INTENTION TO USE AI CHATBOT AMONG GENZ' PERSONAL FINANCIAL PLANNING IN KLANG VALLEY MALAYSIA

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BY

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

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DECLARATION

I hereby declare that:

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

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

(3) Sole contribution has been made by me in completing the FYP.

(4) The word count of this research report is **21,418** words.

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Finally, I would like to thank my friends, who have been my solid support system throughout this journey. I am especially grateful to Ms. Mina Ong, Mr. James Goh, Mr. Evan Sim, and Mr. Sky Lu for their invaluable assistance in addressing the challenges I faced during this research. Their support and encouragement made this journey smoother and more fulfilling.

DEDICATION

The unwavering support, encouragement, and sacrifice of my beloved family has been the foundation of my entire journey. Your belief in my abilities is my greatest source of strength and inspiration.

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LIST OF ABBREVIATION

AI - Artificial Intelligence

AVE Average Variance Extracted

C - Confidentiality

FC - Facilitating Conditions

IOU - Intention to Use

NLP - Natural Language Processing

PE - Performance Expectancy

PLS-SEM - Partial Least Squares Structural Equation Modelling

PMT - Protection Motivation Theory

PS - Perceived Severity

PV - Perceived Vulnerability

R2 R-Square

RC - Response Costs

RE - Response Efficacy

SE - Self-Efficacy

TAM - Technology Acceptance Model

UTAUT - Unified Theory of Acceptance and Use of Technology

VIF - Variance Inflation Factor

PREFACE

This research project was undertaken as part of my academic journey to fulfil the requirements for my final-year project from UTAR. The study reflects my interest in exploring the intersection of artificial intelligence and financial planning, particularly the intention to use AI chatbots among Generation Z in Klang Valley, Malaysia.

Generation Z was chosen as the focal demographic due to their unique characteristics as digital natives. They are born into a world shaped by rapid technological advancements, highly adaptable to new technologies and are early adopters of digital solutions. This generation's reliance on digital platforms for everyday activities, including banking and financial planning, makes them a key demographic for understanding the potential of AI chatbots in transforming financial services. Furthermore, with growing financial independence and the need for effective financial management, Generation Z's preferences and intention are critical to shaping future trends in the fintech sector.

Throughout the project, I encountered many challenges that required resolve and problem-solving skills. From developing a conceptual framework to analyzing the data collected, every step of the journey is an opportunity to grow and learn. This experience deepened my understanding of academic research and enhanced my critical thinking and analytical skills.

In my sincere hope that this research is able to contribute to the academic field and provides meaningful insights for financial institutions aiming to improve the intention and effectiveness of AI chatbots for personal financial management.

ABSTRACT

This study examines Generation Z's intention to use AI chatbots for personal financial planning in Klang Valley, Malaysia. By integrating the Protection Motivation Theory (PMT) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the research explores how cybersecurity concerns, threat appraisals, and enabling factors influence the intention to use AI chatbots.

Key factors analysed include trust, performance expectancy, self-efficacy, perceived vulnerability, response efficacy, and response costs. These variables are evaluated to understand Generation Z ‘s intention to use in AI chatbot technologies in their personal financial planning. The study highlights barriers such as privacy concerns, confidentiality, and perceived threat severity are identified as critical challenges to intention to use AI chatbot.

Moreover, quantitative approach was adopted using a structured questionnaire to collect data from 350 respondents within the target population. Statistical analysis was performed by using SMARTPLS 4.0 to assess the relationship between the identified factors and the overall intention of using an AI chatbot for financial management. The findings provide valuable insights for financial institutions to design and implement AI solutions that meet Gen Z’s unique preferences and expectations, increase user satisfaction, and foster continued usage intentions.

Additionally, this research contributes to the academic understanding of AI chatbot intention in personal financial planning, addressing gaps in the application of PMT and UTAUT to this field and providing actionable recommendations for industry stakeholders.

Keywords: AI Chatbots, Generation Z, Intention to Use, Personal Financial Planning, Protection Motivation Theory (PMT), Unified Theory of Acceptance and Use of Technology (UTAUT)

CHAPTER 1: INTRODUCTION

1.0 Introduction

Chapter 1 provides a comprehensive introduction to the study by introducing the background, outlining key issues, and identifying the research objectives and questions. Additionally, it highlights the structure, significance, and scope of the investigation.

1.1Research Background

With artificial intelligence (AI) technology, computers and machines can imitate human abilities such as study, understanding, problem-solving, strategic decision-making, creativity, and independence. AI integration has involved different industries, bringing revolutionary change in modern society, and the banking industry is no exception. For instance, AI based chatbots were increasingly used in banking sector to handle customer demand, process transactions, provide personalized financial advice, streamline operations and improve customer experience (Koster, 2024).

The increasing popularity of big data has promoted the integration of artificial intelligence and business operations. This allows organisations to adopt artificial intelligence technology more easily and more feasible. According to a recent study by Rustambek (2023), businesses can effectively leverage artificial intelligence algorithms and machine learning capabilities to automate tasks, analyse data, and provide personalized user experiences on websites. For example, by analysing user data such as browsing behaviour, preferences, and demographics, AI algorithms can aggregate data, filter data, and provide accurate recommendations or product suggestions in human decision-making (Huang et al., 2021). This personalization approach results in a more interactive and engaging website that increases user satisfaction and conversion rates.

Furthermore, Rustambek (2023) also mentions that AI algorithms have significantly contributed to delivering personalized support with chatbots, which process natural language and interpret user intention to address inquiries immediately. The same study highlights how AI algorithms can monitor website traffic and detect abnormalities to maintain and safeguard user's data from potential data breaches and relieve concerns about unauthorized access and theft.

The rise of AI has significantly impacted every sector, including banking and financial institution; AI-powered chatbots are becoming increasingly popular because they allow bankers, financial institution, and users to analyse complex data. AI based chatbots, which use NPL (Natural Language Processing) to simulate human conversations, are increasingly used to improve customer service and operational efficiency. However, intention and effectiveness of AI technologies can vary significantly depending on their specific use (IBM, n.d.). For example, AI chatbots provide instant responses, personalized advice, and assistance with routine financial tasks to make the user's or banking sector's financial management more accessible and efficient. These chatbots can learn and simulate human conversation using NLP to enhance customer service and operational efficiency (Capacity, 2024).

Regarding financial planning, AI chatbots offer a promising solution by providing personalized advice, enhancing predictive analytics, and promoting financial advisors (Udeh et al., 2024). As technology advances nowadays, the role of artificial intelligence in financial planning is expanding quickly; AI can provide businesses and individuals with unprecedented opportunities for achieving their personal financial goals and securing their financial future.

For instance, take Bank of America's AI chatbot "Erica"; the application of AI chatbots is even more advanced. The Erica AI chatbot can leverage predictive analytics and machine learning and provide solid personalized financial advice based on customers' spending habits and behaviors (Hwang & Kim, 2021). Likewise, in October 2022, Wells Fargo launched a new virtual assistant chatbot called Fargo that leverages Google Cloud's advanced language models to provide personalized responses and proactive insights on spending, financial forecasts, and budgets to the user (Consumer Financial Protection Bureau, 2023).

On the other hand, the Malaysian banking sector has begun exploring using chatbots to provide advanced service to customers, but the chatbot still has limited capabilities. For example, the CIMB EVA chatbot can overview transactions via chat and handle large volumes of inquiries from small and medium-sized businesses simultaneously accessed in December 2016. However, the EVA chatbot only answers queries on products, financial eligibility, and financial status (CIMB Bank, 2020). Similarly, RHB Bank’s chatbot allows customers to apply for their personal loans through the messaging platform with their Chatbot (Tan, 2017). Apart from that, those chatbots mainly focus on customer service and information dissemination and lack advanced features to analyse personal financial situations and provide accurate recommendations to users. Compared with Erica and Fargo's AI chatbot, this highlights the untapped potential for Malaysian banks to leverage AI chatbots to enhance customer experience and drive better financial decisions among Malaysians.

Besides this, AI chatbots are becoming increasingly important to banks and financial institutions because competitive advantage and customer loyalty are key factors in the highly competitive market. These chatbots allow the banking sector to provide 24/7 customer support, lower operational costs, and deliver personalised experiences that enhance customer satisfaction. This means that an efficient service that AI chatbots provide can lead to higher customer retention rates and foster brand loyalty.

Although AI chatbots can offer many advantages, some challenges still require further exploration. For example, issues such as data privacy concerns, trust, and the ability of chatbots to fully replicate human interactions are important needs in the banking industry (Kanaparthi, 2024). Additionally, researcher Kanaparthi (2024) also mention that not all customers are comfortable with AI managing sensitive financial data. The difference between customer expectations and chatbot performance and the impact on customer loyalty remains uncertain. Therefore, examining how AI chatbots can effectively support financial institutions while overcoming these challenges is necessary to ensure their long-term success and sustainability.

On the other hand, the Credit Counselling and Management Agency (AKPK) data reveals that 38,9% of individuals cite the high cost of living as a significant issue, while 36% attribute their financial struggles to poor financial planning. At the same time, according to the Ministry of Finance (2023), from 2014 until May 2023, a total of 31,140 youths have been declared bankrupt. Furthermore, the Ministry of Finance (MOF) noted that one-third of those struggling with debt earn an annual income of less than RM24,000, or RM2,000 per month. The high cost of living and poor financial planning are the main issues Malaysians face with debt issues. This highlights the urgent need for government and financial institutions to prevent Generation Z from facing continued financial deterioration, affecting the country's economic growth and the financial institutions' revenue and risk management. Therefore, as a financial institution, it is vital to understand the possible opportunities of AI technology, how to enhance this cohort's financial literacy, and the aid of AI-powered chatbot personal financial services to support their customers.

