows the weakest impact on ROA. Sub-sample analyses across early (2018–2020) and post-adoption (2020–2024) periods results remain consistent further confirming the reliability of the findings across different adoption stages.

5.2 Implications of the Study

The findings of this study carry several important practical implications for multiple stakeholders within the banking sector. For policymakers, the findings suggest the necessity of active promotional policies for the use of AI technologies in commercial banks, which should be pursued along with higher goals of digital transformation of the whole financial industry. Promotion should be accompanied by the creation of relevant regulatory frameworks, detailed guidelines on ethical use, robust cybersecurity measures, and continuous monitoring to help ensure responsible implementation and risk mitigation. Additionally, policymakers could also consider the possibility of offering incentives for AI investments, through tax benefits or grants, for example, that could motivate banks toward innovative technology with sustained operational resilience.

The study highlights for bank managers and practitioners the strategic need to tease out the differences among AI technologies themselves and their individual effects on financial performance. Machine learning, for example, has the potential to drive medium-term profit growth through the advanced capabilities it provides for decision-making, risk assessment, and predictive analytics. Robotic process automation indicates substantial long-term benefits through smoothing and automating repetitive tasks of operations and improving efficiency, reducing human error over time. While AI chatbots-primarily customer-facing tools-need careful consideration over implementation costs, integration processes, and staff training to avoid placing short-term burdens on finances and ensuring contributions to customer service goals.

Moreover, the study points out that the adoption of AI cannot be seen in isolation. Financial benefits can be realized to the fullest only when technological investment is balanced with sound credit risk management, capital buffers, and operational governance. In this way, through a combination of technological investments with strong credit risk management, adequate capital buffers, and good operational governance, banks can capitalize on AI not only for enhancing profitability but also for increased resilience, adaptation to changing market conditions, and developing

a leading position in the rapidly digitalized financial industry. Overall, these findings provide actionable insights for policymakers and banking professionals aiming to strategically implement AI technologies to achieve sustainable growth and long-term value creation.

5.3 Limitations of the Study

Despite providing valuable insights into the impact of AI adoption on bank profitability, this study is subject to several limitations that should be acknowledged. First, this analysis focuses only on Malaysia's ten largest listed commercial banks, which may limit the general applicability of the findings to smaller banks, non-bank financial institutions, or other financial institutions in other countries. Smaller institutions may face different resource constraints, varying levels of technological readiness, and distinct regulatory pressures, which can result in disparities in the outcomes of AI applications. it focuses on only the ten largest commercial banks in Malaysia, which may limit the generalizability of the results to smaller banks or other countries.

Secondly, the adoption of AI is measured with dummy variables, which only indicate whether a particular technology has been adopted, but it is not capable of capturing the power, intensity, size, or efficiency of the application of that particular technology. The implication is that the sophistication of AI development in different banks might not be accurately captured, which might result in a potential underestimate or overestimate effect of AI technology on financial performance.

Third, the study is based on secondary data sourced from published financial statements and external databases that might be prone to variations in reporting standards, disclosure quality, or accounting practices between banks and over time. Furthermore, publicly available data may not reflect internal operational changes or proprietary artificial intelligence initiatives that could affect performance.

5.4 Recommendations for Future Research

Building on the limitations identified, future research could extend this study in several important ways. For instance, the research can be expanded with a larger sample, which may include small banks, Islamic banks, as well as non-bank financial institutions, with a comparison analysis being performed on a cross-country basis, which may be within the ASEAN region or other emerging economies. This would help to enhance the external validity of the findings and contribute to a deeper understanding of institutional and regulatory differences in AI applications.

Second, more advanced, continuous indicators of AI adoption, such as AI investment, application intensity, implementation scope, AI maturity index, or the number of AI applications used, may be employed for use in future research. With the use of these indicators, researchers would be able to evaluate the effects of varying application levels on performance outcomes and better capture the heterogeneity in AI use.

Furthermore, future research can also expand the scope of analysis to examine the interactions between AI adoption and other key performance indicators, such as customer satisfaction, operational efficiency, risk management effectiveness, and overall digital transformation maturity. By examining these aspects, it might contribute to a more thorough comprehension of how AI can boost the banking sector's competitiveness and generate long-term value.

5.5 Conclusion

This study examines the impact of AI adoption such as machine learning (ML), AI chatbots (ACBT), and robotic process automation (RPA) on the financial performance (ROA) of Malaysian commercial banks from 2015 to 2024. The findings reveal that ML drives medium-term profitability, RPA delivers significant long-term efficiency gains, and ACBT has limited or negative short- to medium-term financial impact. These results underscore the importance of integrating AI

adoption with strong credit risk management and adequate capital buffers to maximise financial benefits.

For policymakers, promoting AI adoption with clear regulations, cybersecurity frameworks, and incentives is essential, while bank managers should carefully manage the implementation, costs, and integration of different AI technologies. Despite its contributions, the study is limited by the sample size, the use of dummy variables for AI adoption, and reliance on secondary data. Future research could expand the sample, employ more detailed AI adoption metrics, and explore interactions with other performance indicators, such as operational efficiency and digital transformation maturity.

