ANALYSING CUSTOMER PROPENSITY FOR EMBRACING ARTIFICIAL INTELLIGENCE (AI) IN BANKING SERVICES

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AUGUST 2024

LAU, LIM, & WONG AI BANKING SERVICE BFN (HONS) AUGUST 2024

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A final year project submitted in partial fulfillment of the requirement for the degree of

BACHELOR OF FINANCE (HONS)

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AUGUST 2024

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ACKNOWLEDGEMENT

We would want to take this time to express how much we appreciate all of the help and encouragement we received while we worked to complete the final year project. Without their assistance, cooperation, and support, this project could not have been completed. We truly appreciate all of their excellent input.

Our study supervisor, Dr. Nurul Afidah Binti Mohamad Yusof, is the first and foremost person for whom we would like to sincerely thank for her unwavering support, wise advice, and insightful contribution. The scope and quality of our studies were greatly influenced by her expertise and dedication. We might not have found the direction and effectively finished the research without her counsel and observations. Our appreciation also goes out to Universiti Tunku Abdul Rahman (UTAR) for giving us the opportunity to conduct this study. We have had no trouble accessing and utilizing data as resources for our study thanks to UTAR's vast database resources.

Furthermore, we are grateful to the respondents for their genuinely useful contributions—160 in all. Our sincere appreciation and gratitude go out to the AI banking researchers whose innovative work served as the basis for our current study. Our study's course has been greatly influenced by their commitment, knowledge, and unwavering quest of information.

Finally, we would like to thank each and every participant for their participation in this final project. The dedication and hard work of each individual has considerably raised the caliber of the research. Without their help, our research would not have been possible. We want to thank everyone one more for helping us with the research.

DEDICATION

This study project is first and primarily dedicated to our group members Lau Yong Zheng, Lim Wei Xiang, and Wong Xin Yi, who worked hard and put in a lot of effort to finish it. Everyone is essential in providing ideas and fixing errors, and it is because to their invaluable contributions that the research is now completed.

Dr. Nurul Afidah Binti Mohamad Yusof, who oversaw our study project, has our sincere gratitude for all of her efforts, support, and advice from the start to finish. We appreciate that she helped us through challenging times with our study project by giving us useful guidance, reliable information, and inspiration.

We sincerely thank the AI banking researchers whose creative work provided the foundation for our current investigation. Their dedication, expertise, and unrelenting search for information have had a significant impact on the direction of our investigation.

Lastly, we would like to dedicate our project to the responders who helped us with the questionnaire and gave us important information for it. We also want to express our gratitude to all of our friends and family for their inspiration and assistance with this research.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
DV	Intention to Adopt Artificial Intelligence
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
PR	Perceived Risk
PT	Perceived Trust
SN	Subjective Norms
UTAUT	Unified Theory of Acceptance and Use of Technology
TPB	Theory of Planned Behavior
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
CA	Cronbach’s Alpha
VIF	Variance Inflation Factor
PLS	Partial Least Square
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait Ratio of Correlation

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PREFACE

Significant research problems and complexity have been brought about by the integration of artificial intelligence (AI) into financial services as a component of digital transformation (M. Sankar et al., 2023). When it came to the use of artificial intelligence and machine learning (AI/ML), Bank Negara Malaysia conducted a survey of 25 financial service providers (FSPs) in the country. The results showed that the majority of FSPs were either implementing AI/ML or starting their own AI/ML projects (Financial Stability Review: Second Half 2022, 2023). But the FSPs also expressed worries about the hazards associated with integrating AI/ML into Malaysia's financial system, particularly model validation, which is the top priority for the FSPs. Furthermore, according to Cheong (2022), just 15% to 20% of Malaysian businesses have completely embraced Industry 4.0, suggesting a low AI acceptance rate. Therefore, this study aims to find out the intention of Malaysian banking residents to adopt AI in banking services.

The title of our study is “Analysing Customer Propensity for Embracing Artificial Intelligence (AI) in Banking Services”. The intention to adopt AI is chosen for our study, while the selected independent variables are perceived ease of use, perceived usefulness, perceived risk, perceived trust, and subjective norms.

We wish that our study could provide insights for future researchers, government bodies and banks, to serve as a foundation for further improvements in utilization of AI and Malaysian banking residents’ intention to adopt AI in banking services.

ABSTRACT

This research purpose is to examine and evaluate the intention to adopt artificial intelligence in banking services in Malaysia. This study applied primary data collection method which is using Google Form questionnaire and survey, and the targeted respondents are Malaysia citizens that is 18 years old or above. There are five independent variables (perceived usefulness, perceived ease of use, perceived trust, perceived risk, subjective norms) and one dependent variable (intention to adopt artificial intelligence in banking services). 183 responses were collected for data analysis and SmartPLS 4 analysis software were used to analyse the data in this research. The result of the research has declared that there are 3 independent variables (perceived usefulness, perceived trust, subjective norms) are significant to the dependent variable, and 2 independent variables (perceived ease of use, perceived risk) is insignificant to the dependent variable. Furthermore, the research also provides appropriate implications, limitations, recommendations, and also reference of the study to future studies related to this topic.

CHAPTER 1: INTRODUCTION

1.0 Introduction

The first chapter talks about the background to research first. Additionally, the problem statement explains the challenges related to this research. Then, in that sequence, the study questions, hypotheses, and objectives are all identified. The significance of conducting this study is then utilized about. The content covered in every chapter is then briefly summarized in chapter layout. Lastly, an overview of the key ideas covered in this chapter is provided in the conclusion.

1.1 Research Background

Artificial intelligence (AI) and robotics technological developments are drastically changing the service delivery environment (Robinson et al., 2020). Artificial intelligence (AI) is quickly influencing front-line customer interactions. AI is often referred to as changing how people "work, live, and interact with each other." Even while traditional human-to-human interactions are still typical, AI is starting to fill tasks that have been considered to be exclusive to humans. This shift not only places traditional employment patterns in jeopardy but also opens the door for creative human-machine partnerships in the delivery of services (Huang & Rust, 2018).

Nowadays, artificial intelligence (AI) is the key driver of innovation, with a wide range of applications in many service sectors (Rust & Huang, 2014). These artificial intelligence (AI) systems automate many areas of daily living in homes, hospitals, hotels, and restaurants (Huang and Rust, 2018). They display traits similar to human intelligence (HI). The integration of artificial intelligence (AI) is blurring the distinction between the digital and physical worlds, leading some to refer to this as the fourth industrial revolution (Schwab, 2016). Some instances include virtual assistants facilitating self-service in customer assistance and sophisticated AI portfolio management systems.

FinTech is becoming a strategic necessity for the banking industry, pushing banks to investigate AI technologies in order to stay competitive and streamline operations (Belanche et al., 2019; Rahman et al., 2021). So, AI is digitizing and revolutionizing various industries, with the banking and finance sectors setting the standard for the automation of internal processes and customer-facing services (Caron, 2019).

The COVID-19 pandemic's push for digitization has expedited the convergence of technology and finance (Alt et al., 2021), which has affected how financial institutions and consumers interact (Shaikh & Karjaluoto, 2015). For example, AI-driven chatbots have become a vital component of customer service in the finance industry, improving user experience and expediting procedures (Kok & Siripipatthanakul, 2023). Notably, AI-driven chatbots have become a preferred technical innovation in the finance industry, enabling smooth communication via text or speech interfaces. By 2025, the chatbot market is expected to increase exponentially, with banking expected to account for the bulk of bot interactions. This highlights the critical role that artificial intelligence will play in transforming client relationships (Caron, 2019).

The strategic importance of AI applications is emphasized, especially in the areas of economic analysis and forecasting (Kok & Siripipatthanakul, 2023). Their work demonstrates how neural network forecasting algorithms may accurately anticipate GDP growth, beating traditional methods and resulting in more precise government estimates. With a predicted 30% increase in national output across sectors by 2030, this innovation is positioned to play a crucial role in Malaysia's pursuit of the objectives outlined in the National Industrial Revolution 4.0 (4IR) Policy (Sanusi et al., 2020).

According to Kok and Siripipatthanakul (2023), AI has a big influence on the financial services sector, providing, in Malaysia’s context, cost savings, risk mitigation, fraud detection, and increased client loyalty. Furthermore, the shift from paper contracts to digital smart contracts emphasizes how AI may help ensure safe transactions without sacrificing authenticity. Furthermore, AI-driven client loyalty forecasting tools offer chances for Islamic banking practices to generate new insights, enabling bank management to maximize customer loyalty programs in Malaysian Islamic banks (Rahman et al., 2021).

1.2 Problem Statement

The integration of artificial intelligence (AI) into financial services as a component of digital transformation has introduced significant research challenges and complexities (M. Sankar et al., 2023). According to Vijai (2019), AI-based banking systems could change work roles and make certain skills redundant, potentially resulting in job losses. Therefore, obtaining user acceptability for AI in banking may be quite difficult. Furthermore, employing AI to automate decision-making and problem-solving procedures may reduce workers' inventiveness and flexibility (Königstorfer & Thalmann, 2020). Therefore, affecting consumers’ intention to adopt artificial intelligence in banking services.

Furthermore, AI integrated banking services may also lead to privacy risks. According to Lui and Lamb (2018), the analysis of vast amounts of consumer data, including social media profiles, credit and debit card information, demographics, purchasing habits, and contact information, is necessary for banking AI systems. The use of AI in this context generates significant concerns regarding the privacy and security of consumers. Apart from that, the incorporation of AI technology into a bank's present infrastructure might disrupt established procedures and create issues about system stability, data privacy, and cybersecurity (M. Sankar et al., 2023). These may affect consumers' intention to adopt artificial intelligence in banking services in terms of perceived risks.

While in Malaysia, Bank Negara Malaysia had surveyed 25 Malaysian financial service providers (FSPs) about their usage of Artificial Intelligence and Machine Learning (AI/ML) and found out that most of the FSPs have been utilizing AI/ML or establishing their AI/ML projects (*Financial Stability Review: Second Half 2022*, 2023). However, the FSPs also raised concerns regarding the risks brought by AI with the implementation of AI/ML in Malaysia's financial system, especially model validation, which is the utmost concern of the FSPs in Malaysia. In order to guarantee that AI/ML models are accurate, dependable, and applicable in a variety of contexts, model validation is a crucial stage (Macgence, 2024). While in the finance sector, the process of model validation guarantees the accuracy and neutrality of AI/ML models that are used to forecast market trends or investment results. However, due to worries about bias and toxicity, large language models (LLMs) have attracted a lot of media attention, which makes it more difficult to validate them in the face of AI's rapid and widespread development (*Adapting Model Validation in the Age of AI | Deloitte Global*, 2023). The main obstacle to validating models is the enormous quantity of data—many times more than that required for classical models—that is required to train and test AI models such as LLMs. Due to its growing complexity and size, AI/ML may be unable to produce correct predictions, and traditional validation techniques may become unfeasible due to the inefficiency of statistical methodologies. Besides, Kok and Siripipatthanakul (2023) also state that the skepticism towards AI remains high among Malaysians despite having a legal framework in place, largely due to past incidents involving data breaches and scandals. The utilization of shared data by AI systems presents significant ethical and legal concerns, especially regarding the allocation of decision-making responsibility and the process of analysis (Sun & Medaglia, 2019). All these issues also affects the intention of consumers' to adopt AI in Malaysian banking services.

Furthermore, Malaysia still has a low AI adoption rate compared to other countries. Cheong (2022) states that just 15% to 20% of Malaysian enterprises have fully integrated Industry 4.0, indicating a low adoption rate. The advantages and incentives for adopting AI are well-recognized; however, governments and enterprises face significant hurdles when applying AI technologies (Kok & Siripipatthanakul, 2023). This is especially true as AI usage spreads throughout Malaysia's institutional, economic, and social frameworks and as the scope and complexity of its applications increase. The incorporation of AI in international financial services has been the subject of earlier studies (Alt et al., 2021; Kaur et al., 2020; Königstorfer & Thalmann, 2020; M. Sankar et al., 2023; Sun & Medaglia, 2019; Vijai, 2019). However, there is insufficient research on the adoption of AI in Malaysian banking services. Therefore, our study will emphasize the banking services of Malaysia.

Prior studies indicate that various factors affect the intention to adopt artificial intelligence (DV). Nonetheless, the impacts of a few factors, such as perceived ease of use (PEOU), perceived usefulness (PU), perceived risk (PR), perceived trust (PT) and subjective norms (SN), are yet unknown.

The term "perceived usefulness" describes someone's opinion that using a specific system would boost their productivity at work (Alt et al., 2021). Perceived usefulness and the performance expectation component of the UTAUT model are connected, according to Li and Kishore (2006). Alt et al. (2021), Noreen et al. (2023), and Rahman et al. (2021) discovered that there is a significant influence on DV by PU. While in Belanche et al. (2019) study, an insignificant relationship was found between PU and DV.

According to Rahman et al. (2021), perceived ease of use is defined as "the extent to which a person believes that using a specific system would be effortless,". DV was found to be significantly related with PEOU, according to studies by Nayanajith (2020) and Sohn and Kwon (2020) study. While in Alt et al. (2021), Ly and Ly (2022) and

Rahman et al. (2021) study, the DV and PEOU were found to have a negligible relationship.

A consumer's anticipation of experiencing a loss while pursuing a desired goal is known as perceived risk (Rahman et al., 2021). A significant relationship has been identified between DV and PR in the Rahman et al. (2021) study. However, it was discovered by Alt et al. (2021) and Noreen et al. (2023) that PR has no significant effect on DV.

Perceived trust is a multifaceted and dynamic concept that is best applicable in uncertain and dangerous circumstances (Rahman et al., 2021). There has been a significant connection between the DV and PT in Rahman et al. (2021), Ly and Ly (2022) and Payne et al. (2018) study. No studies with insignificant results were found.

Subjective norms, according to Noreen et al. (2023), are the behaviors of people who either encourage or disapprove of a particular activity. Ly and Ly (2022), Noreen et al. (2023) and Rahman et al. (2021) found that the DV is significantly influenced by SN. No studies with insignificant results were found.

Previous studies found inconsistencies in the connection between the independent variables (PEOU, PU, PR, PT, and SN) and the dependent variable (DV). It is unclear how the independent and dependent variables are related as a result. Closing the previously noted gap is the aim of this investigation.

Consequently, the aim of this research is to examine the impact of PEOU, PU, PR, PT, and SN on DV for Malaysian banking services.

1.3 Research Objectives

1.3.1 General Objectives

The goal of the study is to find out how likely it is for Malaysians to adopt artificial intelligence (AI) in financial services as well as what factors affect this intention.

1.3.2 Specific Objectives

The specific goals below have been set to achieve our general objectives.