When delving into the statistics of the Malaysian population, we can see that Malaysia is becoming an ageing society consisting mainly of Generation X and Baby Boomers. The part of the population aged 60 and above increased from 5.2% in 1990 to 6.2% in 2000 and 8.0% in 2010 day by day (MSN, n.d.). This trend is expected to enhance significantly in the coming decades. By 2030, Malaysia will become an ageing country, with 14% of the population aged 60 or above, and this is expected to increase to 24% by 2050. For example, this demographic shift mirrors challenges in countries like Japan, where younger generations are increasingly burdened with the financial responsibility of supporting their ageing parents (Lee, 2016). This has led to significant financial pressures on younger populations in Japan, and similar issues are likely to arise in Malaysia as its population ages. Therefore, it is important to study Gen Z's intent to use AI chatbots for personal financial planning. As the next dominant segment of the Malaysian market, Gen Z will face the financial challenges of managing their resources and potentially supporting older family members.

Generation Z is Gen Z or Zoomers and covers the population born between 1995 and 2012 (Aziz, 2021). in 2024, Gen Z is between 17 and 28 years old. With disruptive digital banking services launched, Gen Z is increasingly shifting their preference from traditional banks to digital platforms. They enthusiastically adopt technologies for banking transactions and other digital services, seeking greater convenience despite some associated costs (Golani, 2017). For example, Maybank2u's transaction volume increased from 1.15 billion in 2020 to 1.47 billion in November 2021, a year-on-year increase of 35%. Significant growth in transaction volume and value in Malaysia highlights the growing interest of Gen Z. Digital banks are booming, driven by the appeal of fintech (Dhesi, 2021).

While the introduction provides a good overview of Generation Z, it lacks a detailed explanation of why they are particularly suitable for this study. According to survey from insurance agency, Etiqa (2024), Malaysian Gen Z faces increasing financial challenges such as insufficient emergency funds and difficulty saving money, highlighting the need for convenient and effective financial planning tools. Their survey highlights most of this demographic is actively engaged in saving and investing practices, but many of them are still unsure where to start due to widespread concerns about credit scores and risk. Etiqa Insurance (2024) also highlight that Malaysian Gen Z often turn to online platforms and influencers for financial education, since they prefer solutions that are personalized, interactive and easily accessible.

Apart from that, understanding intentions to use AI chatbots for personal financial management is critical as it reveals factors that influence intentions for the technology, especially among Generation Z. Since this population is a major driver of digital banking trends, investigating their motivations and concerns can help identify key determinants. By analyzing these factors, financial institutions can improve their AI offerings to meet the needs and expectations of Gen Z, increasing user satisfaction, cultivating loyalty, and ensuring long-term success in the highly competitive fintech space.

Apart from this, the present study needs to understand Malaysian Gen Z's intention to use of AI chatbots in their finances. Researcher Aseng (2020) concluded that research focusing on Gen Z is still rare. Moreover, Suhaimi and Hassan (2018) mention most studies were just carry out with Generation Y, not Generation Z. Apart from, studies about the intention to use AI chatbots in personal financial planning in Malaysia are rare (Ni, 2020). Therefore, this is necessary to study because this topic is underdeveloped, and it is possible to examine how generation Z intends to use AI chatbots for their personal financial planning due to the financial burden and high cost of spending nowadays.

As discussed above, it shows an urgency to study the factors influencing Gen Z's intent to use AI chatbots for their better personal financial planning decision. As digital natives, Gen Z is more likely to learn new technologies, making them an essential demographic for understanding the future track for AI Chatbot intention in personal finance planning. By examining their intention, this study investigates the motivators and barriers to intention to use AI chatbots in their personal finance management. The results of this study could give a more profound view for financial institutions in developing effective strategies for motivating Generation Z to use AI-powered chatbots, indirectly enhancing their financial literacy and supporting financial institutions' sustainability and better risk management.

1.2 Research Problem

As Malaysia enters an ageing society, Generation Z is expected to face increasing financial pressure, including the responsibility of supporting ageing parents. While AI-powered chatbots offer potential solutions for managing personal finances, the extent to which Gen Z is willing to embrace these technologies remains uncertain. Key topics such as data privacy concerns, trust in AI and the ability of chatbots to solve complex financial needs remain. Therefore, understanding Gen Z’s intentions to use AI chatbots for financial management is important as this generation will soon dominate the Malaysian market, and this research is critical to enhancing financial instruments and ensuring long-term financial stability.

From the customer consumer behaviour point of view, Generation Z users seek personalized services and intuitive user interfaces, which highlight customization in banking interaction (Kimiagari and Baei, 2024). However, existing products often fail to meet these needs. Generation Z faces technical issues, such as security issues and lack of user-friendly features

(Ali et al., 2022; Bitkina et al., 2022), which may block AI chatbots' consistent usage and trust. Factors such as the severity of threats related to data breaches and the vulnerability of personal financial information further complicate the intention to use AI chatbots (Sebastian, 2023). If users feel their personal data is at risk, they will be significantly less motivated to use AI technology.

These challenges provide banks with opportunities to improve their digital tools, AI chatbots, to better meet the needs of younger consumers, including providing personalized experiences, efficient transactions, and strong security features (Noreen et al., 2023). Enhancing these aspects can increase their engagement and satisfaction with AI chatbot technology.

Theoretically, it is important to identify that technology intention can differ significantly based on contextual factors such as infrastructure, cultural, and user demographics (Vimalkumar et al., 2021). Existing theories on technology acceptance offer valuable insights but also come with limitations (Alshammari et al.,2020). For example, many models fail to adequately account for external factors or the changing requirements of specific user groups such as Generation Z.

To address these gaps, this study proposes a combined theoretical model, combining the UTAUT and PMT. This model explores the factors that affect Gen Z’s intention to use AI chatbots for financial management. By integrating these theories, this study provides a comprehensive framework covering safety-related issues and practical elements influencing technology intention. This approach is particularly relevant for understanding how Gen Z interacts with AI-powered financial tools in Malaysia.

Although research on artificial intelligence chatbots has been carried out in fields such as the hospitality industry (Cheah et al., 2024) and education (Rahim et al., 2022) in the Malaysian context, there is still a significant research gap in the financial field due to the lack of Related research study (Toh & Tay, 2022).

Furthermore, UTAUT has been the basis for numerous studies on factors influencing different technological intentions. Examples of theories that use UTAUT as a basis for research include e-government services (Zeebaree et al., 2022), mobile payments (Chand and Kumar, 2024), and m-health services (Hoque and Sorwar, 2017). However, this application in the context of financial services AI chatbots remains an underexplored topic. Therefore, as AI chatbots grow in importance in the field, the literature lacks comprehensive insights into the specific factors driving their intention, especially among younger users such as Generation Z.

Furthermore, previous research has explored the impact of financial technology on consumer intentions in various areas which are including card payments (Namahoot & Boonchieng, 2023), mobile banking (Mensah & Khan, 2024), and financial applications (Yohanes et al., 2020). Additionally, research has assessed how fintech affects consumers' ability to borrow (Wu et al., 2024), engage in risk sharing, and financial risk management (Sajid et al., 2023). While the role of AI chatbots in financial services is increasingly recognized, understanding how users in emerging markets interact with the technology of AI chatbots remains limited.

Although PMT is widely used in areas such as environmental behavior and health (Kothe et al., 2019), its application in personal financial planning remains underexplored. Specifically, limited research has examined how constructs of PMT (e.g., perceived vulnerability, response efficiency, self-efficacy, and response costs) influence individuals' intentions to use AI chatbots for financial management. Most PMT research focuses on human behavior in other areas, highlighting research gaps.

Furthermore, Kothe et al. (2019) also mention that only a few studies have successfully manipulated PMT variables, and even fewer have examined the effects of these manipulations on intentions. Many studies do not integrate all PMT constructs into a single model, which limits understanding of how these variables interact to influence user intentions.

Technical issues such as privacy concerns and cybersecurity risks are critical to financial decisions; these factors are often addressed in isolation. Researcher Arpaci (2024) emphasizes the need for more comprehensive research that integrates these issues with PMT to understand better how users assess risk and make decisions about using AI chatbots for financial planning.

This research seeks to address these gaps by applying PMT to explore how cybersecurity, privacy, and trust influence Gen Z's intentions to use artificial intelligence chatbots for personal financial management. Thus, this better understanding of how PMT affects financial behavior in a rapidly digitizing environment can be achieved.

Regarding personal financial planning for Generation Z, UTAUT may have limited predictive power. Therefore, this study combines UTAUT with PMT to better understand the factors influencing using artificial intelligence chatbots for personal financial management. PMT, developed by Rogers (1975), focuses on individual responses to threats, while UTAUT explains how performance drives technology intention. Together, these theories provide a powerful framework to gain insights into Gen Z's intention in AI chatbots for their financial planning.

Therefore, this study introduces a theoretical model combining UTAUT and PMT frameworks to examine the factors influencing Generation Z's willingness to use artificial intelligence chatbots and their impact on personal financial planning. The UTAUT model can explain up to 70% of the variance in behavioral intentions (Venkatesh et al., 2003) and is particularly relevant to this study. Integrating UTAUT with PMT provides a comprehensive approach that addresses security concerns and practical factors driving technology intention. This makes the model ideal for investigating Gen Z's intentions to adopt AI chatbots in financial management.