Overall, the study confirms that AI adoption can enhance bank profitability if implemented strategically and provides a foundation for further research into sustainable AI-driven growth in the banking sector.

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Appendices

Annual report details on bank AI adoption:

AI Technologies	Banks	Year	Details
Machine Learning	Maybank	2020	The Group leveraged machine learning for effective credit decision-making and enhanced analytics for more personalised customer engagement
	CIMB	2019	CIMB Group Risk began to develop stronger predictive risk models via cutting edge Machine Learning techniques as part of a pivotal strategic plan under the Forward23 initiative. This year also saw the introduction of machine learning for optimisation in AML Alerts.
	RHB	2020	RHB formally acknowledged implementing advanced analytics and machine learning to enhance credit risk measurement. The Group developed a Machine Learning-based behavioural analytics model with early warning capabilities to strengthen oversight
	Public Bank	2020	The Group intensified the usage of artificial intelligence and machine learning capabilities in dashboard monitoring platforms for faster and more efficient monitoring of metrics and applications
	Hong Leong Bank	2019	The application of artificial intelligence ("AI") and machine learning and automated technologies via a 'Predictive Customer Intent CRM System' to serve customers in a more predictive and intuitive manner
	Ambank	2023	Tapping into the potential of AI and machine learning to mitigate risks, boost efficiency and devise smart customer value propositions.
	Alliance Bank	2019	Integrating ML into its mobile app for smart payment reminders and predictive credit scoring
	Affin Bank	2024	The launch of two Machine Learning Use Case Models was listed as an achievement under the Data Strategy and Enterprise Data Hub (EDH) Key Achievements
	UOB Malaysia	2018	The Bank implemented a data analytics-powered credit underwriting engine to assess the creditworthiness of small business customers, leading to a reduction of turnaround time and a 50 per cent reduction in the default rate for small business loans.

	OCBC Malaysia	2019	Confirmed the active use of sophisticated modeling: "Application models are also used in the credit decision process for most products to enable objective, consistent and fast decisions
AI Chatbot	Maybank	2019	Launched a "Live Chat" function on the Maybank2u and mobile app for Premier Wealth customers, providing real-time answers.
	CIMB	2016	Launched CIMB EVA (Enhanced Virtual Assistant), a mobile banking application positioned as the first virtual assistant designed to help customers with their daily banking needs
	RHB	2017	RHB collaborated with RinggitPlus to launch the first online financial application processing chatbot in ASEAN
	Public Bank	-	There is no verifiable evidence in the public disclosure's completion of an AI-chatbot deployment
	Hong Leong Bank	2018	Launched "HALI," an internal AI chatbot to answer staff queries on HR procedures and branch operations, aiming for greater operational efficiency.
	Ambank	2018	AMY™ Virtual Assistant was officially launched on 28 October 2018 and integrated into the AmOnline app to help customers with credit card-related enquiries.
	Alliance Bank	2023	The Bank introduced BOB, the new BizSmart® Chatbot that provides 24/7 customer self-help via WhatsApp
	Affin Bank	2023	Launched Affina, an AI-based digital assistant on the AffinAlways website, in February 2023
	UOB Malaysia	2020	UOB Malaysia launched Mighty Insights, an AI-driven financial management tool integrated within its mobile banking app
	OCBC Malaysia	2020	The Bank formally introduced OCBC RM Chat, specifically defined as "the country's first secure chat service that enables Premier Banking and Premier Private Client customers to communicate and place daily banking instructions securely with their Relationship Managers
Robotic Process Automation (RPA)	Maybank	2020	Successfully deployed 132 Robotic Process Automation (RPA) systems to replace 1,379 manual tasks, streamlining operational processes for greater efficiency
	CIMB	2017	The Robotic Process Automation project was launched as part of efficiency initiatives,

			focusing on automating repetitive tasks in banking operations to enhance quality, increase accuracy, and improve staff efficiency
	RHB	2018	A pilot implementation of Robotics Process Automation took place in 2018, contributing to 27,000 man hours saved through automation efforts. RPA was also listed as a focus area for improving Intellectual Capital.
	Public Bank	2020	Robotic process automation was deployed for repetitive and low-value tasks, contributing to significantly enhanced operational efficiency and productivity
	Hong Leong Bank	2018	HLB Rolled out Robotic Process Automation projects.
	Ambank	2021	AmBank was progressively implementing end-to-end business process reengineering and robotic process automation to drive better productivity and business efficiency. AmBank had already utilised more than 60 RPA bots for operational efficiency.
	Alliance Bank	2018	adopted RPA in August 2018, automating internal processes to significantly reduce turnaround time
	Affin Bank	2022	AFFIN Group leveraged RPA to automate a total of 27 processes in 2022, bringing the total automated processes to 48, translating to cost savings of approximately RM500,000
	UOB Malaysia	2021	UOB Malaysia and its innovation accelerator, The FinLab, launched JomX, an initiative designed to help SME customers access digital solutions, including those specialising in robotic process automation
	OCBC Malaysia	2017	Officially deployed its first two "robots" to automate processes across its group, including operations relevant to Malaysia in November 2017.