1) To examine whether there is a significant relationship between PEOU and intention to adopt artificial intelligence in Malaysian banking services.
2) To examine whether there is a significant relationship between PU and intention to adopt artificial intelligence in Malaysian banking services.
3) To examine whether there is a significant relationship between PR and intention to adopt artificial intelligence in Malaysian banking services.
4) To examine whether there is a significant relationship between PT and intention to adopt artificial intelligence in Malaysian banking services.
5) To examine whether there is a significant relationship between SN and intention to adopt artificial intelligence in Malaysian banking services.

1.4 Research Questions

The following research questions are created to give our study a clear path.

1) Is there a significant relationship between PEOU and intention to adopt artificial intelligence in Malaysian banking services?

2) Is there a significant relationship between PU and intention to adopt artificial intelligence in Malaysian banking services?
3) Is there a significant relationship between PR and intention to adopt artificial intelligence in Malaysian banking services?
4) Is there a significant relationship between PT and intention to adopt artificial intelligence in Malaysian banking services?
5) Is there a significant relationship between SN and intention to adopt artificial intelligence in Malaysian banking services?

1.5 Hypothesis of the Study

H1: There is a significant relationship between PEOU and intention to adopt artificial intelligence in Malaysian banking services.
H2: There is a significant relationship between PU and intention to adopt artificial intelligence in Malaysian banking services.
H3: There is a significant relationship between PR and intention to adopt artificial intelligence in Malaysian banking services.
H4: There is a significant relationship between PT and intention to adopt artificial intelligence in Malaysian banking services.
H5: There is a significant relationship between SN and intention to adopt artificial intelligence in Malaysian banking services.

1.6 Significance of Study

First and foremost, this research is crucial because it has the potential to broaden our theoretical understanding of FinTech and the function of AI in banking services. This study also made use of the Technology Acceptance Model (TAM), the Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Planned Behavior (TPB) and Theory of Reasoned Action (TRA), as proposed by Alt et al. (2021). Since all of the variables are based on the previously discussed theoretical framework, future researchers conducting similar studies will find it easier to comprehend and apply this research.

Furthermore, this study's result could also have a big impact on how financial institutions are shaped in the future. Analyzing the variables affecting the adoption of AI in banking provides important insights into the competitive landscape and industry trajectory as technology continues to transform the sector (Rahman et al., 2021). Through examining the variables that impact banks' choices to incorporate artificial intelligence (AI) into their processes, scholars can clarify the fundamental forces, obstacles, and prospects influencing this revolutionary advancement.

In addition, the findings in banking services provide financial institutions, industry stakeholders, and policymakers with a guide (Belanche et al., 2019). It offers helpful direction for resource allocation, strategic planning, and regulatory frameworks, enabling well-informed decision-making in a setting that is becoming more and more digital. Furthermore, by learning more about banks' goals for adopting AI, it becomes possible to identify potential roadblocks and enablers, which opens the door for focused interventions aimed at boosting adoption rates and optimizing the technology's advantages.

On top of that, the findings also advance larger conversations about financial inclusion, innovation, and competitiveness (Alt et al., 2021). Researchers can give light on how these technologies alter client experiences, risk management procedures, and business models within the industry by dissecting the motivations behind banks' adoption of AI. This information not only helps people comprehend technology trends on a deeper level but also helps develop plans for using AI to promote financial inclusion and long-term growth.

1.7 Chapter Layout

The problem statement and research background are presented in the first chapter, together with an explanation of the selection of the study area. The study's questions, objectives, and hypotheses are also developed. There is also a discussion on the study's significance.

An overview of earlier studies on the intention to embrace artificial intelligence may be found in chapter two. This includes a review of factors and theoretical frameworks used in previous research. In addition, variable definitions are given. This chapter is a coherent presentation of previous researchers' findings in the subject topic.

The research methodology is covered in chapter three. The design of the study, sample size selection, sampling technique, and research instruments are all covered in this chapter. In addition, the procedures for processing and analyzing data are explained.

The results of the research are presented in chapter four. Achieving research objectives requires the effective presentation of study findings. Chapter four emphasizes descriptive, preliminary, and inferential analytical results.

The research findings are analyzed in detail and summarized in chapter five. Finally, authorities are given recommendations for implementing the findings. Finally, the study's restrictions are explored, along with ideas for how to overcome them.

1.8 Conclusion

In a nutshell, the application of AI in Malaysian banking services has both advantages and disadvantages. While technology may simplify banking procedures and increase convenience, it also brings up issues with employment security and personal data protection. Even while many Malaysians are willing to utilize AI in banking, banks are concerned about ensuring that it functions well and without causing any complications. Some Malaysians remain skeptical about AI due to prior data breaches. In comparison to other countries, Malaysia does not use as much AI in banking. This is due to a lack of study on how artificial intelligence may aid Malaysian banking. Therefore, it's essential to determine the advantages and disadvantages of AI in banking to guarantee that it's used in a way that maximizes benefits and minimizes risks. Therefore, this study's objective is to gain a better comprehension of the factors influencing Malaysian banks' intentions to implement AI. PU, PEOU, PR, PT, and SN are the variables that will be examined.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Chapter 2 is arranged as follows. The first part studied the literature regarding on the dependent variable, intention to adopt artificial intelligence in banking services in Malaysia. The second part discussed the relationship between this dependent variable and five independent variables, which including PU, PEOU, PR, PT, and SN. The third part explained the theoretical framework. The fourth part represents the conceptual framework. Lastly, the fifth part discussed the study's hypotheses.

2.1 Review of Literature

This section will discuss about the previous study on intention of an individual to adopt AI in banking services. The independent variables that have been analyzed are PU, PEOU, PR, PT, and SN. These variables are discussed and explained about the influence towards intention of an individual to adopt artificial intelligence in banking services.

2.1.1 Intention to adopt artificial intelligence in banking services

Term artificial intelligence (AI) encompasses a broad spectrum of scientific disciplines, such as mathematics, psychology, theology, dialects, and other related topics (Scarcello, 2018). AI provides crucial advantages for the world economy and the industry of financial services. According to previous studies, artificial intelligence (AI) might boost the value of the worldwide financial services sector by up to $1 trillion yearly (Noreen et al., 2023). Moreover, Noreen et al. (2023) predict that the entire financial industry will continue to expand at a 6% compound annual growth rate (CAGR) to meet USD 28.529 trillion by year 2025 and year 2030. The substantial use of artificial intelligence in the restructuring of financial services, particularly after the COVID-19 reimbursement, is primarily responsible for this rise (Noreen et al., 2023).

The COVID-19 epidemic has accelerated the migration to digital technology, forcing banks to quickly move to rural assistance and marketing (McKinsey, 2020). This change is being greatly aided by the advent of artificial intelligence (AI), as more banks are putting AI-based apps into place to save money, enhance anti-money laundering procedures, identify and avoid fraud, and build stronger client relationships (Alt et al., 2021). Artificial intelligence (AI)-based chatbot technology, which interacts with consumers and carries out routine activities via chat or speech interfaces, is one of the most significant technological advancements in the finance sector (Alt et al., 2021).

Currently, in order to stay on par in the financial services industry, banks are looking for artificial intelligence solutions to replace expensive, time-intensive, and repetitive jobs. (Rahman et al., 2021). Alsheibani et al. (2018) propose that implementing artificial intelligence tools improves consumer satisfaction and daily activities' efficiency. According to Vijai (2019), fundamental artificial intelligence (AI) applications used by banks, for example, chatbots, personalized services, and even artificially intelligent machines for self-servicing, produce more efficiency than conventional human advising services. A humanoid robot named Nao responds to clients in certain Bank of Tokyo branches by interpreting their emotions through their tone of conversation and gestures. In contrast to humans, Nao is capable of multilingual communication and is able to provide 24-hour online banking services. The Bank of Tokyo has effectively given branch employees greater flexibility in using these apps, enabling them to concentrate on additional value-added services (Rahman et al., 2021).

The financial industry sector has grew from Banking 1.0, which was founded on conventional and classical banking, to Banking 4.0, featuring the application of artificial intelligence (AI) and other modern technologies in various banking fields. Banks have been implementing modern and contemporary technologies in order to remain relevant and competitive. For instance, Barclays Bank launched Banking 2.0 in the 1960s and brought in automated teller machines (ATMs). Banking 4.0 was introduced in 2017 as a result of the quick development of AI technologies, which also helped to lower the cost of handling and storing data and speedier communication (Noreen et al., 2023).

Malaysia, as one of the developing countries, is also heading towards Artificial Intelligence development. Organizations like Malaysian Digital Economy Corporation (MDEC) have launched several programs to follow the trend of Artificial Intelligence services. To support the National AI Framework and make sure Malaysia is moving in the correct direction towards creating an AI ecosystem, MDEC formed an AI unit with both domestic and foreign specialists (Rahman et al., 2021).

2.1.2 Perceived Usefulness

Perceived Usefulness (PU) was said to be a variable that directly affect intention to adopt AI in banking services. PU illustrates that individual's belief that utilizing a specific system would improve the work performance (Alt et al., 2021). According to Li and Kishore (2006), perceived usefulness is highly related to the performance expectation component in UTAUT model. Moreover, studies have also found that PU does a positive influence on the intention to adopt technologies (Alt et al., 2021).

Studies has been discussed by previous researchers on PU influencing intention to adopt artificial intelligence in banking services. The results found was inconsistent from each research. Several studies have shown significant results between the two variables in developing countries such as Malaysia (Rahman et al., 2021), Romania (Alt et al., 2021), Cambodia (Ly & Ly, 2022), Pakistan, China, Iran, Saudi Arabia, Thailand (Noreen et al., 2023), and Portuguese (Silva et al., 2023). Moreover, there is another research by Alqutub (2023) also supported that PU has significant relationship towards the intention to adopt AI in banking services in Saudi Arabia which makes the results more reliable.

There are some possible explanations that could explain having positive chemistries between PU and intention to adopt artificial intelligence in banking services. Firstly, artificial intelligence (AI) technologies boost operational effectiveness and efficiency by optimizing banking procedures, minimizing errors, and boosting transaction processing (Alsheibani et al., 2018; Vijai, 2019). Moreover, artificial intelligence could also enhance risk management by accurately identify and avoid fraud, where also providing personalized and 24-hour functioning services to the customers, which fulfil most customers' satisfaction (Alt et al., 2021; McKinsey, 2020).

However, Belanche et al. (2019) indicated that they have found insignificant relationship between PU and intention to adopt AI in banking services in United State of America, United Kingdom, and Portugal. This may be possibly due to different settings in the research which leading various results. For instance, Alt et al. (2021) and Belanche et al. (2019) uses the same data analysis method which is the Structural Equation Modeling (SEM), but Belanche et al. (2019) consists of data in different countries which may lead to difference in the result.

In overall, the existing studies has shown inconsistent results on PU influences the intention to adopt AI in banking services. Most of the previous studies examined that PU has significant influence on the intention to adopt artificial intelligence in banking services, while only some studies clarified insignificant results. These skew outcomes may be caused by different respondents as individuals have their own genders, age, habits, and awareness.

2.1.3 Perceived Ease of Use

Perceived ease of use (PEOU) was also one of the main elements that affects the intention to adopt AI in banking services. According to Alt et al. (2021), PEOU is defined as "the extent to which a person believes that using a specific system would be effortless". Li and Shore (2006) mentioned that PEOU is believed to be comparable to the effort expectancy which is construct in the UTAUT model. Caffaro et al. (2020) mentioned that PEOU is a significant variable which influence the adoption of new AI gadgets.

Based on the previous research, the result studied on influence of PEOU towards the intention to adopt artificial intelligence in banking services is different. There are several researchers discovered that PEOU has a positive influence on intention to adopt artificial intelligence in banking services. The results have come from various developed countries such as Sri Lanka (Gayan, 2020), Saudi Arabia (Alqutub, 2023) and South Korea (Sohn & Kwon, 2019). According to Kasilingam (2004), individuals are more willing to adopt artificial intelligence systems when they are backed by technological infrastructure such as "chat applications," "internet-enabled phone plans," and also "user- friendly designs." PEOU is anticipated to positively influence behavior towards adoption of technology, since consumers have preconceived notions about how easy for it to use (Kasilingam, 2004).

However, some research has proved that PEOU has negative influence on intention to adopt AI in banking services. These results also came from some developing countries such as Malaysia (Rahman et al., 2021), Romania (Alt et al., 2021), and Cambodia (Ly & Ly, 2022). There is also some possible explanation for this result. Pikkarainen et al. (2004) mentioned that this insignificant result may be due to technology adoption for PEOU is via PU. Moreover, Rahman et al. (2021) discussed that bank customers value artificial intelligence's advantages over its usability, and perceived ease of use is lessened by their familiarity with internet-based banking and smart gadgets. In the study from Rahman et al. (2021), it also mentioned that Malaysian customers considered artificial intelligence's sophistication is compatible with other modern technologies, which would also lessen the importance of accessibility.

In overall, the existing studies has shown inconsistent results on PEOU influences the intention to adopt artificial intelligence in banking services. Several studies have presented that PEOU may have significant connection towards intention to adopt AI in banking services. However, certain studies argued that PEOU may also has negative influence on intention to adopt AI in banking services.

2.1.4 Perceived Risk

Perceived risk (PR) refers to the concerns where an individual has the possibility of losing their personal information without the acknowledgement of themselves which causing risk on losing their wealth or safety (Akturan & Tezcan, 2012). According to Kolodinsky et al. (2004), individuals are often more worried about the safety of their information when it comes to virtual situations. Moreover, individuals were also worried that their personal information may be disclose to other businesses to make private trades (Kolodinsky et al., 2004).

Studies have been examined that PR has insignificant influence towards intention to adopt AI in banking services. This statement was supported by studies from Malaysia Rahman et al. (2021), Romania Alt et al. (2021), and Pakistan, China, Iran, Saudi Arabia, and Thailand Noreen et al. (2023).

There is some possible explanation on perceived risk having insignificant relationship with intention to adopt AI in banking services. Firstly, Alt et al. (2021) indicates that the insignificant result may be due to the larger percentage of the participants in their study were youngsters with highly educated and was aged 24 or below. According to Akturan and Tezcan (2012), younger generations have better knowledge on the use of mobile phones, online banking transactions as well as virtual-related activities. Furthermore, Rahman et al. (2021) declares that Artificial Intelligence (AI) banking services is somehow still new in the market causing the individuals to have not fully developed the awareness of the risks in this banking system. From the study results in Rahman et al. (2021), the main obstacles to integrate Artificial Intelligence (AI) technology into banking services is the safety of the data and the privacy concerns of the customers.

In overall, the existing studies has shown consistent results on perceived risk influences the intention to adopt AI in banking services. All of the studies have supported that PR has insignificant influence on intention to adopt AI in banking services. This may be due to adopting artificial intelligence in banking services is fresh and new in current industry. Individuals nowadays have not started to develop the awareness of the risk for this new technology. It may also because the respondents of this study are mostly youngsters lower than 24 years old which have better understanding of internet usage than the older generation.