1.3 Research Questions

To answer the problem mentioned above statement and identify the factors that influence Gen Z's intention to use AI chatbots for personal financial planning, this study addressed the following general research questions:

1. Do effect effortancy, performance effectancy, and trust influence Generation Z’s intention to use an AI chatbot for personal financial planning?

2. Do the threat apprisals (security, severity, and susceptibility to the threat) influence Generation Z’s intention to use an AI chatbot for personal financial planning?

3. Do the coping apprisals (response efficacy and self-efficacy) influence Generation Z’s intention to use an AI chatbot for personal financial planning?

Specifically, the following are the research questions:

RQ1: Does trust affect Generation Z's use of AI chatbots for personal financial planning?

RQ2: Does performance expectancy affect Generation Z’s intention to use an AI chatbot for personal financial planning?

RQ3: Does effort expectancy affect Generation Z’s intention to use an AI chatbot for personal financial planning?

RQ4: Does perceived vulnerability affect Generation Z’s intentions to use AI chatbots for personal financial planning?

RQ5: Does perceived severity affect Generation Z’s intention to use an AI chatbot for personal financial planning?

RQ6: Does self-efficacy affect Gen Z’s willingness to use an AI chatbot for personal financial planning?

RQ7: Does Gen Z’s willingness to use AI chatbots for personal financial planning affect the response efficiency?

RQ8: Does response costs affect Generation Z’s intention to use an AI chatbot for personal financial planning?

RQ9: Does confidentiality concern affect Generation Z’s intention to use an AI chatbot for personal financial planning?

RQ10: Do privacy concerns affect Generation Z’s intention to use AI chatbots for personal financial planning?

1.4 Research Objective

The objective of this study has two goals. First, it aims to investigate the threat and enabler factors that influence Gen Z's intention to use AI-powered chatbots for their personal financial planning. Secondly, it attempts to integrate UTAUT and PMT to comprehensively investigate the threat and coping appraisal influence on user intention to use AI-powered chatbots among Malaysian Gen Z.

Therefore, the following are the specific objectives:

RO1: Examine the influence of trust on intentions to use an AI chatbot for personal financial planning among generation Z.

RO2: Examine the influence of perceived usefulness on intentions to use an AI chatbot for personal financial planning among generation Z.

RO3: Evaluate the influence of perceived ease of use on intentions to use an AI chatbot for personal financial planning among generation Z.

RO4: Examine the influence of perceived vulnerability on intentions to use an AI chatbot for personal financial planning among generation Z.

RO5: Examine the influence of perceived severity on intentions to use an AI chatbot for personal financial planning among generation Z.

RO6: Examine the influence of self-efficacy on intentions to use an AI chatbot for personal financial planning among generation Z.

RO7: Examine the influence of response efficiency on intentions to use an AI chatbot for personal financial planning among generation Z.

RO8: Examine the influence of response costs on intentions to use an AI chatbot for personal financial planning among generation Z.

RO9: Examine the influence of confidentiality concerns on intentions to use an AI chatbot for personal financial planning among generation Z.

RO10: Examine the influence of privacy concerns on intentions to use an AI chatbot for personal financial planning among generation Z.

1.5 Scope of study

This scope of study will cover several key areas necessary to understand Gen Z’s intentions for using AI chatbots in personal financial planning. The focus is on Gen Z, born in Malaysia between 1995 and 2012 at age 17-28. This group was chosen because of their increasing reliance on digital platforms and financial transaction technology. The research will be conducted in the Klang Valley, Malaysia, considering the region's unique economic, cultural and technological landscape influencing financial behavior and technology intention. This study employs the threat factors from PMT and enabler factors from UTAUT to study various factors that affect Gen Z’s intention to use AI-powered chatbots for their personal financial planning.

1.6 Significance of the research

This study will help one understand how threat appraisals, cope appraisals, cybersecurity concerns, performance expectations, trust and facilitation conditions influence the intention of AI chatbots among Gen Z in Malaysia. The results of this study are expected to contribute to and benefit national prosperity, allowing Malaysia government decision and policy makers to obtain insights into the country's economic growth strategies. The results also benefited multiple stakeholders, such as financial institutions, in developing marketing strategies to promote their AI-powered chatbot for financial management and adding knowledge to the literature for academics.

1.6.1 Industry: Financial Institutions

For financial institutions, this research will highlight the key aspects of AI chatbots that need improvement to meet user demands and needs. By understanding those areas, banks can continue to enhance their chatbot services to provide a better and more professional user experience. Additionally, this research will help financial institutions better understand user behaviour trends and enable them to lay out effective and efficient strategies to promote their AI chatbot to help users analyse their financial behaviours. Therefore, this understanding can help to improve customer satisfaction and increase the intention rates of AI chatbots.

1.6.2 Government: Policy Maker

For governments, this research will provide a valuable highlight into user cybersecurity concerns about AI chatbots. This knowledge can help development of specific rules and regulations to protect users and promote the benefits of AI chatbots through targeted communication campaigns. By addressing these issues, governments can create a more secure AI chatbot environment and encourage more users to embrace these technologies to manage personal financial planning.

1.6.3 Consumer

For a user this study will attempt to encourage users to have favorable attitudes and perceptions towards digital transformation in the traditional banking industry. Addressing their concerns can help shift their mindsets and increase their acceptance of AI chatbots. Users will benefit from enhanced convenience, efficiency, and personalized services that AI chatbots can provide, ultimately improving their overall banking experience and personal financial.

1.6.4 Body of Knowledge and academics

Lastly, for academics, this study will provide a clear understanding of the importance and impact of AI chatbot intention among Generation Z in Malaysia. It offers valuable knowledge and generates fresh ideas for further research. Academics can build and research these findings to explore new aspects of AI chatbot intention and continue contributing to advancing knowledge in the AI chatbot field.

1.7 Chapter summary

In summary, this chapter provides a brief overview of the research background, problem statement and research significance. This research aims to provide a valuable view into the banking sector by utilizing the PMT and UTAUT frameworks, which are well-established theories in assessing intention to use. By applying these frameworks, we can evaluate the alignment between customer intentions and perceptions regarding AI-enabled chatbots, identify service delivery gaps, and pinpoint improvement areas. This approach allows us to understand better customer intentions and how Malaysian banks can optimize their chatbots to enhance the customer’s intention to use AI chatbots in their financial planning. Thus, this study focuses on AI chatbots within Klang Valley, Malaysia.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Chapter 2 will explore the literature review in more detail and further expand knowledge surrounding the research topic. It presents the critical review and results of past research in similar domains. This chapter also highlights the underlying theory and explains how the underpinning theories were grounded to form this study's conceptual framework and hypotheses.

2.1Underlying Theory

2.1.1 Protection motivation theory (PMT)

PMT is a conceptual, theoretical framework commonly used to study how individuals react when perceiving a threat. It explores how fear-inducing messages can prompt people to take protective action or avoid behaviour that could cause harm to themselves or others. This theory belongs to the expectancy-value theory, which holds that a person's beliefs or attitudes will ultimately drive his or her behaviour (Wang et al., 2019).

PMT explain how individuals decide on their actions by assessing potential threats and assessing their ability to respond. In threat assessment, individuals evaluate the severity and susceptibility of a threat. Other than that, coping appraisal focuses on assessing the effectiveness of existing coping mechanisms, the potential costs or challenges of implementing these mechanisms, and the individual's confidence in successfully executing these strategies (Shafiei & Maleksaeidi, 2020). Rogers' (1985) PMT framework was expanded to include cybersecurity factors such as confidentiality and privacy, allowing for a more comprehensive exploration of intentions for using AI chatbots. This inclusion is due to a lack of understanding of how confidentiality and privacy impact the decision to adopt an AI chatbot for personal financial planning.

The basis for increasing cybersecurity awareness of AI chatbots comes from various fields, including behavioral science, psychology, and information security (Maddux & Rogers, 1983). Protection Motivation Theory (PMT) is particularly helpful in providing insights into how individuals assess risk and engage in protective behaviors when interacting with AI chatbots. PMT suggests that users' protective actions depend largely on their perceptions of vulnerability, the severity of the threat, and the effectiveness of strategies available to reduce risk (Arpaci & Bahari, 2023).

Furthermore, PMT suggests that compassion for others is not simply an automatic response to their suffering but a social mechanism facilitating connections between individuals. The theory highlights how approach and avoidance motivations influence people's decisions to take or not take specific actions. For example, empathic people may better understand the emotional impact of misleading financial on personal financial planning, increasing their perception of threats and motivating them to take protective measures.

When discussing the use of AI chatbots for personal financial planning, the term “perceived threat” can refer to the risk of relying on a chatbot's inaccurate or misleading financial advice and the potential financial and emotional consequences of such advice. Financial stress is crucial in shaping perceptions of these threats and their effectiveness. For example, individuals facing financial difficulties may view the threat of receiving bad advice as more severe because of the potential for further financial harm in an already precarious situation. Additionally, financial hardship may reduce a person's sense of effectiveness because they may doubt their ability to discern or respond to inaccurate advice. Therefore, PMT can provide a useful framework for understanding the link between personal financial difficulties and the apparent reliability of AI chatbots.