2.1.5 Perceived Trust

According to Rahman et al. (2021), when it comes to circumstances that are unpredictable and dangerous, perceived trust is the most applicable concept due to its complex and dynamic nature. Trust is believed to have a straight effect on an individual's intention to use internet banking and may also indirectly influence the behavior intention of an individual by supporting performance expectancy in the UTAUT model (Gefen et al., 2003). Liébana-Cabanillas et al. (2018) indicated that fostering connections with clients and enhancing system security depends on trust.

Studies has found that PR has positive influence towards intention to adopt AI in banking services. This statement was supported by several developing countries such as Malaysia (Rahman et al., 2021), Cambodia (Ly & Ly, 2022), United State of America (Payne et al., 2018), and Portuguese (Silva et al., 2023). Rahman et al. (2021) believes that individuals' intentions to embrace new technology can be increased by fostering trust in the implementation of novel technology in financial transactions. Moreover, McKnight et al. (2002) also indicates that individual may gain trust on artificial intelligence in banking services when they are more familiar with the features of online banking and will be more willing to share their private information on online banking services. Payne et al. (2018) also believes that perceived trust has the possibility to boost the future adoption of artificial intelligence banking services and encourage individuals to adopt more mobile banking practices over time.

In overall, the existing studies has shown consistent results on perceived trust influences the intention to adopt AI in banking services. All of the studies have discussed that perceived trust has significant relationship on adopting artificial intelligence in banking services. Studies believed that AI in banking services will no longer be rare in the near future.

2.1.6 Subjective Norms

Subjective norms (SN) represent the actions of those in society who either endorse, condone, or reject a certain action (Noreen et al., 2023). Subjective norms describe the social restraints placed on powerful individuals, including relatives, friends, family, and coworkers. If an individual anticipate that others will act in a similar manner, they are more incline to adhere to social norms (Ly & Ly, 2022).

According to our research, studies has examined that SN has a positive effect towards the intention to adopt AI in banking services. These studies' results were found in many developing countries such as Malaysia (Rahman et al., 2021), Cambodia (Ly & Ly, 2022), Pakistan, China, Iran, Saudi Arabia, Thailand (Noreen et al., 2023), South Korea (Sohn & Kwon, 2019), United State of America, United Kingdom, and Portugal (Belanche et al., 2019).

These studies may have some possible explanations. Firstly, respondents are conscious about their social connections (Ly & Ly, 2022). Furthermore, Rahman et al. (2021) also pointed that when friends and family provide positive feedback about a financial service, people are more likely to follow their recommendations on adopting artificial intelligence (AI) banking. Individuals are having more trust on recommendations from social influencers, close friends, and also their family when making service purchases (Rahman et al., 2021). Individual's intentions to embrace or utilize artificial intelligence gadgets are significantly affect by social media. Individual's intentions on adopting artificial intelligence gadgets may be cause by the influence of the well reputation social influencer which promoting an artificial intelligence banking service (Gursoy et al., 2019).

In overall, the existing studies has shown consistent results on SN influence towards intention to adopt AI in banking services. All the studies have concluded that subjective norms have significant relationships with intention to adopt artificial intelligence in banking services. Rahman et al. (2021) suggests that developing opinion leaders among current consumers or well-known figures is one of the best ways for executives in banking business to promote the advantages of AI in financial industries through social platforms and conventional media channels. Besides that, individuals are more often to follow their close relationships partners' recommendation when come to making choices or purchases (Rahman et al., 2021).

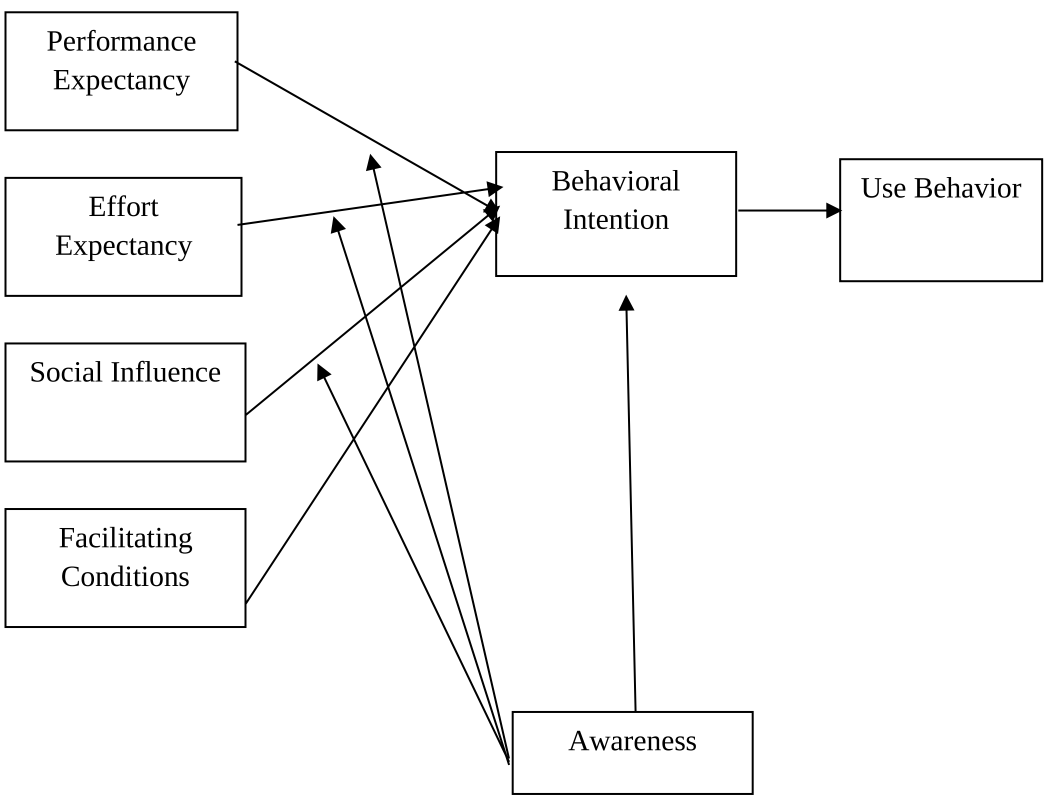
2.2 Theoretical Framework

There are several theories proposed by the previous studies to clarify the relationship between intention to adopt AI in banking services and its independent variables, which are PU, PEOU, PR, PT, and SN. The theories mentioned are Unified Theory of Acceptance and Use of Technology (UTAUT) and Theory of Planned Behavior (TPB).

2.2.1 Unified Theory of Acceptance and Use of Technology

Figure 2.1

Unified Theory of Acceptance and Use of Technology



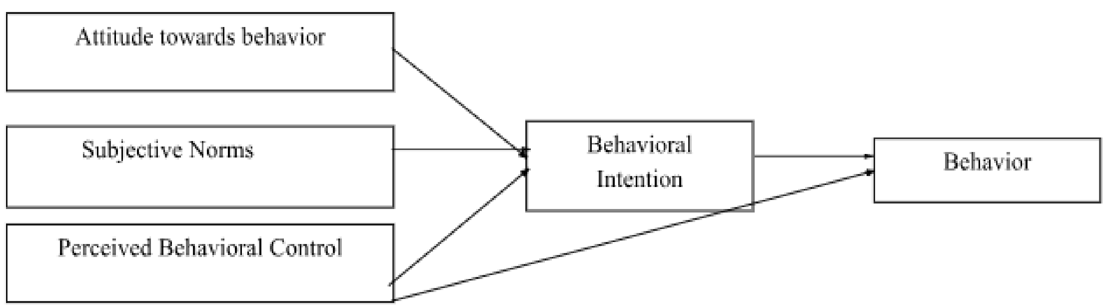
Source: Venkatesh et al. (2003)

UTAUT is developed to clarify an individual's intention to adopt information technology and their behavior (Venkatesh et al, 2003). UTAUT has four key elements which are performance expectancy, facilitating conditions, social influence, and effort expectancy. According to Momani (2020), UTAUT was invented with combining of eight recognized theories of technology adoption into a cohesive whole. UTAUT was known as an efficient and effective model as it was used to compare with eight theories of technology adoption in every determinant, concepts, and viewpoints. Furthermore, UTAUT is a useful theory for researchers and practitioners looking to improve the adoption and implementation of new technologies since it has been commonly used in many fields to investigate the elements influencing technology acceptance and usage (Momani, 2020).

2.2.2 Theory of Planned Behavior

Figure 2.2

Theory of Planned Behavior



Source: Ajzen (1991)

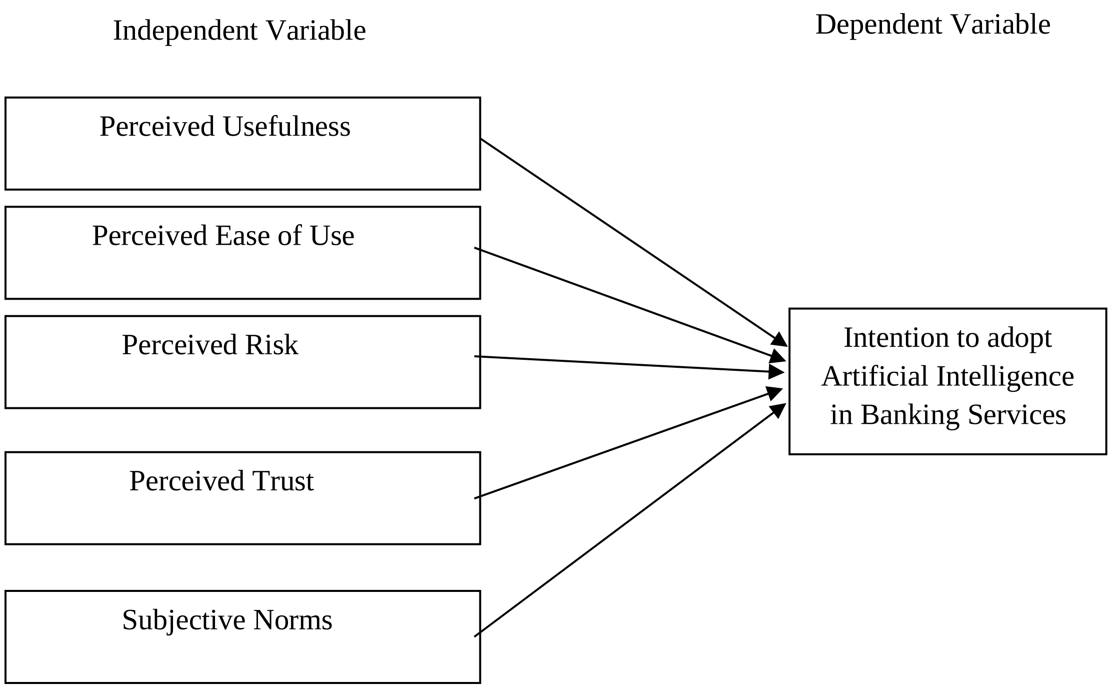
TPB was developed as Theory of Reasoned Action was found having limitations on only focusing on completely volitional control (Ajzen, 1991). TPB has one new variable added, perceived behavioral control, which differs from the Theory of Reasoned Action (Godin & Kok, 1996). Perceived behavioral control acts as a vital role in this theory as it affects the behavior intention and also the behavior of a person (Ajzen, 1991). This theory was widely used in various of studies and mainly in the literature on information systems and also pro-environmental behaviors (George, 2004;

Yuriev et al., 2020). According to George (2004), Theory of Planned Behavior is a well-made theory to investigate an individual's action on certain behaviors and the intention of an individual.

2.3 Conceptual Framework

Figure 2.3

Conceptual Framework



Above is the conceptual framework created by implementing the theoretical models mentioned in the previous section. The function of this framework in Figure 2.3 is to analyze the intention to adopt artificial intelligence in financial industries in Malaysia. There are 5 independent variables was included in this framework which are PU, PEOU, PR, PT, and SN are involved in this conceptual framework. Through our previous research, it refers that these five independent variables have shown significant influence on intention to adopt AI in banking services. Thus, this conceptual framework will be used to test the reliability of the study. Hypotheses will be discussed on the following section depending on the conceptual framework discussed above.

2.4 Hypotheses Development

2.4.1 Perceived Usefulness towards Intention to adopt AI in banking services

According to our previous research, some studies have took their actions on analyzing the intention to adopt AI in banking services in several developing countries such as Malaysia (Rahman et al., 2021), Romania (Alt et al., 2021), Cambodia (Ly & Ly, 2022), Pakistan, China, Iran, Saudi Arabia, Thailand (Noreen et al., 2023), and Portuguese (Silva et al., 2023) and the results have shown that PU has a significant influence towards the intention to adopt artificial intelligence in banking services. Furthermore, Alqutub (2023) also supports that perceived usefulness has a significant relationship with intention to adopt AI in banking services in Saudi Arabia.

However, Belanche et al. (2019) indicated that PU has insignificant relationship with intention to adopt artificial intelligence in banking services in United State of America, United Kingdom, and Portugal.

H_0: There is an insignificant relationship between PU and intention to adopt AI in banking services in Malaysia.
H_1: There is a significant relationship between PU and intention to adopt AI in banking services in Malaysia.

2.4.2 Perceived Ease of Use towards Intention to adopt AI in banking services

Previous research has studied that PEOU has a significant influence towards intention to adopt artificial intelligence in banking services in Sri Lanka (Gayan, 2020), Saudi Arabia (Alqutub, 2023) and South Korea (Sohn & Kwon, 2019).
However, several research on developing countries such as Malaysia (Rahman et al., 2021), Romania (Alt et al., 2021), and Cambodia (Ly & Ly, 2022) indicated that PEOUhas an insignificant relationship with intention to adopt AI in banking services.

H_0: There is an insignificant relationship between PEOU and intention to adopt AI in banking services in Malaysia.
H_1: There is a significant relationship between PEOU and intention to adopt AI in banking services in Malaysia.

2.4.3 Perceived Risk towards Intention to adopt AI in banking services

Based on previous research, studies have found out that individuals are deterred to adopt AI in banking services. They have lower likelihood of adopting AI in banking services. This statement was supported by research on Rahman et al. (2021) in Malaysia, Alt et al. (2021) in Romania, and Noreen et al. (2023) in Pakistan, China, Iran, Saudi Arabia, and Thailand. These studies mentioned has clarified that their result on perceived risk has an insignificant relationship towards the intention to adopt artificial intelligence in banking services.

H_0: There is an insignificant relationship between PR and intention to adopt AI in banking services in Malaysia.

H_1: There is significant relationship between PR and intention to adopt AI in banking services in Malaysia.

2.4.4 Perceived Trust towards Intention to adopt AI in banking services

According to previous research, studies have analyzed that PT has significant influence towards intention to adopt AI in banking services in several countries such as Malaysia (Rahman et al., 2021), Cambodia (Ly & Ly, 2022), United State of America (Payne et al., 2018), and Portuguese (Silva et al., 2023).

H_0: There is an insignificant relationship between PT and intention to adopt AI in banking services in Malaysia.
H_1: There is a significant relationship between PT and intention to adopt AI in banking services in Malaysia.

2.4.5 Subjective Norms towards Intention to adopt AI in banking services

Numerous research has studied that subjective norms have significant relationship towards intention to adopt AI in banking services. This result was found in many countries such as Malaysia (Rahman et al., 2021), Cambodia (Ly & Ly, 2022), Pakistan, China, Iran, Saudi Arabia, Thailand (Noreen et al., 2023), and South Korea (Sohn & Kwon, 2019). Furthermore, Belanche et al. (2019) also indicates that their study on subjective norms has a positive influence towards intention to adopt artificial intelligence in banking services in United State of America, United Kingdom, and Portugal.

H_0: There is an insignificant relationship between SN and intention to adopt AI in banking services in Malaysia.
H_1: There is a significant relationship between SN and intention to adopt AI in banking services in Malaysia.

2.5 Conclusion

This section has discussed the review of literature on the independent variables (intention to adopt AI in banking services in Malaysia) and dependent variables (PU, PEOU, PR, PT, and SN) in the chapter. Moreover, theoretical framework and conceptual framework has also studied in this section. Lastly, a hypothesis of our study has been developed.

CHAPTER 3: METHODOLOGY

3.0 Introduction

A thorough explanation of the investigation's approach is given in this chapter. It begins by outlining the chosen strategy and examining the study design. After that, it explores the various techniques for gathering data. The sample design, research instruments, construct management, and data processing techniques that are essential to this study are also covered in length in this chapter. Finally, it provides a detailed explanation of the selected data analysis process.

3.1 Research Design

According to Asenahabi (2019), research design is a systematic framework that directs researchers in problem-solving and knowledge advancement. It outlines the procedures for efficiently gathering and analyzing data. Qualitative and quantitative research design are the two types of research designs.

Quantitative research design implemented techniques that generate numerical data from empirical observations, enhancing statistical analysis (Asenahabi, 2019). The time and energy needed for researchers are reduced by using statistical approaches in the statistical analysis of quantitative research (Daniel, 2016).

In order to find out whether bank clients want to use AI-based financial services, quantitative research is used in this study. A series of questions in the questionnaire are related to the research topic and designed as closed-ended questions for the respondents to choose only from a fixed list of answers (Asenahabi, 2019).

3.2 Data Collection

The data collecting stage of the research process is one of the most important ones. The study's potential conclusion will depend on how accurate the data was obtained. Primary data and secondary data are the two categories of data collecting methodologies, according to Hox and Boeije (2005). Primary data is implemented in this study to collect and meet the study goals.

3.2.1 Primary Data

Primary data is the information gathered firsthand directly by the researchers from sources such as people, groups, or the environment for the purpose of study (Sekaran, 2003). There are a few data collection strategies such as interviews, observations, questionnaires, and focus groups. The questionnaire strategy is used in this study as it consumes lesser research time and energy, which is more efficient than other strategies (Sekaran, 2003). Questionnaires are sent to the intended respondents to get the data needed for this investigation. In the questionnaires, there will be a number of questions related to the intention of bank customers for using AI-based bank services.

3.3 Sampling Design

3.3.1 Target Population

The target population refers to the total set of people from whom a sample can be obtained. (Mcleod, 2023). To gather and analyze the appropriate data, the researchers must ensure that the respondents are from the target group. In other words, ensuring that the survey participants are eligible is critical.

This research aims to look at the elements that impact people's intentions to use artificial intelligence in Malaysian banking services. As a result, this study's target demographic is Malaysian banking residents.

3.3.2 Sampling Location

The location where data is collected is referred to as the sampling location. Malaysia was chosen as a sampling location since the target demographic is Malaysian banking residents.

3.3.3 Sampling Elements

Any single unit or case within a target population is considered an element. A sampling strategy will be used to choose certain components from a population for analysis in research. Convenience sampling was utillized in this study to choose Malaysian banking residents as sampling elements or target respondents.

3.3.4 Sampling Technique

Every sample has a same chance of being chosen when using probability sampling (Showkat & Parveen, 2017). A probability sample is one in which each element has a known, non-zero likelihood of being picked. This technique of sampling determines the likelihood that our sample correctly represents the larger population. Non-probability sampling, on the other hand, selects samples using means other than randomness. It is largely dependent on the researcher's judgment, with individuals chosen based on convenience rather than randomization. While The surveys used in this study are intended for Malaysians across a range of demographic categories. Convenience sampling is used in this study to choose the respondents. This sampling method is chosen because we can collect vast amounts of data fast and efficiently (Learn Statistics Easily, 2023). With this sampling technique, it is much easier to achieve our data quotas quickly (Gaille, 2020). Among the best sample techniques for pilot testing is convenience sampling.

3.3.5 Sampling Size

The sample size indicates how many completed responses a survey needs to collect. Determining the sample size is essential to producing statistically meaningful results and guaranteeing the efficient use of research resources (Burmeister & Aitken, 2012). In this study, G*Power 3.1.9.7 software will be used to determine the required sample size (Faul et al., 2007). After running the software, 138 minimum respondents is needed.

3.4 Research Instrument

3.4.1 Questionnaire

A questionnaire comprises a series of questions or prompts designed to get respondents' information directly or indirectly. It is a kind of survey or research instrument (Hassan, 2023). Through a set of questions about a certain topic or study purpose, a large number of participants may have their data collected consistently. Both quantitative and qualitative answers are possible for the questions, which can be either closed-ended or open-ended. A target population's data and insights are frequently gathered via the use of questionnaires in research, marketing, social sciences, healthcare, and many other sectors.

The survey questionnaire for this study is divided into seven sections. Four demographic questions—gender, age group, work status, and familiarity with AI-enabled banking technology—will be asked in section A. While sections from B to G includes questions that relates to the respondents' intention to adopt artificial intelligence and factors that affect their intention to adopt artificial intelligence. The respondents have to answer to questions based on a 5-point Likert scale. As example, Alt et al. (2021) applied 5-point Likert scale to collect data on respondents' PU and PEOU towards the intention to use banking chatbot, while Payne et al. (2018) also applied 5-point Likert scale to measure the respondents' perceived trust towards AI mobile banking services.

3.4.2 Pilot Test

A preliminary test carried out before to a larger-scale investigation is known as pilot testing (Dovetail Editorial Team, 2023a). A pilot study can help determine the direction of a larger study or research project by providing crucial information regarding the study's eventual cost, general feasibility, and possible obstacles once it has begun. In this study, there will be a pilot test of the questionnaire with 50 respondents. After that, the validity and reliability of the gathered data will be assessed using the PLS-SEM technique. The questionnaire's quality will be improved by making the necessary adjustments following the feedback from the respondents.

3.5 Construct Measurement (Scale and Operational Definitions)

A typical survey tool, the rating scale determines whether respondents agree or disagree with statements, making it simple to evaluate and compare findings. The following seven sections comprise the questionnaire: Section A collects demographic data on respondents' understanding of AI-enabled financial technology through four questions using both ordinal and nominal scales. Sections B through G (a total of 28 questions) assess intention to adopt AI, as well as PEOU, PU, PR, PT, and SN using a 5-point Likert scale. The scale ranks the responses from 1 (SD) to 5 (SA).

3.5.1 Scale of Measurement

The next stage after gathering data for a research is to analyze it, which is dependent upon the instruments employed in the data collection process (*Scales of Measurement - Nominal, Ordinal, Interval, Ratio Scales*, n.d.). For instance, we may use nominal scale to gather qualitative data, where respondents choose an option from the list. Ordinal and interval scales are useful tools for representing quantitative data that allow researchers to see the information through numerical values. In this study, all the scales mentioned previously will be utilized in the questionnaire.

3.5.1.1 Nominal Scale

Nominal scales can be utilized to assign values based on attributes to a countable number of different groups (Frost, 2022). These groups can be given any names and have no inherent hierarchy. The respondents' understanding of AI-enabled banking technology, gender, and employment position are measured in this research using a nominal scale. The nominal scale is applied as below:

Figure 3.1

Example of nominal scale

Gender:

( ) Male ( ) Females

3.5.1.2 Ordinal Scale

A measuring scale called an ordinal scale allows data to be ranked without pinpointing the precise distinctions between data items (Gandhi, 2023). It shows the order but not the precise times in between each point. Ordinal scales do not have a clear hierarchy like nominal or interval scales do. However, they don't include details on how much different the ranks are from one another. The age group in this research has been classified as follows:

Figure 3.2

Example of ordinal scale

Age group:

( ) 18 to 29 years old ( ) 30 to 39 years old ( ) 40 to 49 years old ( ) 50 years old and above

3.5.1.3 Interval Scale

A metric scale that represents quantitative values is the interval scale (Statista, n.d.). Between the nominal and ordinal scales in terms of measurement levels is where the interval scale sits. Interval data is crucial for research since it can support the majority of statistical tests (Dovetail Editorial Team, 2023b). The questionnaire in this study uses a 5-point Likert scale, which indicates the application of interval scale. An example of interval scale is provided as below:

Table 3.1

Example of interval scale

	SD	D	N	A	SA
Managing bank transactions with AI-enabled banking technology would be easy for me.	1	2	3	4	5

3.5.2 Origin of Construct

Table 3.2

Summary of Measures used for Present Study

Variables	Source	Number of Items	Previous studies' Cronbach's Alpha	Scale
DV: Intention to adopt artificial intelligence	Alt et al. (2021)	3	0.900	SD (1) to SA (5)
	Rahman et al. (2021)	2	0.926	
	Belanche et al. (2019)	1	0.946	
IV 1: Perceived ease of use	Rahman et al. (2021)	4	0.932	SD (1) to SA (5)
IV 2: Perceived usefulness	Rahman et al. (2021)	3	0.972	SD (1) to SA (5)
	Suh and Han (2002)	1	0.973	
IV 3: Perceived risk	Rahman et al. (2021)	4	0.933	SD (1) to SA (5)
	Alt et al. (2021)	1	0.894	
IV 4: Perceived trust	Rahman et al. (2021)	4	0.930	SD (1) to SA (5)
	Suh and Han (2002)	1	0.930	
IV 5: Subjective norms	Rahman et al. (2021)	3	0.878	SD (1) to SA (5)
	Belanche et al. (2019)	1	0.902	

3.5.3 Measurement of Independent Variables and Dependent Variable

This study selects five variables—PEOU, PU, PR, PT and SN—that influence Malaysian banking residents' intention to adopt artificial intelligence. For every item, a five-point Likert scale is employed.

3.5.3.1 Intention to Adopt Artificial Intelligence

The intention to adopt artificial intelligence is measured using 6 items, and the sample items are taken from Rahman et al. (2021), Alt et al. (2021), and Belanche et al. (2019). Sample items include "*I plan to use AI-enabled banking technologies to manage banking transactions.*", "*I would use AI-enabled banking technologies to manage banking investments.*", "*I plan to use the AI-enabled banking technologies whenever the occasion comes.*", "*I would want to employ the AI-enabled banking technologies in the near future.*", "*I am likely to employ the AI-enabled banking technologies in the near future.*", and "*My plan is to employ AI-advisors instead of any human financial advisor.*".

3.5.3.2 Perceived Ease of Use

PEOU is assessed by using 4 items. The items were adapted from Rahman et al. (2021) which include "*I plan to use AI-enabled banking technologies to manage banking transactions.*", "*Managing bank transactions with AI-enabled banking technology would be easy for me.*", "*Getting abilities with AI-enabled banking technology comes easy for me.*", "*I would find it easy to communicate with AI in banking since it does not need much of my brain energy.*", and "*Using AI-enabled banking technology is simple.*".

3.5.3.3 Perceived Usefulness

PU is measured using 4 items, which are from Rahman et al. (2021) and Suh and Han (2002). The sample items include "*I would do more successful bank transactions if I use AI-enabled banking technologies.*", "*Using AI-enabled banking technology would increase my productivity in managing banking transactions.*", "*AI-enabled technologies in banking might be effective in managing banking transactions.*", and "*Using AI-enabled banking technology is crucial for assisting my financial tasks.*"

3.5.3.4 Perceived Risk

PR is assessed using 5 items, which are from Rahman et al. (2021) and Alt et al. (2021). Included items are "*Using AI-enabled technology in banking activities increases the risk of fraud against my bank account.*", "*Financial risk arises with using AI-enabled technologies in banking services for my bank account.*". "*I believe that using AI-enabled technologies in banking harms my privacy.*", "*AI-enabled banking technology might not function correctly, which could lead to issues with my bank account.*", and "*Using the AI-enabled banking technology may result in the collection, tracking, and analysis of personal data.*"

3.5.3.5 Perceived Trust

PT is determined by using 5 items from Rahman et al. (2021) and Suh and Han (2002). The sample items included are: "*AI-enabled banking services are reliable.*", "*AI banking-enabled technology delivers financial services that are in my best interests.*", "*AI banking-enabled technology provides access to honest and real banking services.*", "*The AI banking-enabled technology effectively accomplishes its duty of delivering* *financial services.*", and "*I believe in the benefits of the judgments made by this AI-enabled banking technology.*"

3.5.3.6 Subjective Norms

Subjective norms is assessed by using 4 items from Rahman et al. (2021) and Belanche et al. (2019), which includes "*In general, I would want to follow my group of friends to employ AI banking technology.*", "*People close to me believe I should employ AI banking enabling technologies.*", "*People I know may persuade me to test out AI-enabled banking technologies for managing banking investments.*", and "*Reports from the media influence me into trying with AI-enabled banking systems for money management.*".

3.6 Data Processing

Before data analysis, data preparation procedures are completed. The collection, cleaning, and labeling of data utilizing a range of techniques into meaningful information is known as data processing. Data verification, data coding, data editing, and questionnaire checking are some of the procedures that go into data processing. Questionnaires are distributed to the intended sample as part of the data gathering process. Subsequently, an accuracy and availability check are implemented for the dataset.

3.6.1 Data Collecting

The process of obtaining and examining information connected to variables is known as data collecting. Researchers can test hypotheses, assess findings, and address research problems through the rigorous approach of data collecting. Data on the independent and dependent variables were gathered using a questionnaire survey. The study team randomly distributed questionnaires to responders. Data collection methods include online and physical surveys, with questionnaires distributed to Malaysian banking residents at least 18 years old and above.

3.6.2 Data Checking

Data checking involves scrutinizing collected data to ensure its accuracy and availability. To ensure there are enough survey respondents, this procedure involves going over questionnaire responses. Following the completion of the surveys, additional analysis is performed on the data to verify its validity. Surveys that include incomplete or missing data are not returned. This is an essential step since it ensures data integrity and guards against mistakes before the analysis stage.