2.1.2 Unified Theory of Acceptance and Use Of Technology (UTAUT)

UTAUT extends of TAM (Venkatesh et al., 2003). This theory aims to predict users' intentions to adopt information systems and their actual usage behavior. The study of individual intentions and information technology use has become mature in information systems (Venkatesh et al., 2007). UTAUT has proven its strengths as a powerful framework, offering great potential to help organizations assess the impact of emerging technologies (Garavand et al., 2022).

Over the years, many researchers have applied UTAUT in various studies. For example, Alghazi et al. (2021) analyzed key determinants of intentions to learn with UTAUT using mobile devices. Moon et al. (2020) applied this theory to study factors influencing the use of mobile apps by people with visual impairments. Furthermore, the researchers Hoque and Sorwar (2017) have adopted the UTAUT framework to study the effect of mobile health (mHealth) services among older adults. These studies highlight the relevance and utility of UTAUT in different contexts.

Trust is one of the additional independent variables in this study. According to researchers Han and Conti (2020), trust is the understanding that a system or service is reliable and honest. Past research has shown that people's intentions to adopt new technologies are heavily influenced by their level of trust. It is generally considered critical to the UTAUT model. Therefore, trust is included in this study as an independent variable representing users’ confidence in AI chatbots.

In this research, UTAUT will explore the intention of using AI chatbots in personal finances among Generation Z in Malaysia. Performance expectancy was an independent variable in this study and reflected generation Z's expectations about the effectiveness of using online dating apps. Finally, Facilitating Conditions refers to the availability of resources and supports that enabled Generation Zin in this study to adopt AI chatbots.

2.2 Review of Variables

2.2.1 Independent Variables- Self-Efficacy

Research on self-efficacy explores how interactions with chatbots influence this construct, particularly in visual design. Some studies suggest frequent and satisfying chatbot interactions enhance students' self-efficacy, engagement, and learner autonomy (Durak, 2022). For example, Liu et al. (2022) studied artificial intelligence educational chatbot designed to increase students' emotional confidence and self-efficacy by leveraging structured conversation templates and cultivating emotional connections.

Another study examines a chatbot created to deliver stress management techniques, finding that its use significantly improves well-being and stress levels, indirectly enhancing self-efficacy(Khanthavit & Khanthavit, 2023). The studies also explore the role of virtual experimental platforms, which may include chatbot-like interfaces, in improving students' self-efficacy within experimental settings

Additional research investigates how self-efficacy impacts user experience assessments in chatbot interactions, offering insights into how this psychological factor shapes perceptions and satisfaction (Gonzalez-Cacho & Abbas, 2022). Moreover, Sakane et al. (2023) explore the impact of a mobile health AI on self-efficacy related to health behaviours. Although this study does not focus on chatbots, it provides valuable insights into how digital tools can influence self-efficacy in health-related contexts.

Therefore, understanding how chatbots can impact self-efficacy is critical to designing effective AI chatbots to enhance user confidence and performance. By leveraging insights from these studies, this study explores how self-efficacy affects users' intentions to use an AI chatbot for personal financial planning.

2.2.2 Independent Variables- Response Efficacy

Response efficacy is a key concept in Protection Motivation Theory (PMT) and refers to the degree to which an individual believes that taking a recommended action will effectively reduce personal threats (Bigsby & Albarracín, 2022). According to Zhang et al. (2022), response efficacy involves a cognitive process in which individuals form thoughts and evaluate their ability to respond to threats.

Many studies have examined the impact of response efficacy. For example, Alraja et al. (2023) studied how fear affects end-user compliance with computer usage guidelines and found that perceptions of response effectiveness significantly influenced users' computer-related behaviors. Similarly, Chou et al. (2024) concluded that response efficacy positively affects attitudes toward safety-related behaviors, thereby increasing the likelihood of engaging in such behaviors.

Therefore, in the context of this study, it is expected that users would be more likely to employ the chatbot if they believe its recommendations are responsive. If users believe that AI chatbots can effectively help them manage their finances, reduce financial risks, and achieve financial goals, their willingness to engage in and rely on chatbots will increase. This study explores how response efficacy affects individuals' attitudes and intentions toward using artificial intelligence-driven financial planning tools.

2.2.3 Independent Variables- Response Costs

Response costs refer to the perceived expense or inconvenience of implementing protective measures. Higher response costs are generally associated with a lower willingness to adopt adaptive responses (Lahiri et al., 2021). These costs often involve the removal of rewards or positive consequences for engaging in specific undesirable behaviours and are considered significant barriers to completing conservation actions (Kothe et al., 2019).

Key attributes of coping costs include unpleasantness, difficulty, inconvenience, expense, disruption to daily life, complexity, disruption of habits, effort required, social embarrassment, and additional time commitment (Rodrigues et al., 2023; Arena et al., 2022). In this research, response costs were related to adaptive coping responses, including monetary investment, personal time, and effort required. High response costs reduce the likelihood of selecting an adaptive response, resulting in opportunity costs associated with taking recommended actions to avoid threatening events (Schipper, 2020).

2.2.4 Independent Variables- Perceived Vulnerability

Perceived vulnerability is a person's perception of their susceptibility to risks (Bú et al., 2021). It reflects a person's beliefs about the likelihood of a threat occurring or the risk of something going wrong (Gebrehiwot & van der Veen, 2020). This concept highlights how people perceive factors beyond their control, which can lead to insecurities and potentially negative outcomes (Zarlengo, 2012). It also includes sensitivity involving future vulnerabilities or potentially dangerous adverse consequences. The cognitive aspect of this structure includes emotional components such as fear, anxiety, and worry.

Lichtenberg et al. (2020) also investigated the perceived vulnerability of older adults and its correlates of age-related financial vulnerability. The results of this study reveal a strong correlation between age-related financial vulnerability and perceived financial vulnerability, making theoretical and empirical contributions to our understanding of how older adults perceive financial risk.

In the context of AI chatbots, perceived vulnerability during the threat assessment process involves assessing the severity of the threat by estimating the likelihood of poor personal financial planning. Fear mediates vulnerability perceptions and overall threat appraisals (Vrhovec & Mihelič, 2021).

Therefore, understanding perceived vulnerability is critical in the context of Gen Z’s financial planning and their use of AI chatbots. By addressing the fears and anxieties associated with these areas, targeted interventions can be developed to enhance the intention and effective use of AI technologies, ultimately reducing perceived threats and improving overall outcomes.

2.2.5 Independent Variables- Perceived Severity

Perceived severity refers to an individual's fear of the potential consequences of a threat (Sukeri et al., 2020). It means how a user views a severe health event's potential harm or importance. This insight may be related to future events or current problems from existing problems. Each individual's perception of severity varies, reflecting their subjective perception of the severity of the condition and its consequences (Kim & Kim, 2020). Additionally, perceptions of threat severity may influence users' emotional responses, which can influence an individual's response to a situation. (Conrad et al., 2022)

According to Preissner et al. (2022), within the framework of protection motivation theory, perceived severity includes psychological and physical dimensions. This includes assessing the potential consequences of financial decisions, such as losses, financial instability and stress. For example, in the context of personal financial planning using AI chatbots, perceived severity can reflect an individual's assessment of the severity of financial risk and the potential impact on their financial stability and future goals.

2.2.6 Independent Variables- Confidentiality

Confidentiality protects and limits data use and storage (Bos, 2020). This is important when considering AI chatbots, especially in financial management. AI chatbots often handle large amounts of personal and financial information, which is crucial for implementing strong confidentiality measures. Techniques that enable flexible delegation of decryption permissions are crucial for securing chatbot interactions, such as key aggregation techniques that maintain a constant key size regardless of the number of keys (Kumar & Bhatia, 2020). Therefore, access control mechanisms that support data editing and prevent replay attacks are crucial to enhance the security of AI chatbots, enabling users to verify the integrity of their data.

According to research by Chai and Zolkipli (2021), there is a positive relationship between confidentiality and various information security requirements, directly affecting users' willingness to use AI chatbots. Confidentiality builds trust and increases the likelihood of intention, especially when dealing with sensitive information. The researcher also highlights the importance of cybersecurity risk awareness programs, which can further enhance user confidence in using AI chatbots on digital platforms.

Moreover, Young values discussions about confidentiality and is often unsure of how well their information is protected (Kafka et al., 2024). They may feel betrayed if their data is disclosed without consent, which can damage trust. Likewise, users of AI chatbots, especially in sensitive fields such as finance, need to be confident that their information is safe. If confidentiality is breached without clear communication, it can damage the user's relationship with the chatbot and reduce their willingness to continue using the chatbot. Being transparent about when confidentiality may be compromised is key to maintaining user trust and ensuring long-term interactions with AI chatbots.

2.2.7 Independent Variables- Privacy

Privacy is considered a highly personal and sensitive issue for individuals. Privacy, security, and freedom from distractions are often used to describe it (Rath & Kumar, 2021). Privacy is closely related to individuals' control over their personal information and how it is shared. People are increasingly concerned about information privacy, especially when exposed to and adopting new technologies (Quach et al., 2022).

Martínez-Navalón et al. (2023) research highlights that well-executed technological innovation can provide organizations with significant competitive advantages. Effectively managing privacy while ensuring ease of use and building trust can benefit organisations greatly. Ongoing privacy research is crucial in improving service quality and optimizing the use of digital banking technologies to attract the intention to use AI chatbots.

Furthermore, Sebastian (2023) highlights the urgent need for collaborative efforts to enhance data protection and privacy within AI systems, a key issue in the context of AI chatbots for personal financial management. His findings underscore the importance of ongoing research, regulatory measures, and the intention of privacy-enhancing technologies (PETs) in AI models. These efforts are particularly important to ensure that user privacy is protected while advancing AI technology, which is critical to fostering trust among Gen Z and encouraging the intention of AI chatbots in financial planning.

2.2.8 Independent Variables- Performance Expectancy

According to Momani (2020), performance expectancy refers to the perceived benefits an individual anticipates from using a specific technology when performing tasks important to him or her. Consistent with Venkatesh et al. (2003), performance expectations are closely related to perceived usefulness and relative advantage, reflecting the expected benefits of improving consumers' quality of life and job performance. These expectations of achieving desired outcomes through technology have positively influenced intentions to use.

Researchers believe performance expectations are a key factor in the success of chatbot startups. Performance expectancy is when individuals think using the system will help them improve their work performance. Research by Balakrishnan et al. (2022) highlights how adjusting performance expectations proves that chatbots can become more effective tools than traditional information systems. For example, Mogaji et al. (2021) found that AI chatbots can significantly improve the effectiveness of financial activities, especially in personal financial planning.

However, if users perceive an AI chatbot system as too complex or cognitively demanding, its benefits may be compromised. Effort expectancy refers to when the AI chatbot system plays a crucial role in order to help users complete tasks more successfully and efficiently. Therefore, when users find the system easy to use, they can shift the saved time and energy to personal financial planning.

2.2.9 Independent Variables- Trust

Research has consistently emphasized that trust plays a crucial role in influencing students' intentions to adopt modern technologies such as fintech products and services (Alwi et al., 2019; Stewart and Jürjens, 2018). Stewart and Jürjens (2018) found a strong relationship between trust and customers' behavioral intentions to adopt fintech services, a conclusion supported by Alwi et al. (2019) for their fintech-related research. Together, these studies highlight the important predictive power of trust in shaping behavioral intentions for emerging technologies, including artificial intelligence platforms for financial planning.

Additionally, integrating automated portfolio management capabilities that enable AI to execute investment strategies without emotional interference may further enhance customer trust in AI for personal financial planning. Trust can be based on various factors, such as factual knowledge, personal beliefs, or cultural values (Tugade et al., 2021). Fundamentally, trust reflects a party’s confidence in fulfilling its obligations under the agreement (Kusumawati &

Rinaldi, 2020). In digital banking, trust also means a commitment to maintaining the integrity and reliability of digital banking applications (Mufarih et al., 2020).

2.2.10 Independent Variables- Facilitating Conditions

Facilitating conditions include technical support, training, and ongoing assistance that enable users to adopt and utilize new technologies (Venkatesh et al., 2003). These conditions can significantly impact individuals' perceptions of ease of use, which is critical to the successful deployment and sustainability of AI chatbots within organizations. When introducing new technologies into the workplace, these adaptation measures must be developed early to foster positive attitudes and ensure broad acceptance (Dwivedi et al., 2017).

According to Chatterjee et al. (2021), the acceptance of new technologies is primarily affected by facilitating conditions. Successful intention of AI technologies depends on integrating these tools with existing infrastructure and ensuring that this integration is user-friendly (Chatterjee et al., 2021). Therefore, the banking sector must take into account contextual elements like customer perceptions and cultural norms when using AI chatbots.

Management strategies should include comprehensive adaptation to achieve effective integration and acceptance in diverse environments. These strategies should ensure that the chatbot is designed with user demographics and cultural sensitivities in mind, provides adequate user support and aligns the chatbot's communication style and functionality with the user's specific needs and preferences. This approach addresses technological and infrastructural aspects and social and psychological factors influencing technology acceptance and effectiveness.

2.2.11 Dependent variables- Intention to use

UTAUT is widely used to explain users' intentions and behaviors when adopting information systems. Researchers often adapt models to specific contexts and continue to find positive results (Ayaz & Yanartaş, 2020). Venkatesh et al. (2003) demonstrated that UTAUT explained nearly 70% of the variance in behavioral intentions, outperforming other models that explained only below 70% of the variance in the same data. Given these findings, it is reasonable to assume that UTAUT is equally effective in explaining students' acceptance of AI and has the potential to explain more of the variance in their behavioral intentions toward AI intention.

The intention to use a new product or service reflects a customer's readiness and willingness to take a specific action (Eslami et al., 2022). It can be understood as a commitment to follow through on a planned action when an individual is motivated or has a clear goal. Mohammad Haidar Ibrahim et al. (2019) define intention as the conscious decision-making process that drives a person to engage in particular behaviors.

Some customer intention in the banking industry are affected by convenience, efficiency, trust, and personalized experiences when adopting chatbots (Shaikh et al., 2023). When chatbots provide seamless assistance, solution suggestions, and instant customer service, they will be more adopted, leading to increased customer satisfaction and engagement. Furthermore, in terms of PMT, individuals' intentions to act in a protective manner are influenced by their perceptions of threat severity, vulnerability, response effectiveness, and self-efficacy (Fischer-Preßler et al., 2021).

When PMT is applied to using AI chatbots for personal financial planning, findings suggest that users are more likely to adopt chatbot recommendations when they perceive that the benefits (response efficacy) outweigh potential risks in financial planning. Since financial planning is an ongoing decision-making process, users' perceptions of threat severity and vulnerability play a role. Moreover, trust in technology is a critical factor influencing intention and use (Shahsavar & Choudhury, 2023). When users feel that the balance between risk and reward is favorable, they are more inclined to trust AI chatbots and rely on their advice for personal financial planning.

2.3 Hypothesis development

2.3.1 Self-Efficacy And Intention To Use

Self-efficacy has been widely studied as a key factor influencing financial behaviors and technology intention. The research Him et al. (2019) established a relationship between financial self-efficacy and stress levels in student loan repayment. They also mention that individuals with higher financial self-efficacy experienced lower stress and were better equipped to manage their loans. This suggests that individuals with greater confidence in their financial abilities perceive financial tasks as less challenging.

Similarly, Hoffman and Plotkina (2021) examined how mastery experiences build financial self-efficacy. Their study showed that individuals with successful experiences managing financial tasks exhibited higher confidence in handling future financial decisions. This reinforces the notion that past successes foster increased self-efficacy, which can positively influence financial management.

However, Muslichah (2018) found that self-efficacy did not significantly influence intentions to use academic information systems (AIS) despite its importance as a determinant of perceived usefulness. This suggests that the impact of self-efficacy on technology intention may vary across contexts. Therefore, further investigation is needed to understand the role of self-efficacy in the context of the intention of AI chatbots for personal financial planning. Therefore, the hypothesized conducted is:

H1: Self-Efficacy has significant effect on Intention To Use

2.3.2 Response Efficacy And Intention To Use

Maddux and Rogers (1983) highlighted the importance of response efficacy in shaping individuals' intentions to adopt preventive behaviors, particularly when perceived threats are high. Response efficacy is the belief that engaging in a particular behavior, such as using a financial planning chatbot, will effectively mitigate risks (Boss et al., 2015). In personal financial planning, users must perceive the AI chatbot as a reliable tool that enhances financial security by offering timely advice and alerts.

Research on response efficacy has yielded mixed findings. Warkentin et al. (2016) discovered that response efficacy did not significantly influence the continued use of anti-malware software, while Vedadi and Warkentin (2020) identified it as a critical factor in promoting the continued use of password protection tools. Similarly, Al-Emran et al. (2021) found that response efficacy positively influenced the intention to use smartwatches. These varied outcomes indicate that the impact of response efficacy may differ across contexts.

Given the emerging role of AI chatbots in personal financial planning, the extent to which response efficacy influences their intention remains unclear, especially in the Malaysian context. Thus, further research is necessary to determine whether users believe that AI chatbots can effectively assist in managing their financial well-being. Therefore, the hypothesis is:

H2: Response efficacy has a significant effect on Intention To Use

2.3.3 Response Cost And Intention To Use

Response costs, which include unpleasantness, difficulty, inconvenience, expense, disruption to daily life, complexity, effort, habit disruption, social embarrassment, and additional time, are significant barriers to adopting new functions of technologies (Rodrigues et al., 2023; Arena et al., 2023). When individuals perceive these costs as high, they may be deterred from engaging with adaptive technologies like AI chatbots for personal financial planning, as the perceived burdens may outweigh the benefits.

For example, Hanus and Wu (2018) conducted research among 274 employees in Finland and found that complying with information security intentions (ISI) was perceived as time-consuming, inconvenient, and disruptive to work tasks. Similarly, Hanus and Wu (2016) observed that high response costs, such as the effort and time needed to implement security measures, reduced students' intentions to engage with information security practices.

On the other hand, Fischer-Preßler el al. (2022) point out that response costs were not significant in the initial intention to use an app but became more relevant as users continued to engage with the app. Non-users who did not experience major effort beyond installation initially disregarded response costs. However, once they transitioned to regular users, response costs became important in determining continued usage.

For Gen Z in Malaysia’s Klang Valley, response costs may also play a key role in their decision to use AI chatbots for financial planning. If these users believe the technology is too complex or time-consuming, they may be less willing to adopt it despite its potential benefits, such as personalized financial advice and convenience. Therefore, the hypothesis is:

H3: Response cost has a significant effect on Intention To Use

2.3.4 Perceived Vulnerability And Intention To Use

Perceived vulnerability refers to an individual’s assessment of the likelihood and potential consequences of encountering a threat, including beliefs about risks and negative outcomes. It encompasses emotional responses such as fear, anxiety, and worry, which are often driven by factors beyond an individual’s control (Vrhovec & Mihelič, 2021; Lichtenberg et al., 2020; Gebrehiwot & van der Veen, 2020).