3.6.2.1 Data Editing

Data editing is an essential part performed upon receiving survey responses. To reduce any potential bias, it entails closely examining, assessing, and adjusting the data. By correcting discrepancies and verifying the veracity of the data that respondents have submitted, this procedure seeks to improve the overall caliber of the data.

3.6.2.2 Data Coding

Upon completion of the surveys, it is important to categorize and summarize every questionnaire result. To improve survey data utilization and enhance analytical results, data coding is necessary. A computer can interpret a numerical code that represents distinct answers to a question; this is known as data coding. All the codes represent different viewpoints within the same question. Numerical replies are entered into a computer and translated from a non-numeric format to a numerical format for statistical computations. Data coding makes it possible to effectively reduce lengthy textual content into a concise data report, which simplifies information organization and analysis.

3.7 Data Analysis

PLS-SEM is a statistical program that is utilized in this study to examine the data. This section includes tests for reliability, normalcy, partial least square correlation, and descriptive analyses.

3.7.1 Descriptive Analysis

Analyzing and summarizing a data collection using statistical techniques is known as descriptive analysis, often known as descriptive analytics or descriptive statistics (PESTLEanalysis Team, 2020). Other forms of data analysis are not concerned with forecasting future patterns; here is where descriptive analysis varies. Instead, by processing the data in ways that increase its importance, it concentrates on drawing conclusions from the past. Characterizing and explaining the characteristics of certain data sets is made easier with the help of descriptive statistics, which provide clear explanations of sample and data measurements (Hayes, 2024). Among the most well-known ideas in descriptive statistics are central tendency measures. Examples of terminology that are often used in several branches of mathematics and statistics to define and characterize a data collection include the mean, median, and mode. The demographic information in Section A is derived from the design of the questionnaire, which describes the characteristics of the population. The characteristics of research participants will be assessed using descriptive analysis, as demographic data is quantitative in nature.

3.7.2 Reliability Test

To determine the scale's reliability, a reliability test is conducted. Cronbach's alpha is being used in this work as a reliability test. Since most of the questionnaire's questions employ a five-point Likert scale, Cronbach's alpha (CA) is the most appropriate formula to gauge internal consistency when such questions are present.

Table 3.3

Rules of Thumb for Cronbach's Alpha Reliability Coefficient

Range for Cronbach's Alpha (CA)	Strength of Internal Consistency
< 0.6	Poor
0.6 to < 0.7	Moderate
0.7 to < 0.8	Good
0.8 to < 0.9	Very Good
0.9	Excellent

Source: Hejase and Hejase (2013)

The reliability level was divided into Five groups, namely poor, moderate, good, very good, and excellent, as can be seen in the above table. It is regarded as having poor internal consistency if the CA value is less than 0.6. The CA value that is less than 0.7 and higher than or equal to 0.6 indicates a moderate level of reliability. It is regarded as having good reliability if the CA value is more than 0.7, equal to, or less than 0.8. The reliability of the data is very good if the CA value is less than 0.9 and falls within or equal to 0.8. Finally, it shows excellent reliability if the CA value is equivalent to or greater than 0.9. Therefore, a CA value of more than 0.6 indicates that the results are credible.

3.7.3 Variance Inflation Factor (VIF)

The variance inflation factor is applied to assess the degree of multicollinearity (I. Team, 2024). The use of multiple regression analysis allows one to look at how several factors affect a certain result. The result that is impacted by the IVs, or the model's inputs, is known as the DV. When one or more of the IVs have a linear connection, or correlation, this is known as multicollinearity. If the Variance Inflation Factor (VIF) is 1, it indicates that the variables are uncorrelated. If their VIF falls between 1 and 5, they are deemed strongly connected; if it rises over 5, they are deemed moderately linked. The VIF points to a higher likelihood of multicollinearity, which makes more research necessary. A value in excess of 10 in the VIF indicates severe multicollinearity, which has to be corrected.

3.7.4 Partial Least Square Regression (PLS)

A statistical technique called partial least squares regression is used to show how independent and dependent variables relate to one another. For datasets with strong multicollinearity, it is beneficial. This method takes into consideration the relationships between the independent variables to generate a model that best describes the variance in the dependent variable.

3.7.4.1 Partial Least Square Correlation (PLSC)

Statistical analysis of the linkages and interconnections between independent variables is done through the use of partial least squares correlation (PLSC). It is extremely beneficial in finding common information across independent variables and can handle enormous volumes of data.

3.7.4.2 Average Variance Extracted (AVE)

According to Fornell and Larcker (1981), the average variance extracted (AVE) measures the amount of variation that a construct extracts from its indicators as opposed to the variance brought on by measurement error. According to Analysis INN (2020), it is highly advised to have an AVE of at least 0.50. Having said that, an AVE of less than 0.50 means that more mistakes are being explained by your items than by the variation in your conceptions. Every construct in a measurement model must have an AVE calculated for it, and this value must be at least 0.50.

3.7.4.3 Heterotrait-Monotrait Ratio of Correlation

Henseler et al. (2014) presented the HTMT as a correlation estimator between two latent variables. The multitrait-multimethod (MTMM) matrix serves as its foundation, and correlations are examined within to evaluate discriminant validity. Any HTMT result in more than 0.90 indicates a possible deficiency in discriminant validity. On the other hand, when two reflectively assessed constructs have an HTMT score less than 0.90, discriminant validity between them has been proven (Ringle et al., 2024).

3.7.5 Bootstrapping

In statistics, bootstrapping is a hypothesis testing technique that creates several simulated samples by resampling a single dataset (Joseph, 2023). Following that, these samples are utilized to do hypothesis testing, calculate standard errors, and create confidence intervals. Using this strategy, as opposed to more conventional ones, with a smaller dataset, researchers can get a more precise sample distribution.

3.7.5.1 Coefficient of Determination- R square

The statistical model's prediction accuracy is measured by the coefficient of determination, or R^2 (Turney, 2022). It shows how effectively the result is captured by the dependent variable in the model. R^2 values vary from 0, which denotes no predictive ability, to 1, which denotes flawless prediction. In general, the accuracy of the model's predictions increases with the R^2 value's proximity to 1.

3.7.5.2 Path Coefficient

Using path analysis, one may look at the relationships between a group of endogenous (dependent) and exogenous (independent) factors, both directly and indirectly (*Path Analysis -- Advanced Statistics Using R*, n.d.). When using numerous input, mediators, and output, path analysis may be thought of as an extension of regression and mediation analysis. Typically, path coefficients fall between −1 and +1 (Hair et al., 2021). Strong negative associations are indicated by coefficients near −1, whereas strong positive relationships are suggested by coefficients around +1. Though theoretically incorrect, values can fall below -1 or rise over +1, particularly in extreme situations when collinearity is present. If the path coefficient is more than +/−1, it is deemed unsatisfactory and techniques to minimize multicollinearity must be used.

3.8 Conclusion

Chapter 3 outlines a number of research techniques and focuses on examining the relationship between Malaysian banking residents and their intention to adopt artificial intelligence in Malaysian banking services. It entails examining the connections between the dependent variable—Intention to Adopt Artificial Intelligence—and a number of independent variables, such as PEOU, PU, PT, PR, and SN. This chapter will provide an explanation and analysis of the procedures and details used in this investigation. Next, in the next chapter, the findings and analysis will be presented.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

In chapter four, carries out analysis of data. The analysis of data and graphics with SmartPLS 4.0. A survey of 160 Malaysian bank customers who use online banking was conducted. Numerous research involving numerical data or tables, including conclusions on the significant correlations between independent and dependent variable and descriptive analyses, will be presented and debated in this chapter.

4.1 Result of Pilot Test

The procedure employed to evaluate reliability and ensure that the questionnaire's responses are consistent across variables is known as pilot testing. Because robustness and reliability were crucial to this study, 50 respondents who were Malaysian banking clients were chosen to take part in this particular test for additional analysis.

Table 4.1

Pilot Test Result

Construct	Item	Outer Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)

DV	DV1	0.908	0.952	0.953	0.806
	DV2	0.879			
	DV3	0.890			
	DV4	0.865			
	DV5	0.910			
	DV6	0.933			
PEOU	PEOU1	0.883	0.912	0.916	0.790
	PEOU2	0.907			
	PEOU3	0.877			
	PEOU4	0.889			
PR	PR1	0.846	0.884	0.936	0.674
	PR2	0.807			
	PR3	0.813			
	PR4	0.801			
	PR5	0.837			
PT	PT1	0.819	0.887	0.891	0.689
	PT2	0.800			
	PT3	0.852			
	PT4	0.806			

	PT5	0.870			
PU	PU1	0.731	0.725	0.723	0.546
	PU2	0.791			
	PU3	0.736			
	PU4	0.694			
SN	SN1	0.885	0.788	0.856	0.601
	SN2	0.721			
	SN3	0.657			
	SN4	0.818			

The pilot test’s results are displayed in Table 4.1, and the matching Cronbach's Alpha (CA) values are, in that order, 0.952, 0.912, 0.884, 0.887, 0.725, and 0.788. Tavakol and Dennick (2011) state that levels of CA between 0.70 and 0.95 are appropriate. Therefore, it can be concluded that the questionnaire used in this study is suitable in terms of dependability.

4.2 Descriptive Analysis

To make sure the data is easily understood, a descriptive analysis will be completed first. The demographic data gathered in the survey's Section A is subjected to a descriptive analysis. Second, descriptive analysis is also performed on the data for each variable in Section B to Section G. Tables and pie charts are created in the analysis that follows in order to compile our data.

4.2.1 Respondents' Demographic Profile

This section contains four demographics information including gender, age group, employment status, and knowledge about AI banking enabled technology. The table is used to analyze each item based on those observations. Furthermore, 160 respondents in total are online banking users in Malaysia.

4.2.1.1 Gender

Table 4.2

Frequency Table of Gender

Gender	Frequency	Percentage (%)	Valid Percent	Cumulative Percentage (%)
Male	66	41.25	41.25	41.25
Female	94	58.75	58.75	100
Total	160	100	100	

The survey included 160 participants in all, as Table 4.2 demonstrates. Moreover, the observation exists that there are higher numbers of females than men. As indicated by table 4.2, 94 respondents, representing 58.75% of the total, were female, and 66 respondents, representing 41.25% of the total, were male.

4.2.1.2 Age Group

Table 4.3

Frequency Table of Age Group

Age Group	Frequency	Percentage (%)	Valid Percent	Cumulative Percentage (%)
18-29 years old	124	77.50	77.50	77.50
30-39 years old	23	14.38	14.38	91.88
40-49 years old	10	6.25	6.25	98.13
50 years old and above	3	1.88	1.88	100
Total	160	100	100	

Table 4.3 demonstrates how participants are further categorized to four groups based on the age ranges to which they belong. The majority of responders, or 124 out of the total number, are between the ages of 18 and 29, as Table 4.3 demonstrates. Moreover, 10 respondents, or 6.25% of the total, are 40 to 49 year-old, while 23 respondents, or 14.38% of the total, are 30 to 39 year-old. Finally, the lowest percentage of respondents (3 participants) are those who are 50 years of age or older, accounting for only 1.88% of all respondents.

4.2.1.3 Employment Status

Table 4.4

Frequency Table of Employment

Employment Status	Frequency	Percentage (%)	Valid Percent	Cumulative Percentage (%)
Public sector	10	6.25	6.25	6.25
Private sector	28	17.50	17.5	23.75
Self employed	19	11.88	11.88	35.63
Unemployed	98	61.25	61.25	96.88
Retiree/Pensioner	5	3.13	3.125	100
Total	160	100	100	

As shown in Table 4.4, the respondents are categorized into five employment status, including public sector, private sector, self-employed, unemployed and retiree or pensioner. Most of the respondents are unemployed, including the students, which have 61.25% of respondents (98 respondents). The other respondents that are employed are in the public sector (6.25% respondents) and private sector (17.5%). Besides, the respondents that are retiree or pensioner have 3.13%, which is 5 respondents in our survey.

4.2.1.4 Knowledge about AI Banking Enabled Technology

The 160 respondents are surveyed whether they know anything about AI banking enabled technology as shown in Table 4.5. The respondents who answer ‘Yes’ in this question have 68.75% (110 respondents), which is more than respondents answer in ‘No’, which have 31.25% of the respondents (50 respondents).

Table 4.5

Frequency Table of Knowledge about AI Banking Enabled Technology

Knowledge about AI Banking Enabled Technology	Frequency	Percentage (%)	Valid Percent	Cumulative Percentage (%)
Yes	110	68.75	68.75	68.75
No	50	31.25	31.25	100
Total	160	100	100	

4.2.2 Central Tendencies Measurement of Constructs

The overall result, the corresponding measurement, and the median, mean, and standard deviation for the independent and dependent variable's each item is shown in the section that follows.

Table 4.6

Mean, Median, Mode and Standard Deviation of Variables

Items		Mean	Median	Standard Deviation
Intention to Adopt Artificial Intelligence in Banking Services (Dependent Variable - DV)				
DV1	I plan to use AI-enabled banking technologies to manage banking transactions.	4.231	4.000	0.818
DV2	I would use AI-enabled banking technologies to manage banking investments.	4.138	4.000	0.915
DV3	I plan to use the AI-enabled banking technologies whenever the occasion comes.	4.250	4.000	0.769

DV4	I would want to employ the AI-enabled banking technologies in the near future.	4.263	4.000	0.872
DV5	I am likely to employ the AI-enabled banking technologies in the near future.	4.325	4.000	0.851
DV6	My plan is to employ AI-advisors instead of any human financial advisor.	4.188	4.000	1.017
Perceived Ease of Use (Independent Variable 1 - PEOU)				
PEOU 1	Managing bank transactions with AI-enabled banking technology would be easy for me.	4.331	4.000	0.680
PEOU 2	Getting abilities with AI-enabled banking technology comes easy for me.	4.275	4.000	0.709
PEOU 3	I would find it easy to communicate with AI in banking since it does not need much of my brain energy.	4.238	4.000	0.813
PEOU 4	Using AI-enabled banking technology is simple.	4.300	4.000	0.725
Perceived Usefulness (Independent Variable 2 - PU)				
PU1	I would do more successful bank transactions if I use AI-enabled banking technologies.	4.225	4.000	0.839
PU2	Using AI-enabled banking technology would increase my productivity in managing banking transactions.	4.363	4.000	0.687

PU3	AI-enabled technologies in banking might be effective in managing banking transactions.	4.331	4.000	0.830
PU4	Using AI-enabled banking technology is crucial for assisting my financial tasks.	4.356	4.000	0.721
Perceived Risk (Independent Variable 3 - PR)				
PR1	Using AI-enabled technology in banking activities increases the risk of fraud against my bank account.	4.094	4.000	0.896
PR2	Financial risk arises with using AI-enabled technologies in banking services for my bank account.	3.988	4.000	1.009
PR3	I believe that using AI-enabled technologies in banking harms my privacy.	3.856	4.000	1.086
PR4	AI-enabled banking technology might not function correctly, which could lead to issues with my bank account.	4.075	4.000	0.968
PR5	Using the AI-enabled banking technology may result in the collection, tracking, and analysis of personal data.	4.138	4.000	0.872
Perceived Trust (Independent Variable 4 - PT)				
PT1	AI-enabled banking services are reliable.	4.125	4.000	0.867
PT2	AI banking-enabled technology delivers financial services that are in my best interests.	4.194	4.000	0.781

PT3	AI banking-enabled technology provides access to honest and real banking services.	4.138	4.000	0.835
PT4	The AI banking-enabled technology effectively accomplishes its duty of delivering financial services.	4.263	4.000	0.773
PT5	I believe in the benefits of the judgments made by this AI-enabled banking technology.	4.238	4.000	0.843
Subjective Norms (Independent Variable 5 -SN)				
SN1	In general, I would want to follow my group of friends to employ AI banking technology.	4.156	4.000	0.915
SN2	People close to me believe I should employ AI banking enabling technologies.	4.169	4.000	0.926
SN3	People I know may persuade me to test out AI-enabled banking technologies for managing banking investments.	4.156	4.000	0.828
Overall				
Intention to Adopt Artificial Intelligence in Banking Services (Dependent Variable - DV)		4.232	4.000	0.874
Perceived Ease of Use (Independent Variable 1 - PEOU)		4.286	4.000	0.732
Perceived Usefulness (Independent Variable 2 - PU)		4.319	4.000	0.769
Perceived Risk (Independent Variable 3 - PR)		4.030	4.000	0.966
Perceived Trust (Independent Variable 4 - PT)		4.191	4.000	0.820

Subjective Norms (Independent Variable 5 -SN)	4.175	4.000	0.880

From Table 4.6 shown, PU has highest mean with a value of 4.319 and PR has the least mean with a value of 4.030. Furthermore, all variables have a mean with higher than 4.1, except the PR has a mean that is lower than 4.1. Additionally, the median value of all the independent and dependent variables is 4.