Research by Park et al. (2024) showed that perceived vulnerability significantly affects users' attitudes, while perceived self-efficacy has no similar effect. Their findings highlight that perceived response efficacy (a component of the coping appraisal process) has a smaller impact on attitudes than perceived severity and vulnerability, which are central to the threat appraisal process. They emphasized that external threats are persistent and unpredictable and recommended that service providers continue to strengthen artificial intelligence cloning services, respond to new risks, and improve security measures.

Bauer and Bernroider (2015) studied how an information security awareness program (ISAP) affects user perceptions of severity, vulnerability, self-efficacy, and response effectiveness. Their study showed that ISAP positively affected perceived severity, coping efficacy, and self-efficacy but had a weak negative relationship with perceived vulnerability. This suggests that while awareness programs increase users' confidence in managing risks, they do not necessarily increase their feelings of vulnerability. Similarly, the research also found that although threat awareness was a strong predictor of perceived severity, it did not significantly affect perceived vulnerability (Hanus & Wu, 2016; Martens et al., 2019).

These studies highlight perceived vulnerability's subtle role in shaping users' attitudes and behaviors toward technology. In using AI chatbots for personal financial planning, it is crucial to understand how Gen Z in the Klang Valley perceive vulnerability, as this may influence their intention to adopt these tools. If they see AI chatbots as a way to mitigate financial risk and uncertainty, their perceived vulnerability may drive their intention to use the technology. Therefore, this study proposes the following hypothesis:

H4: Perceived vulnerability has a significant effect on Intention To Use

2.3.5 Perceived Severity And Intention To Use

Perceived severity refers to an individual's assessment of the seriousness of a potential threat, influencing emotional responses and subsequent behavior. In protection motivation theory (PMT), perceived severity covers psychological and physical aspects (Sukeri et al., 2020; Kim & Kim, 2020).

Research consistently highlights that perceived severity is key in shaping intentions to adopt new technologies. For example, Wei et al. (2020) found that perceived severity significantly affects intentions and actual intentions of mHealth technologies. Similarly, Alaiad et al. (2020) showed that patients who perceive a health threat are more inclined to adopt mobile health applications, suggesting that heightened threat perception can drive technology intention in healthcare settings. Wei et al. (2020) further emphasized that perceptions of health threats directly influence users' perceptions of the usefulness of these technologies.

In another study, Sreelakshmi and Prathap (2021) studied Indian consumers during the COVID-19 pandemic and found that high perceived severity and vulnerability strongly influenced the intention of mobile payment technologies. Consumers are aware of the seriousness of health threats, so consumers adopt these technologies as protection. Similarly, Daragmeh et al. (2021) confirmed that increased awareness of health risks during the pandemic accelerated the use of digital wallets and viewed this behavior as a form of health protection. This is consistent with previous research highlighting the role of technology, including financial services, in building resilience during crises.

In the context of AI chatbots for personal financial planning, perceived severity may similarly impact Gen Z in Klang Valley, Malaysia. If they believe financial risks are serious, they may be more inclined to adopt AI chatbots to mitigate those risks and safeguard their financial well-being. Based on this, this study proposes the following hypotheses:

H5: Perceived severity has a significant effect on Intention To Use

2.3.6 Confidentiality And Intention To Use

Confidentiality plays a crucial role in influencing users' trust and willingness to adopt AI chatbots, especially in the sensitive area of financial management. It refers to protecting personal and financial information through strong security measures such as encryption and access controls. When users are confident that their data is secure, they are more likely to trust and use AI chatbots to manage financial tasks.

The study by Chai and Zolkipli (2021) highlighted the positive relationship between confidentiality and information security requirements, showing that it directly affects users' intention to adopt AI chatbots. This is especially important for users dealing with sensitive information, as they are more likely to interact with a chatbot when they trust that their data will remain confidential. Young users, especially Gen Z, are highly aware of data privacy and are more inclined to adopt AI-driven solutions if they feel their personal and financial data are well protected.

Similarly, Normalini et al. (2019) found that confidentiality significantly positively impacted customers' intention to continue using online banking services. The study concluded that maintaining confidentiality promotes continued usage, as accurate and secure data management is critical to the banking industry. From a user's perspective, security factors such as authentication and confidentiality are key factors in their decision to continue using online banking platforms. Suh and Han (2003) also emphasized the importance of confidentiality in e-commerce and highlighted the risks posed by hackers who may intercept or tamper with sensitive information during data transmission.

Given the importance of data security in financial transactions, especially for Gen Z users, the confidentiality of AI chatbots will likely be a key determinant of their intention to adopt these tools for financial planning. Therefore, the hypothesis is proposed as follows:

H6: Confidentiality has a significant effect on Intention To Use

2.3.7 Privacy And Intention To Use

Privacy is a key factor influencing users' decisions to adopt AI chatbots, especially in sensitive areas such as financial management. Privacy concerns often surround how AI systems collect, store and share personal data. Users who feel their personal information is fully protected are more likely to trust and interact with an AI chatbot.

Research shows that strong privacy measures can increase user confidence in digital services. For example, research by Lutz and Tamò-Larrieux (2021) highlights that privacy concerns significantly influence users' intentions to adopt emerging technologies such as AI chatbots. The "privacy paradox" phenomenon often occurs, where users express privacy concerns but may not always change their behavior. However, regarding technology that appears to infringe on user privacy, user concerns become a decisive factor in their decision-making process (Yao et al., 2024).

In the context of AI chatbots, privacy concerns are particularly important due to the sensitivity of users' data when providing personalized services. For example, in financial applications, users may be required to share personal and financial information, increasing their perceived risk and leading to concerns about potential data misuse or leakage. Without strong privacy protections, these concerns may reduce users' willingness to adopt such technologies.

The study by Martinez-Navarone et al. (2023) and Sebastian (2023) further highlights the importance of implementing privacy-enhancing technologies (PET) in AI chatbots. Such technologies ensure greater control and security over personal data and can significantly enhance user trust, especially among privacy-sensitive groups like Generation Z. Therefore, the following hypotheses are proposed:

H7: Privacy has a significant effect on Intention To Use

2.3.8 Performance Expectancy And Intention To Use

Performance expectancy refers to an individual's belief that utilizing a specific technology will improve their performance or efficiency in completing tasks (Venkatesh et al., 2003). The research shows that performance expectations influence consumers' decisions to adopt new technologies. When users believe a technology can provide tangible benefits, such as increased productivity or efficiency, they are more likely to adopt and use it regularly. This concept also applies to artificial intelligence chatbots (M et al., 2024).

For example, Camilleri's (2024) study found a positive relationship between performance expectations and intentions to use ChatGPT, suggesting that performance expectations are the main driver of technology intention, albeit slightly affected by workload expectations. Similarly, Chen et al. (2022) found a positive relationship between performance expectations and intention to adopt fintech services, suggesting that when users believe technology will enhance their financial tasks, they are more inclined to use it. Syakinah (2024) further strengthens this finding, showing that higher performance expectations increase users' willingness to use AI services.

Considering that AI chatbots for personal financial planning can provide customized advice and improve financial management skills, Gen Z’s performance expectations in the Klang

Valley may significantly influence their willingness to adopt such tools. If users believe an AI chatbot can enhance their financial planning, they are more likely to integrate it into their daily lives. So the hypothesis is:

H8: Performance expectancy has a significant effect on Intention To Use

2.3.9 Trust And Intention To Use

Trust is an individual's subjective attitude when making decisions in vulnerable situations (Zerilli et al., 2022). In the world of technology, trust allows users to believe that a specific device or system will help them achieve their desired results. For example, users rely on Google Maps, trusting that it will provide accurate directions and successfully guide them to their destination (Chang et al., 2017).

Trust is widely recognized as a key factor influencing user behavior and is often integrated into technology acceptance models to predict behavioral intentions. The study by Zhong et al. (2022) emphasized that trust positively impacts users' behavioral intentions, further emphasizing the role of trust in technology intention. Furthermore, Miltgen et al. (2013) found that trust was the strongest predictor of intention to use artificial intelligence for iris scanning, even more so than other influencing factors. This highlights the important role trust in AI systems and their providers plays in users' decisions to adopt such technologies.

In the context of AI chatbots for personal financial management, trust may play a significant role in Gen Z's decision to adopt these tools. Trust in the accuracy, security, and reliability of chatbots and trust in service providers may directly impact whether users feel comfortable and confident using artificial intelligence for their financial planning needs. Therefore, this study hypothesis is:

H9: Trust has a significant effect on Intention To Use

2.3.10 Facilitating Condition And Intention To Use

Facilitating conditions refer to the availability of necessary infrastructure, both technical and organizational, that supports the use of a particular technology (Abbad, 2021). In the case of AI chatbots for personal financial planning, these conditions may include a user-friendly interface, reliable internet access, technical assistance, and easy integration into daily routines. When these conditions are met, they can significantly influence users' intentions to adopt and continuously use the technology (Chatterjee et al., 2021). A conducive environment increases the likelihood that users will engage with the technology.