Besides, analyzing the variability in the data is possible according to the standard deviations. Regarding the independent variables, the standard deviation of PR is the largest (0.966), while the standard deviation of PEOU is the least (0.732). Nearly 0.8 standard deviations have been identified in the remaining variables.

4.3 Measurement Model Analysis

4.3.1 Indicator Reliability

The extracted average variance, composite reliability, Cronbach's alpha, and outer loadings are shown in Table 4.7. Together with the findings for the earlier criterion, the results for the extracted average variance, composite reliability, Cronbach's alpha, and outer loadings must all be greater than 0.5.

Table 4.7

Reliability Statistics and Validity

Construct	Item	Outer Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
DV	DV1	0.809	0.878	0.908	0.623
	DV2	0.846			
	DV3	0.755			
	DV4	0.811			
	DV5	0.830			
	DV6	0.671			
PEOU	PEOU1	0.751	0.793	0.863	0.612
	PEOU2	0.805			
	PEOU3	0.796			
	PEOU4	0.776			
PU	PU1	0.848	0.748	0.842	0.572
	PU2	0.752			
	PU3	0.726			
	PU4	0.690			
PR	PR1	0.731	0.849	0.890	0.619
	PR2	0.813			

	PR3	0.832			
	PR4	0.784			
	PR5	0.770			
PT	PT1	0.810	0.830	0.880	0.596
	PT2	0.783			
	PT3	0.763			
	PT4	0.680			
	PT5	0.816			
SN	SN1	0.843	0.809	0.874	0.635
	SN2	0.816			
	SN3	0.771			
	SN4	0.753			

4.3.2 Outer Loadings

The outer loadings result at the significance level of 0.05 are displayed in Table 4.7. According to Moscato (2023), when the outside loadings exceed 0.7, it is indicated that the indicator's reliability has been determined. It has been allowed to have outer loadings greater than 0.6. In general, its value falls between 0.671 to 0.848, satisfying the 0.6 threshold for acceptability. As can be seen from the findings above, every outside loading figure is over 0.7, which is regarded as extremely satisfactory. For all results except DV 6 (0.671), PU4 (0.690), and PT4 (0.680), the acceptable threshold of 0.6 is exceeded. Consequently, every variable will be incorporated into the model for estimate, and the outcomes are considered valid.

4.3.3 Internal Consistency Reliability

The Cronbach's Alpha values using SmartPLS 4 with a 95% confidence interval as well as a significance level of 0.05 are given in Table 4.7. The degree to which items are correlated with one another and yield dependable and consistent outcomes is measured by Cronbach's Alpha, an internal consistency measurement. From Table 4.7 shown, the independent variables such as DV (0.878), PR (0.849), PT (0.830), and SN (0.809) have very good reliability since the values fall between 0.80 and 0.90. While the PEOU (0.793) and PU (0.748) have good reliability since their values fall between 0.70 and 0.80.

Table 4.7 also displays the composite reliability outcome with a 95% confidence interval and a 0.05 level of significance. According to Moscato (2023), the build is considered reliable if the composite reliability is more than 0.75. All of the composite reliability values in Table 4.7, which range from 0.842 to 0.908, show that a high level of internal consistency has been reached. As shown, DV (0.908) has the highest value, then following PR (0.890), perceived trust (0.880), SN (0.8174), PEOU (0.863), and PU (0.842) has the lowest value. Since every figure is higher than 0.75, all of them may be considered as reliably estimated.

4.3.4 Convergent Validity

Furthermore, the result of Average Variance Extracted (AVE) with 95% confidence level shown in Table 4.7. AVE is a measure of a construct's variation relative to the amount caused by measurement error; levels above 0.7 are regarded as extremely large, and an amount of 0.5 is seen as acceptable. The average amount of variation that a latent construct may theoretically explain in the observed variables to which it is related is known as the AVE estimate, according to Farrell (2010). According to Moscato (2023), if the construct has an AVE value of more than 0.50, it is taken to be reliable. From Table 4.7, it indicates that the range of AVE falls between 0.572 and 0.635, which means that all variables are reliable. As shown, subjective norms have the largest value (0.635), and the following is the DV (0.623), PR (0.619), PEOU (0.612), PT (0.596) and PU (0.572).

4.3.5 Discriminant Validity

Table 4.8 below shows the result of Heterotrait-monotrait ratio (HTMT).

Table 4.8

Discrimination Validity Test

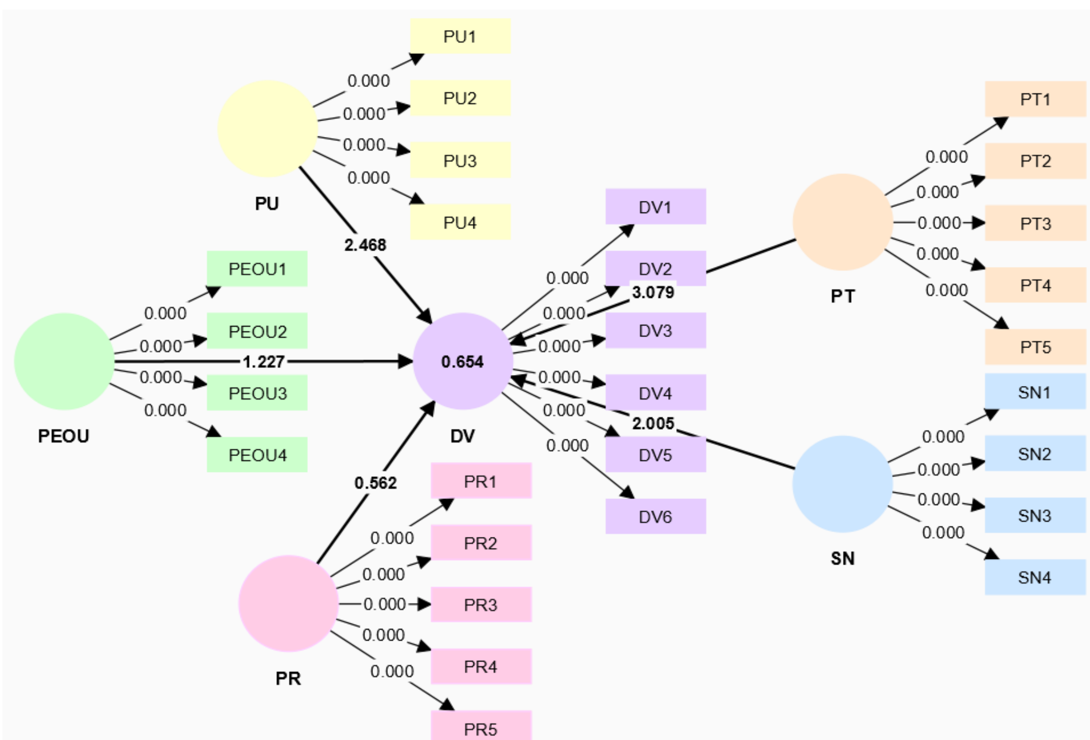
	DV	PEOU	PR	PT	PU	SN
DV						
PEOU	0.569					
PR	0.293	0.254				
PT	0.853	0.542	0.400			
PU	0.707	0.698	0.285	0.566		
SN	0.734	0.364	0.396	0.765	0.550	

According to Franke and Sarstedt (2019), the heterotrait-monotrait ratio of correlations (HTMT) is a useful substitute test for discriminant validity since it serves as an estimator of disattenuated (completely dependable) construct correlations. In addition, it takes into account a maximum population correlation of just 0.90 instead of presuming a unit correlation between the construct measures. This indicates that the HTMT value should be not above 0.9. According to Table 4.8, a strong relationship exists between DV and SN (0.734), and PT (0.853). In general, PR has a poor relationship with other variables, such as with PT (0.400) and DV (0.293).

4.4 Structural Model Analysis

Figure 4.1

Bootstrapping (SMART-BT 4.0) with t-statistics result



4.4.1 Variance Inflation Factors (Collinearity)

The Variance Inflation Factors (VIF) in our study are used to determine the collinearity issues. As stated by C. Team (2023), if the VIF is above 4, it should be considered looking into multicollinearity. If the VIF is more than 10, a significant amount of multicollinearity needs to be adjusted. Since all of the values in Table 4.9 are lower than 4, there are no multicollinearity issues between the independent and dependent variables.

Table 4.9

Collinearity Test (VIF)

Construct	Variance Inflation Factors (VIF)
PEOU > DV	1.545
PR > DV	1.163
PT > DV	1.967
PU > DV	1.661
SN > DV	1.822

4.4.2 Bootstrapping Test

In this analysis, the t-values and the statistical significance of the path coefficient were computed using the bootstrapping option. Table 4.10 displays all computed values and Table 4.11 shows the total effects result.

Table 4.10

Bootstrapping test

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values	Significance ($p < 0.05$)
PEOU > DV	0.109	0.106	0.089	1.227	0.220	Insignificant
PR > DV	-0.040	-0.038	0.072	0.562	0.574	Insignificant
PT > DV	0.460	0.434	0.149	3.079	0.002	Significant
PU > DV	0.233	0.248	0.094	2.468	0.014	Significant
SN > DV	0.214	0.232	0.107	2.005	0.045	Significant

Table 4.11

Total Effects Result

	Total effects
PEOU > DV	0.109
PR > DV	-0.040
PT > DV	0.460
PU > DV	0.233
SN > DV	0.214

This study examined whether the relationship between DV, and five independent variables, including PEOU, PR, PT, PU, and SN, is significant. According to Leguina (2015), the relationship between the DV and independent variables are shown by the total effects value. Positive total effects indicate that the dependent variable rises along with the independent variable; negative numbers, on the other hand, indicate the opposite.

In Table 4.10, it shows the p-value of PEOU is 0.220, that is greater than 0.05 significance level. Hence, there is no significant relationship between PEOU and DV at 95% confidence level.

Moreover, the p-value of PR is 0.574, that is also greater than 0.05 significance level. Hence, there is no significant relationship between PR and DV at 95% confidence level.

Furthermore, PT has a p-value with 0.002, that is lower than 0.05 significance level. Hence, the relationship between PT and DV is significant at 95% confidence level. As Table 4.11 shown, total effects of PT on the dependent variable are 0.460, indicating that the PT improves the DV.

In addition, PU has a p-value with 0.014, that is lower than 0.05 significance level. Hence, the relationship between PU and DV is significant at a confidence level of 95%. As Table 4.11 shown, total effects of PU on the dependent variable are 0.233, indicating that the PU improves the DV.

Lastly, SN has a p-value with 0.045, that is lower than 0.05 significance level. Therefore, the relationship between SN and DV is significant at 95% confidence level. As Table 4.11 shown, total effects of SN on the dependent variable are 0.214, indicating that the SN improves the DV.

4.4.3 R^2 Measures

Table 4.12

R^2 Result

	R-square	R-square adjusted
DV	0.654	0.642

According to Turney (2022), R^2 demonstrates how well the dependent variable in the model captures the outcome. An R^2 model's near to 1 indicates the way well it predicts the future. Moreover, the R-square value shows how much of the variance in the response variable can be explained by the predictor variables in the model (Bobbitt, 2022). When the response variable has a value of 1, it means that the predictor variables fully explain it. According to Table 4.12, the dependent variable's (DV) R-square adjusted value is 0.642, implying a strong predictive model.

4.5 Conclusion

The data gathering process, which involved 160 respondents who were Malaysian banking customers, was described in depth in this chapter using a questionnaire. To process the data analyzing, SmartPLS 4.0 is used in our research. Here, scale measurement, descriptive analysis, and reliability analysis are the main topics. These test results are displayed in tabular form. Additionally, Cronbach's Alpha, composite reliability, and outer loadings all show good reliability for all variables. AVE greater than the suggested cutoff of 0.5 indicates convergent validity. Furthermore, this model does not encounter the multicollinearity problem. From the Bootstrapping test, PEOU and PR are insignificant in this model, while PT, PU and SN are statistically significant in this model.

CHAPTER 5: DISCUSSION, CONCLUSION, AND IMPLICATION

5.0 Introduction

In this chapter, conclusions for data analysis have been made based on previous chapters with further details. First, results of the statistical and descriptive analysis are presented. The explanations for these results are then examined. The report then makes recommendations for possible uses of the results. Lastly, it addresses the of the study and suggests future research topics.

5.1 Summary of Descriptive and Statistical Analysis

The study's descriptive and statistical analysis data from Chapter four is compiled in this part. The information, which was gathered from 160 respondents, is exclusive to Malaysian residents who are between the ages of 18 and over 50. After filtering the data, 160 sets of questionnaires collected via Google Forms and in-person field visits were examined. The research provides important new insights into the dataset by identifying key linkages and learnings, as well as the features of the variables.

5.1.1 Summary of Descriptive Analysis

Throughout the survey, out of 160 participants, there are 41.25% of male participants and 58.75% of female participants. Most participants were around 18 to 29 years old (77.50%), and unemployed (61.25%). Furthermore, most of the respondents have knowledge on AI banking enabled technology.

5.1.2 Summarization of Statistical Analysis

Table 5.1

Summarization for Statistical Findings

Independent Variables	T-statistics	P-value	Results
PEOU	1.227	0.220	Insignificant
PU	2.468	0.014	Significant
PR	0.562	0.574	Insignificant
PT	3.079	0.002	Significant
SN	2.005	0.045	Significant

Based on Table 5.1, PU, PT, and SN are significant relationships towards the DV, while PEOU and PR have insignificant relationships towards the DV as their p-value are higher than the significant level, which is 0.05.

5.2 Discussion on Major Findings

5.2.1 Perceived Ease of Use

Based on the result given by the Smart-PLS software, an insignificant relationship is found between PEOU and DV in Malaysian banking services. The total effect of 0.109 shows that PEOU has a positive relationship with DV. The result received is similar to Rahman et al. (2021), Alt et al. (2021), and Ly & Ly (2022). This means that the PEOU does not bring any effect to the Malaysian banking residents' intention to apply AI in Malaysian banking services.

5.2.2 Perceived Usefulness

From the result from Smart-PLS software, a significant relationship is found between PU and DV in Malaysian banking services. The total effect of 0.233 shows that PU has a positive relationship with DV. The result is similar to Rahman et al. (2021), Noreen et al. (2023), Alqutub (2023), Alt et al. (2021), and Silva et al. (2023) findings. Therefore, PU can positively impact the intention of Malaysian banking residents to apply AI in Malaysian banking services.

5.2.3 Perceived Risk

An insignificant relationship between DV in Malaysian banking services and PR is also found from the result from Smart-PLS software, which is similar to Noreen et al. (2021), Rahman et al. (2021), and Alt et al. (2023) findings. Through our study, the total effect of -0.040 shows that PR has a negative relationship with DV. Therefore, PR does not bring any effects to the intention of Malaysian banking residents to adopt AI in Malaysian banking services.

5.2.4 Perceived Trust

A significant result is also found in the relationship between DV in Malaysian banking services and PT, which is the same as the findings of Rahman et al. (2021), Ly & Ly (2022), Payne et al. (2018), and Silva et al. (2023). The total effect of 0.460 also shows that PT has an upward relationship with intention to adopt artificial intelligence. Therefore, perceived trust can positively affect Malaysian banking residents' intention to adopt AI in Malaysian banking services.

5.2.5 Subjective Norms

Through the result from Smart-PLS, a significant relationship between SN and DV in Malaysian banking services has been identified. The result is similar to findings of Ly & Ly (2022), Noreen et al. (2023), Sohn & Kwon (2019), Rahman et al. (2021), and Belanche et al. (2019). Besides, the total effect of 0.214 indicates that there is a significant connection between SN and DV. Therefore, SN can positively affect Malaysian banking residents' intention to adopt AI in Malaysian banking services.

5.3 Implications of Study

The management implications are given in this section. The focus is on the steps that institutions like banks, governments, and universities may take to further the goal of adopting artificial intelligence into Malaysian banking services.

5.3.1 Managerial Implications

From the output given in Smart-PLS software, it showed that PEOU and PR have an insignificant relationship with DV. Although insignificant, there are still many rooms for future studies on this topic since artificial intelligence related topics are still relatively new. There were also several studies that showed significant results on the independent variables mentioned. With different demographics, the results may also be different.

Besides, PU has a significant relationship with DV in Malaysian banking services. To further increase Malaysian banking residents' intention to adopt AI in banking services, banks and the government need to come up with effective solutions. Banks can promote artificial intelligence with a simpler user interface, which easen the whole banking process, making it easier to get skilled in using AI banking enabled technology. While for the government, they can hold seminars to let the banking residents have a better understanding of the overall process, increasing their financial literacy.

Furthermore, PT also has a significant relationship with DV in Malaysian banking services. Same as PU, banks and government also acts as a vital role in ensuring the reliability of AI banking enabled technology to the banking residents. For banks, they can promote the functions of the AI banking enabled technology in completing daily transactions and providing advice to the users, which increases the banking residents' trust towards AI banking enabled technology. While the government can promote the safety and effectiveness of AI banking enabled technology to the banking residents, which also make AI banking enabled technology more trustworthy.

Lasty, a significant relationship is also found between SN and DV in Malaysian banking services. To influence banking residents on the adoption of AI banking enabled technology, universities and banks are responsible to promote the benefits brought by

AI banking enabled technology, by holding talks or competitions, or even sharing information through social media. Banks can invite celebrities as ambassadors of the AI banking enabled technology, which will attract more potential clients and increase their intention to adopt AI in Malaysian banking services.

5.4 Limitation of study

In this part, the constraints of the research will be concerned. Firstly, the sampling distribution of this research is not equivalent. From our questionnaire analysis, we found that most of the respondents are unemployed. Furthermore, the age group of the respondents are mostly around 18 years old to 29 years old. These conditions may cause our results to be not reliable and having the possibility of sampling bias.

Furthermore, questionnaire may not have sufficiently represented the distinct viewpoints of those banking customers who use Islamic banking or other specialized banking services. Moreover, although quantitative method surveys are relatively more efficient and effective on data collecting and answer comparison, it restricts the ability to fully comprehend respondent’s opinions and experiences on intention to adopt artificial intelligence in banking services.

Last but not least, this study excluded any potential moderators or mediators and only concentrated on the straight forward connections between the dependent variables and independent variables on intention to adopt AI in banking services. Additionally, this study did not include some possible variables, like perceived behavioral control (PBC) that providing a possibility of positive or negative influence on the adoption of artificial intelligence.

5.5 Recommendations

There are several recommendations which could address these limitations, and these could able the future researchers to have better understanding on the topic of intention to adopt AI in banking services.

First and foremost, the respondents of the questionnaire on this research has to be equivalent. This was said because it can reduce the risk of sampling bias and also providing more reliable result as this study is to analysis for the whole Malaysia country. Thus, by doing this the accuracy, statistical power, and also the accuracy of the result will be improved as well.

Furthermore, future studies should consider integrating both qualitative and quantitative method. Qualitative techniques such as focus groups or in-depth interviews would bring a deeper understanding of the varied viewpoints and experience of the respondents, including those who engaged in specialized banking services like Islamic banking. Insights from qualitative research combined with quantitative research data can offer a better insights of the variables impacting artificial intelligence adoption in Malaysian financial services.

Last but not least, future studies should incorporate with more possible variables and also investigate potential mediators and moderators. Researchers could identify more variables impacting adoption intentions by integrating relevant information. Moreover, assessing mediating and moderating variables will yield a more thorough grasp of the elements at play and a deeper understanding of the factors influencing the adoption of artificial intelligence in banking services. This strategy will improve the breadth and relevance of the study results.

5.6 Conclusion

This study aims to identify the factors that influencing the intention to adopt artificial intelligence in banking services in Malaysia. There are five independent variables studied which are PU, PEOU, PR, PT, and SN. Qualitative method which is Questionnaires was carried out to collect the data for this study.

The final result that was indicated in this study was that there are 3 out of 5 variables, which is PU, PT, and SN is having a positive relationship with intention to adopt AI in banking services. However, PEOU and PR was found insignificantly influencing the intention to adopt artificial intelligence in banking services. There were previous studies proving that PEOU was having a positive relationship with intention to adopt AI in banking services, however, negative result was investigated in this research. These results were discussed and implications were also provided in the previous sections. Moreover, the limitation of study and their recommendations were also provided for future studies. This study is proudly to be mentioned that it could provide some insights for the upcoming studies regarding on the variable selection, data collecting, and respondent screening.

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APPENDICES

Appendix 31: Permission to Conduct Survey

UNIVERSITI TUNKU ABDUL RAHMAN *DU012(A)*

Wholly owned by UTAR Education Foundation *(200201010564(578227-M))*

Faculty of Business and Finance
Jalan Universiti, Bandar Barat, 31900 Kampar, Perak
Phone: 05-468-8888
https://fbf.utar.edu.my/

26th July 2024

To Whom It May Concern

Dear Sir/Madam,

Permission to Conduct Survey

This is to confirm that the following students are currently pursuing their *Bachelor of Finance (Honours)* program at the Faculty of Business and Finance, Universiti Tunku Abdul Rahman (UTAR) Perak Campus.

I would be most grateful if you could assist them by allowing the student to conduct his research at your institution. All information collected will be kept confidential and used only for academic purposes.

The student are as follows:

Name of Student	**Student ID**
Lau Yong Zheng	20ABB01690
Lim Wei Xiang	20ABB05194
Wong Xin Yi	21ABB04780

If you need further verification, please do not hesitate to contact me.

Thank you.

Yours sincerely,

Yi

…………………………………

Dr Wei Chooi Yi
Head of Department
Faculty of Business and Finance
Email: weicy@utar.edu.my

Administrative Address: Jalan Sg. Long, Bandar Sg. Long, Cheras, 43000 Kajang, Selangor D.E.
Tel: (603) 9086 0288 **Homepage: https://utar.edu.my/**

Appendix 3.2: Survey Questionnaire

ANALYSING CUSTOMER PROPENSITY FOR EMBRACING ARTIFICIAL INTELLIGENCE (AI) IN BANKING SERVICES

This is a research on analysing customer propensity for embracing Artificial Intelligence (AI) in banking services. In this questionnaire, we will be asking about your opinion towards embracing Artificial Intelligence (AI) in banking services.

* Indicates required question

Personal Data Protection Statement

Please be informed that in accordance with Personal Data Protection Act 2010 ("PDPA") which came into force on 15 November 2013, Universiti Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal information.

Notice:

1. Personal data refers to any information which may directly or indirectly identify a person which could include sensitive personal data and expression of opinion. Among others it includes:
a) Name
b) Identity card
c) Place of Birth
d) Address
e) Education History
f) Employment History
g) Medical History
h) Blood type
i) Race
j) Religion
k) Photo
l) Personal Information and Associated Research Data

2. The purposes for which your personal data may be used are inclusive but not limited to:
a) For assessment of any application to UTAR
b) For processing any benefits and services
c) For communication purposes
d) For advertorial and news
e) For general administration and record purposes
f) For enhancing the value of education
g) For educational and related purposes consequential to UTAR h) For replying any responds to complaints and enquiries
i) For the purpose of our corporate governance
j) For the purposes of conducting research/ collaboration

3. Your personal data may be transferred and/or disclosed to third party and/or UTAR collaborative partners including but not limited to the respective and appointed outsourcing agents for purpose of fulfilling our obligations to you in respect of the purposes and all such other purposes that are related to the purposes and also in providing integrated services, maintaining and storing records. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.

4. Any personal information retained by UTAR shall be destroyed and/or deleted in accordance with our retention policy applicable for us in the event such information is no longer required.

5. UTAR is committed in ensuring the confidentiality, protection, security and accuracy of your personal information made available to us and it has been our ongoing strict policy to ensure that your personal information is accurate, complete, not misleading and updated. UTAR would also ensure that your personal data shall not be used for political and commercial purposes.

Consent

1. By submitting this form you hereby authorise and consent to us processing (including disclosing) your personal data and any updates of your information, for the purposes and/or for any other purposes related to the purpose.

2. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

3. You may access and update your personal data by writing to us at jason.yzlau@1utar.my.

1. **Acknowledgment of Notice** *

Mark only one oval.

- [ ] I have been notified by you and that I hereby understood, consented and agreed per UTAR above notice.
- [ ] I disagree, my personal data will not be processed.

2. By participating in this study, your participation is voluntary. Your information will be kept confidential and will only be used in this study. *

Mark only one oval.

- [ ] Agree

Section A: Demographics

3. Gender *

Mark only one oval.

- [ ] Male
- [ ] Female

4. Age Group *

Mark only one oval.

- 18-29 years old
- 30-39 years old
- 40-49 years old
- 50 years old and above

5. Employment Status *

Mark only one oval.

- Public sector
- Private sector
- Self employed
- Unemployed
- Retiree/Pensioner
- Other: ______________________

6. Do you know anything about AI banking enabled technology? *

Mark only one oval.

- Yes
- No

Skip to question 7

Section B: Perceived ease of use

INSTRUCTIONS: In this section, you are required to read the statements and select only ONE option for each statement. Please indicate your degree of agreement using the following scale. Your responses should reflect your own experiences and opinions. You are highly encouraged to answer all the questions honestly.

1 = "Strongly disagree"
2 = "Disagree"
3 = "Neither agree or disagree"
4 = "Agree"
5 = "Strongly agree"

7. Managing bank transactions with AI-enabled banking technology would be easy for me. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

8. Getting abilities with AI-enabled banking technology comes easy for me. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

9. I would find it easy to communicate with AI in banking since it does not need much of my brain energy. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

10. Using AI-enabled banking technology is simple. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Section C: Perceived usefulness

INSTRUCTIONS: In this section, you are required to read the statements and select only ONE option for each statement. Please indicate your degree of agreement using the following scale. Your responses should reflect your own experiences and opinions. You are highly encouraged to answer all the questions honestly.

1 = "Strongly disagree"
2 = "Disagree"
3 = "Neither agree or disagree"
4 = "Agree"
5 = "Strongly agree"

11. I would do more successful bank transactions if I use AI-enabled banking technologies. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

12. Using AI-enabled banking technology would increase my productivity in managing banking transactions. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strong Agree

13. AI-enabled technologies in banking might be effective in managing banking transactions. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strong Agree

14. Using AI-enabled banking technology is crucial for assisting my financial tasks. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strong Agree

Section D: Perceived risk

INSTRUCTIONS: In this section, you are required to read the statements and select only ONE option for each statement. Please indicate your degree of agreement using the following scale. Your responses should reflect your own experiences and opinions. You are highly encouraged to answer all the questions honestly.

1 = "Strongly disagree"
2 = "Disagree"
3 = "Neither agree or disagree"
4 = "Agree"
5 = "Strongly agree"

15. Using AI-enabled technology in banking activities increases the risk of fraud against my bank account. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

16. Financial risk arises with using AI-enabled technologies in banking services for my bank account. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

17. I believe that using AI-enabled technologies in banking harms my privacy. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

18. AI-enabled banking technology might not function correctly, which could lead to issues with my bank account. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

19. Using the AI-enabled banking technology may result in the collection, tracking, and analysis of personal data. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Section E: Perceived trust

INSTRUCTIONS: In this section, you are required to read the statements and select only ONE option for each statement. Please indicate your degree of agreement using the following scale. Your responses should reflect your own experiences and opinions. You are highly encouraged to answer all the questions honestly.