Previous studies have produced mixed findings regarding the impact of facilitating conditions on behavioral intentions. For instance, Rahim et al. (2022) found that providing adequate support infrastructure positively influenced college students' willingness to use chatbots. Their research demonstrated that access to support systems made students more likely to use such tools for academic purposes. Likewise, Chatterjee and Bhattacharjee (2020) observed that facilitating conditions improved the willingness to adopt AI-based technologies, particularly in scenarios where convenience and usability were prioritized.

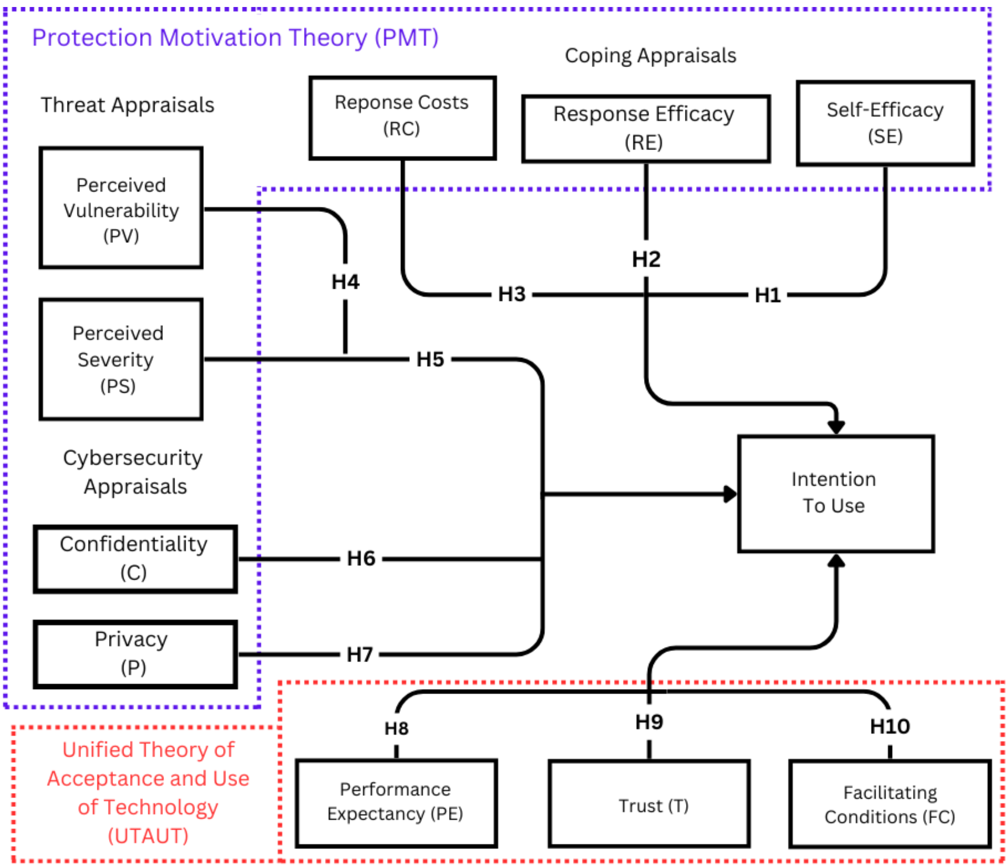
However, not all research supports a positive relationship between facilitating conditions and technology intention. Almari et al. (2020), in their study of British university students, found no significant effect of facilitating conditions on the intention to use chatbots. Similarly, Rahim et al. (2022) reported negative results in a comparable context, suggesting that the presence of technical support or infrastructure does not always lead to a higher intention to adopt AI technologies.

Given these mixed results, there is a need to examine how AI chatbots can facilitate personal financial planning, especially among Generation Z in Klang Vallet, Malaysia, because the unique social, cultural and technological landscape may lead to different outcomes. Therefore, the hypothesis is:

H10: Facilitating Condition has a significant effect on Intention To Use

2.4 Research Framework

Figure 2.4: Proposed Conceptual Framework



Source: Develop for the research

Figure 2.4 presents a proposed conceptual framework for studying Gen Z's intentions to use AI chatbots for personal financial planning. The framework incorporates Protection Motivation Theory (PMT) elements, including response appraisals, threat appraisals, and cybersecurity appraisals. Additionally, it integrates constructs from UTAUT, such as performance expectancies, trust, and facilitative conditions, to explore factors influencing Generation Z's intention of AI chatbots to manage personal finances.

From a PMT perspective, the framework combines response, threat, and cybersecurity assessments to assess how perceived risks and coping mechanisms influence users' motivation to adopt AI chatbots. At the same time, the components of UTAUT were integrated to examine how technology-related factors influence Gen Z's intentions to use AI chatbots to manage personal financial planning. By combining these two theoretical models, this study aims to comprehensively understand the determinants driving Generation Z's intention of AI chatbots.

2.5 Chapter Summary

In short, this chapter has been shaped by the dependent variable and the independent factors. Furthermore, a four-factor research framework has been established to examine the relationship between the independent and dependent variables. Additionally, Chapter 3 will outline the research approach.

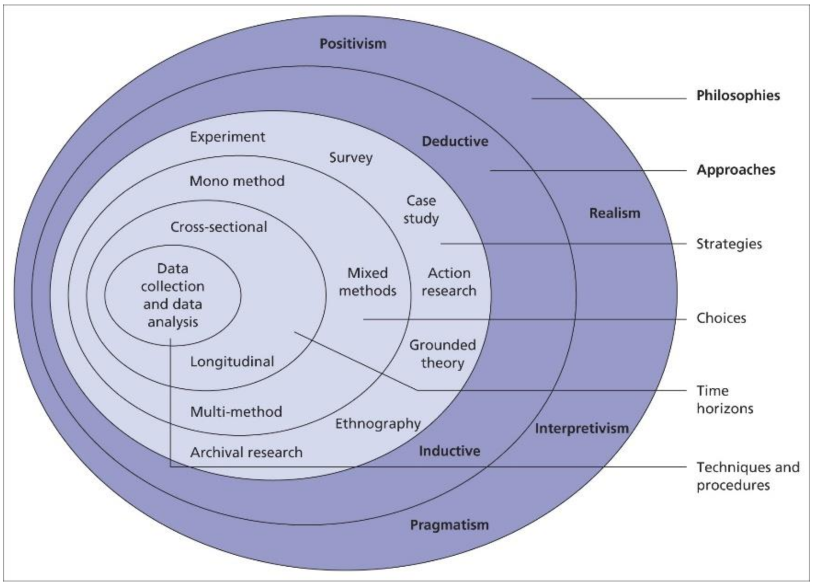
CHAPTER 3: RESEARCH METHODOLOGY

3.0 Introduction

Chapter 3 provides an overview of the techniques used in this investigation. The first section presents the research design describing the research methodology. Subsequent sections include data collection, sampling techniques, research instruments, assessment construction, data processing, and analysis.

3.1 Research Philosophy

Figure 3.1 Research onion



Source: Saunders, M., Lewis, P., & Thornhill, A. (2016). Research Methods for Business Students (7th ed.). Pearson

Figure 3.1 shows the “research onion” model developed by Saunders, Lewis, and Thornhill (2016) and often used in any social sciences to construct research theory. This study will adopt the positivist philosophy as quantitative data, enabling precise calculations and predictions of future behaviour and trends. This approach is essential in disciplines such as demography and economic development. Researcher Ryan (2018) also supports positivism, which emphasises that there must be a logical relationship between variables, which aligns with the principles of natural science. Therefore, in this study, positivism philosophy can help researchers formulate general laws and draw conclusions based on statistical evidence and generalizations, which can help understand Gen Z's intentions to use AI chatbots for personal financial planning in Klang Valley, Malaysia.

In this study, a deductive approach will be used. Due to its systematic nature, this approach is particularly suitable for developing a review process that starts with established theory, formulates specific hypotheses, and tests these hypotheses using empirical data (Woiceshyn and Daellenbach, 2018). The deductive approach's structured approach integrates seamlessly with the development review process and is designed to improve research quality through iterative feedback and revision. By refining the hypotheses and research design in this way, the development review process supports the testing and validation of theory.

3.2 Research Design

Quantitative research is consistent with the positivist ideology, which emphasizes objective measurement and empirical testing of hypotheses through observable data (Bryman, 2016). In this study, a positivist approach guided the use of structured surveys and questionnaires to collect numerical data on adopting artificial intelligence chatbots for personal financial planning among Gen Z undergraduate students in the Klang Valley. By focusing on measurable variables, positivist and quantitative methods can provide a solid framework for understanding AI Chatbot intention patterns, as they rely on statistical analysis to identify key factors. Thus, this approach can draw broader conclusions about whether people are willing to adopt AI chatbots for financial management (Goertzen, 2017).

Survey research is a valid and widely recognized method for exploring variables affecting Gen Z for their intention to use AI chatbots in personal financial planning. Although there are potential errors, such as response bias or sampling issues, several strategies can help reduce these risks and make surveys reliable for collecting relevant data (Ponto, 2015). Furthermore, surveys have the advantages of speed, data preservation, and ease of dissemination, making them ideal for collecting large-scale data on technology intention patterns among specific populations (Lefever et al., 2007). Therefore, this study of the questionnaires were generated by using Google Forms and disseminated to various social media channels, such as WhatsApp. In addition to online distribution, physical data was collected by personally distributing the Google Form to respondents.