1 = "Strongly disagree"
2 = "Disagree"
3 = "Neither agree or disagree"
4 = "Agree"
5 = "Strongly agree"

20. AI-enabled banking services are reliable. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

21. AI banking-enabled technology delivers financial services that are in my best interests. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

22. AI banking-enabled technology provides access to honest and real banking services. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

23. The AI banking-enabled technology effectively accomplishes its duty of delivering financial services. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

24. I believe in the benefits of the judgments made by this AI-enabled banking technology. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Section F: Subjective norms

INSTRUCTIONS: In this section, you are required to read the statements and select only ONE option for each statement. Please indicate your degree of agreement using the following scale. Your responses should reflect your own experiences and opinions. You are highly encouraged to answer all the questions honestly.

1 = "Strongly disagree"
2 = "Disagree"
3 = "Neither agree or disagree"
4 = "Agree"
5 = "Strongly agree"

25. In general, I would want to follow my group of friends to employ AI banking technology. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

26. People close to me believe I should employ AI banking enabling technologies. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

27. People I know may persuade me to test out AI-enabled banking technologies for managing banking investments. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

28. Reports from the media influence me into trying with AI-enabled banking systems for money management. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Section G: Intention to adopt Artificial Intelligence in banking services

INSTRUCTIONS: In this section, you are required to read the statements and select only ONE option for each statement. Please indicate your degree of agreement using the following scale. Your responses should reflect your own experiences and opinions. You are highly encouraged to answer all the questions honestly.

1 = "Strongly disagree"
2 = "Disagree"
3 = "Neither agree or disagree"
4 = "Agree"
5 = "Strongly agree"

29. I plan to use AI-enabled banking technologies to manage banking transactions. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

30. I would use AI-enabled banking technologies to manage banking investments. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

31. I plan to use the AI-enabled banking technologies whenever the occasion comes. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

32. I would want to employ the AI-enabled banking technologies in the near future. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

33. I am likely to employ the AI-enabled banking technologies in the near future. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

34. My plan is to employ AI-advisors instead of any human financial advisor. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

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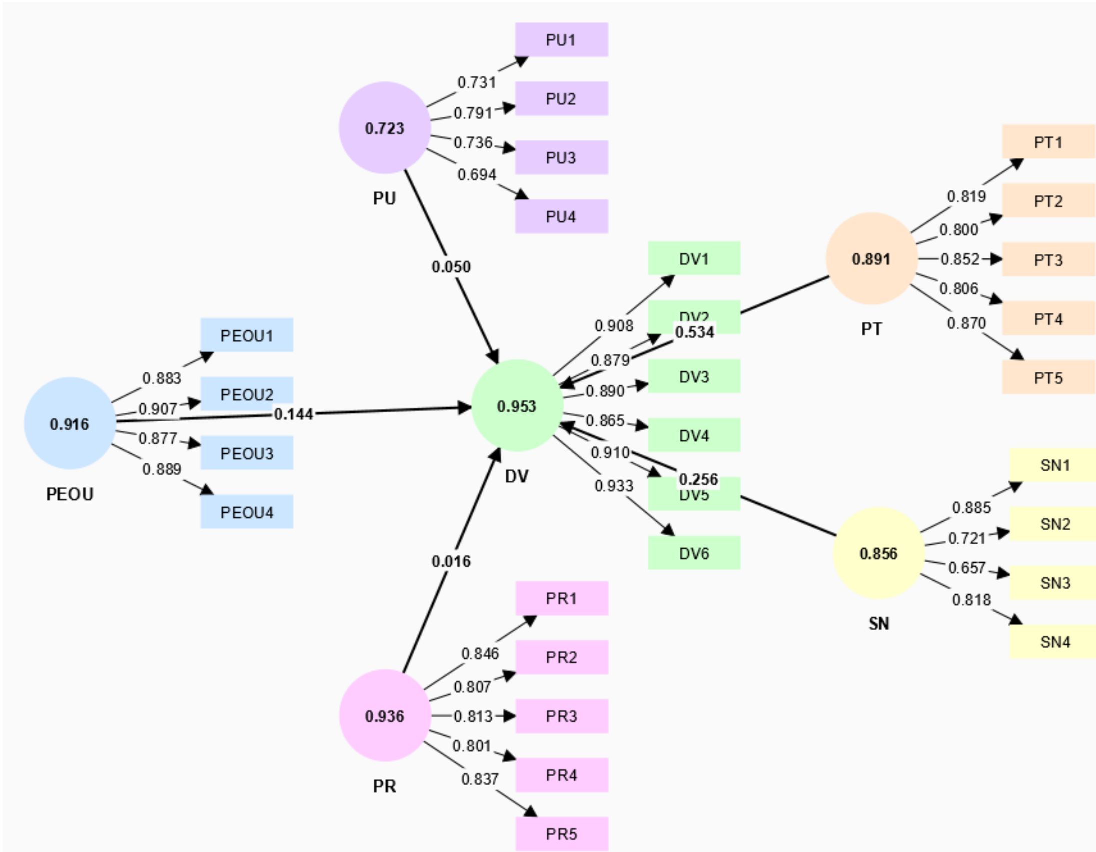
Appendix 4.1: Graphical Output of Pilot Study



Appendix 4.2: Outer Loading Result of Pilot Study

Outer loadings - List

	Outer loadings
DV1 <- DV	0.908
DV2 <- DV	0.879
DV3 <- DV	0.890
DV4 <- DV	0.865
DV5 <- DV	0.910
DV6 <- DV	0.933
PEOU1 <- PEOU	0.883
PEOU2 <- PEOU	0.907
PEOU3 <- PEOU	0.877
PEOU4 <- PEOU	0.889
PR1 <- PR	0.846
PR2 <- PR	0.807
PR3 <- PR	0.813
PR4 <- PR	0.801
PR5 <- PR	0.837
PT1 <- PT	0.819
PT2 <- PT	0.800
PT3 <- PT	0.852
PT4 <- PT	0.806
PT5 <- PT	0.870
PU1 <- PU	0.731
PU2 <- PU	0.791
PU3 <- PU	0.736
PU4 <- PU	0.694
SN1 <- SN	0.885
SN2 <- SN	0.721
SN3 <- SN	0.657
SN4 <- SN	0.818

Appendix 4.3: Construct Reliability and Validity Test on Pilot Study

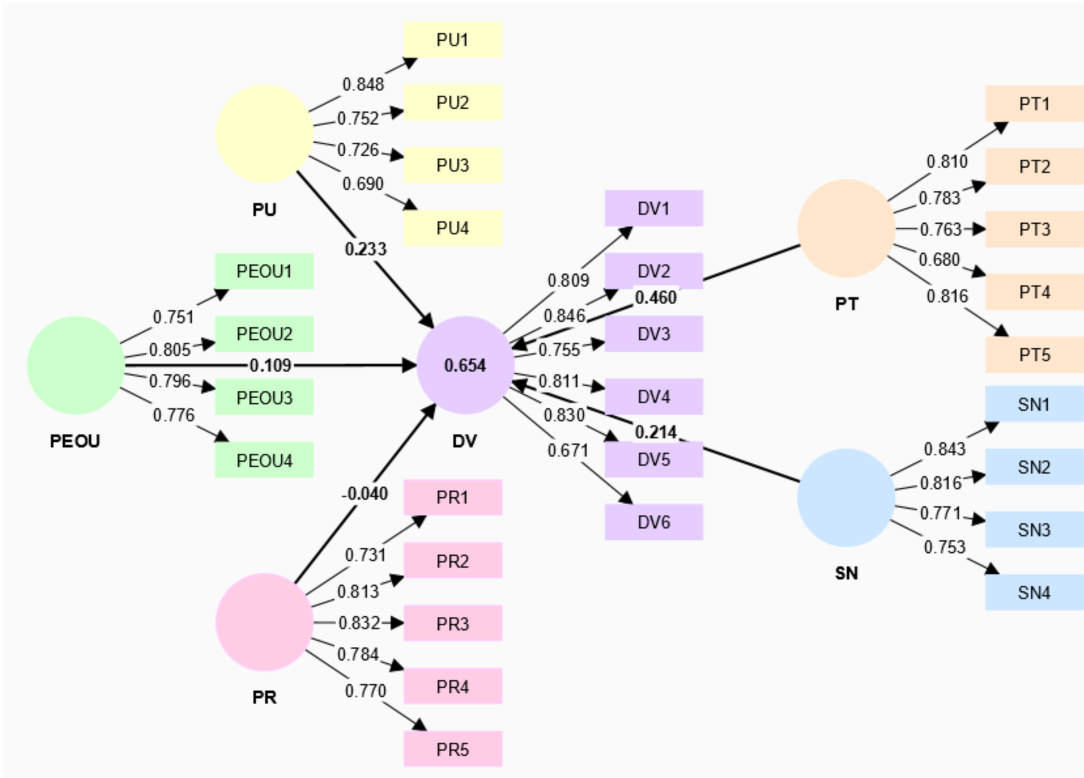
Construct reliability and validity - Overview				
	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
DV	0.952	0.953	0.961	0.806
PEOU	0.912	0.916	0.938	0.790
PR	0.884	0.936	0.912	0.674
PT	0.887	0.891	0.917	0.689
PU	0.725	0.723	0.828	0.546
SN	0.788	0.856	0.856	0.601

Appendix 4.4: Bootstrapping test of Outer Loadings

Outer loadings - Matrix

	DV	PEOU	PR	PT	PU	SN
DV1	0.809					
DV2	0.846					
DV3	0.755					
DV4	0.811					
DV5	0.830					
DV6	0.671					
PEOU1		0.751				
PEOU2		0.805				
PEOU3		0.796				
PEOU4		0.776				
PR1			0.731			
PR2			0.813			
PR3			0.832			
PR4			0.784			
PR5			0.770			
PT1				0.810		
PT2				0.783		
PT3				0.763		
PT4				0.680		
PT5				0.816		
PU1					0.848	
PU2					0.752	
PU3					0.726	
PU4					0.690	
SN1						0.843
SN2						0.816
SN3						0.771
SN4						0.753

Appendix 4.5: Graphical Output of Actual Study



Appendix 4.6: Outer Loadings Result of Actual Study

Outer loadings - List

	Outer loadings
DV1 <- DV	0.809
DV2 <- DV	0.846
DV3 <- DV	0.755
DV4 <- DV	0.811
DV5 <- DV	0.830
DV6 <- DV	0.671
PEOU1 <- PEOU	0.751
PEOU2 <- PEOU	0.805
PEOU3 <- PEOU	0.796
PEOU4 <- PEOU	0.776
PR1 <- PR	0.731
PR2 <- PR	0.813
PR3 <- PR	0.832
PR4 <- PR	0.784
PR5 <- PR	0.770
PT1 <- PT	0.810
PT2 <- PT	0.783
PT3 <- PT	0.763
PT4 <- PT	0.680
PT5 <- PT	0.816
PU1 <- PU	0.848
PU2 <- PU	0.752
PU3 <- PU	0.726
PU4 <- PU	0.690
SN1 <- SN	0.843
SN2 <- SN	0.816
SN3 <- SN	0.771
SN4 <- SN	0.753

Appendix 4.7: Construct Reliability and Validity Test of Actual Study

Construct reliability and validity - Overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
DV	0.878	0.886	0.908	0.623
PEOU	0.793	0.808	0.863	0.612
PR	0.849	0.871	0.890	0.619
PT	0.830	0.838	0.880	0.596
PU	0.748	0.753	0.842	0.572
SN	0.809	0.818	0.874	0.635

Appendix 4.8: Discriminant Validity Test (HTMT) of Actual Study

Discriminant validity - Heterotrait-monotrait ratio (HTMT) - Matrix

	DV	PEOU	PR	PT	PU	SN
DV						
PEOU	0.569					
PR	0.293	0.254				
PT	0.853	0.542	0.400			
PU	0.707	0.698	0.285	0.566		
SN	0.734	0.364	0.396	0.765	0.550	

Appendix 4.9: Discriminant Validity Test (Cross Loadings) of Actual Study

Discriminant validity - Cross loadings

	DV	PEOU	PR	PT	PU	SN
DV1	0.809	0.446	0.166	0.686	0.559	0.500
DV2	0.846	0.434	0.291	0.630	0.596	0.554
DV3	0.755	0.353	0.156	0.498	0.388	0.408
DV4	0.811	0.475	0.144	0.553	0.492	0.465
DV5	0.830	0.343	0.168	0.532	0.401	0.527
DV6	0.671	0.256	0.315	0.563	0.288	0.508
PEOU1	0.312	0.751	0.180	0.340	0.333	0.277
PEOU2	0.402	0.805	0.167	0.349	0.487	0.199
PEOU3	0.469	0.796	0.109	0.342	0.507	0.221
PEOU4	0.326	0.776	0.153	0.356	0.343	0.217
PR1	0.175	0.209	0.731	0.284	0.120	0.270
PR2	0.232	0.165	0.813	0.226	0.275	0.225
PR3	0.260	0.148	0.832	0.292	0.293	0.307
PR4	0.177	0.143	0.784	0.222	0.099	0.268
PR5	0.150	0.070	0.770	0.285	0.112	0.233
PT1	0.600	0.400	0.319	0.810	0.491	0.496
PT2	0.617	0.459	0.158	0.783	0.421	0.407
PT3	0.530	0.210	0.177	0.763	0.183	0.546
PT4	0.465	0.326	0.311	0.680	0.249	0.414
PT5	0.616	0.295	0.321	0.816	0.384	0.593
PU1	0.480	0.411	0.220	0.354	0.848	0.355
PU2	0.431	0.557	0.149	0.326	0.752	0.279
PU3	0.388	0.435	0.180	0.312	0.726	0.253
PU4	0.468	0.270	0.196	0.386	0.690	0.431
SN1	0.566	0.259	0.266	0.604	0.422	0.843
SN2	0.492	0.262	0.240	0.528	0.444	0.816
SN3	0.395	0.222	0.217	0.386	0.238	0.771
SN4	0.518	0.174	0.326	0.476	0.278	0.753

Appendix 4.10: Correlation Test (Variance Inflation Factors) of Actual Study

Collinearity statistics (VIF) - Outer model - List

	VIF
DV1	2.004
DV2	2.452
DV3	1.832
DV4	2.668
DV5	2.788
DV6	1.582
PEOU1	1.813
PEOU2	1.625
PEOU3	1.482
PEOU4	1.868
PR1	1.750
PR2	1.978
PR3	2.054
PR4	2.018
PR5	2.048
PT1	1.913
PT2	1.706
PT3	1.745
PT4	1.492
PT5	1.902
PU1	1.902
PU2	1.478
PU3	1.500
PU4	1.243
SN1	2.119
SN2	2.002
SN3	1.741
SN4	1.550

Appendix 4.11: Bootstrapping Test of Path Coefficient of Actual Study

Path coefficients - Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
PEOU -> DV	0.109	0.106	0.089	1.227	0.220
PR -> DV	-0.040	-0.038	0.072	0.562	0.574
PT -> DV	0.460	0.434	0.149	3.079	0.002
PU -> DV	0.233	0.248	0.094	2.468	0.014
SN -> DV	0.214	0.232	0.107	2.005	0.045