Cross-sectional studies help examine the prevalence of specific conditions or attributes within a population at a given time, as opposed to tracking new cases over a period (Wang & Cheng, 2020). These studies assess the distribution of variables and the relationships between exposures and outcomes. They are typically quick, cost-effective, and valuable for generating hypotheses that can inform future research(Setia, 2016). Therefore, a cross-sectional study can provide insights into current usage patterns and determinants influencing in the context of AI chatbot intention among Gen Z.

3.3 Sampling Design

3.3.1 Target Population

The focus of this study is on Generation Z, as outlined in Chapter 1, specifically individuals aged 18 to 26 who are actively engaged in various fields of research across Malaysia. This demographic is of particular interest due to their familiarity with digital technologies and their potential readiness to adopt AI chatbots for personal financial planning. Additionally, as AI chatbots are expected to play a significant role in shaping technological advancements over the next two decades, this research aims to uncover the factors that influence Generation Z's willingness to use them.

3.3.2 Sample Frame

A sampling frame is a tool for systematically identifying and selecting participants that best represent the target population. However, this study did not establish a formal sampling frame. Instead, a non-probability sampling method was used, focusing on Generation Z individuals in the Klang Valley, Malaysia. This approach ensures accessibility to participants within the target population, although it inherently limits the generalizability of the study findings.

The study specifically targeted Gen Z in Klang Valley. These Gen Z offer valuable insights into the factors influencing the intention to use AI chatbots for personal financial planning. Their unique perspectives, challenges, and aspirations are critical to understanding how AI technology can enhance financial management practices and improve local banking services, fostering the intention of use AI Chatbot in the financial sector.

3.3.3 Sampling Elements

The sampling element was limited to individuals in Klang Valley, Malaysia. The sample selected was those aged between 16 and 28 who are school students or working in the field and intend to use AI chatbots for personal financial planning in the future period.

3.3.4 Sampling Techniques

In order to draw accurate conclusions, researchers must select a representative sample because collecting data from the entire target population is often impractical (McCombes, 2023). Sampling methods are broadly classified into probability sampling and non-probability sampling (Acharya et al., 2013).

This study used non-probability sampling, specifically judgment sampling, to effectively reach the target respondents. Nonprobability sampling involves a nonrandom selection process, which means that not everyone in the population has an equal chance of being included (Wretman, 2010; Shorten & Moorley, 2014). Judgment sampling allows researchers to select participants based on specific criteria (e.g., ensuring a 2:1 male to female ratio) so that the sample reflects the target population (Elfi & Negida, 2017).

In this study, judgmental sampling focused on selecting specific subgroups of Generation Z within the Klang Valley, ensuring that key demographic attributes relevant to the study were adequately represented.

3.3.5 Sample Size

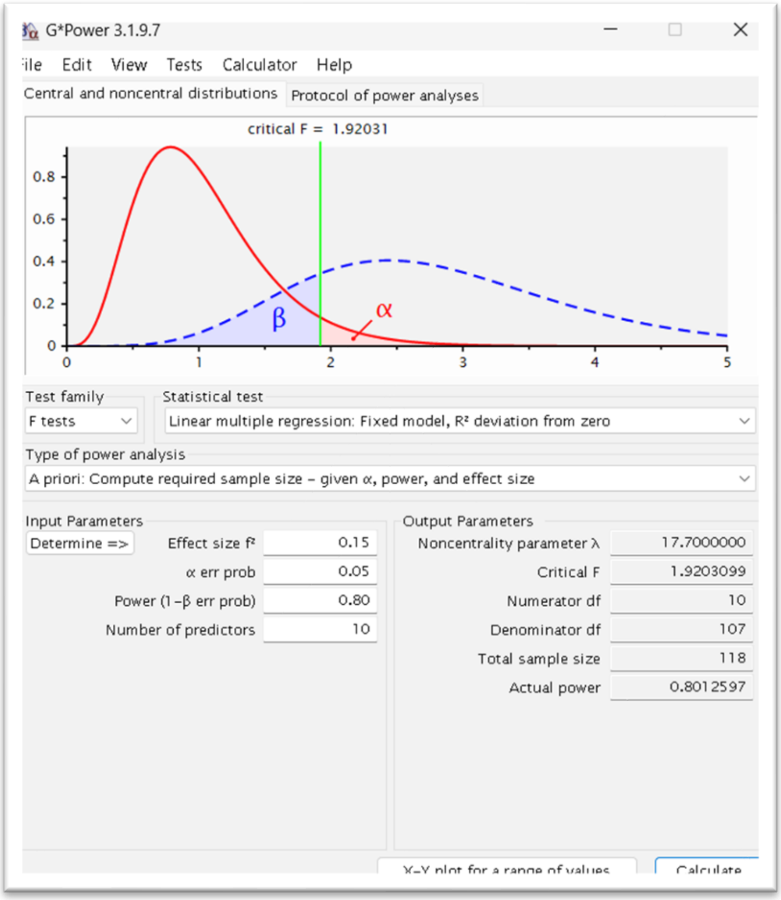
Determining an appropriate sample size is critical to obtaining reliable research results. The guidelines proposed by Roscoe (1975) are still widely used in behavioral research today. He suggested that a sample size between 30 and 500 is generally appropriate and warned that samples that are too large (more than 500) may increase the risk of type II error (Sekaran & Bougie, 2016). For multivariate data analysis, such as regression, Roscoe recommends that the sample size should be at least ten times the number of variables. Several studies (Kumar et al., 2013; Lin and Chen, 2006; Suki and Suki, 2017; Seman et al., 2019; Sultana, 2020) have examined procedures and statistics for determining sample size based on these guideline factors.

Hair et al. (2018) suggested a minimum variable-to-sample ratio of 5:1, with higher ratios (e.g., 15:1 or 20:1) being better. This means that while there should be at least five respondents per independent variable, a ratio of 15 to 20 respondents per variable is ideal. This is consistent with Tabachnick and Fidell's (1989) recommendation to conduct regression analyzes with at least five subjects per variable. While a 5:1 ratio is manageable, aiming for 15:1 or 20:1 can help prevent underpowered research. According to the guidelines, with ten variables in the study, a minimum of 150 responses (15:1) is recommended.

Additionally, GPower analysis was used to calculate statistical power using F-test and Linear multiple regression: fixed model, deviation of R^2 from zero, assuming a medium effect size of 0.15, an alpha level of 0.05, a power of 0.80, 10 predictors, at least 118 samples are required. Figure 3.3 shows the GPower results.

In this study, 350 responses will be collected from Generation Z individuals in Klang Valley, Malaysia. This sample size exceeded the minimum requirements of 150 (based on Roscoe guidelines) and 118 (based on statistical power analysis), ensuring sufficient data for reliable analyses.

Figure 3.3 G*Power Result



Source: Develop for the study

3.4 Instruments and Measurements

3.4.1 Questionnaire Design

The questionnaire for this study was divided into four sections, each designed to collect specific information related to the research objectives.

Section A is a screening question designed to filter out respondents who do not belong to Generation Z or are not residents of the Klang Valley area, thereby minimizing potential sampling error.

Section B This collects the respondents' demographic information, including basic information such as gender, age, education, income, etc.

Section C examines the respondents' familiarity with financial technology, focusing on their understanding of it and related behaviours, such as online banking services.

Section D explores respondents' perspectives on using AI chatbots for personal financial planning. The questions in this section are based on constructs from PMT and UTAUT, as described in the research framework in Chapter 2.

3.4.2 Instrument Development

Table 3.4 contains the information on measurement items in the questionnaire survey.

Table 3.4 Information of Measurement Items

Construct	Measurement Items	Source	Total Items
Self-Efficacy (SE)	SE1: I am confident in my ability to manage my personal finances effectively using an AI chatbot. SE2: I believe I can use AI chatbots to enhance the efficiency and outcomes of my personal financial management. SE3: I am capable of independently using AI chatbots for financial management without needing assistance. SE4: I believe that using AI chatbots enhances the efficiency and outcomes of managing my personal finances. SE5: I have the necessary skills to explore and utilize AI chatbots for various financial tasks	(Mosavian et al., 2023)	5
Response Efficacy (RE)	RE1: I believe AI chatbots offer strong security measures to protect my financial data from unauthorized access.	(Al-Emran et al., 2021)	4

	RE2: I feel secure and confident using AI chatbots to manage my personal financial information. RE3: I trust that AI chatbots help minimize security risks associated with managing financial data. RE4: I confident the AI chatbot to follow strict security protocols to protect my financial information.		
Response Costs (RC)	RC1: I believe the benefits of using an AI chatbot for personal financial management outweigh any associated costs. RC2: I feel the advantages of an AI chatbot justify any required setup or maintenance expenses. RC3: I am concerned that AI chatbots may involve additional, unforeseen expenses, such as data security fees. RC4: I believe following AI chatbot security protocols is manageable and improves the overall experience.	(Al-Emran et al., 2021)	4
Perceived Vulnerability (PV)	PV1: I feel that using AI chatbots could expose my financial data to potential security risks. PV2: I believe there is a possibility of unauthorized access to my financial data when using AI chatbots.	(Mosavian et al., 2023)	5

	PV3: I am concerned that technical issues in AI chatbots might compromise my financial security. PV4: I think my reliance on AI chatbots increases the risk of data breaches. PV5: I feel AI chatbots may make my financial information more vulnerable to cyber threats compared to traditional methods.		
Perceived Severity (PS)	PS1: I am confident that AI chatbots include features designed to secure my financial data. PS2: I believe using AI chatbots can improve both my financial security and productivity. PS3: I trust AI chatbots to offer strong safeguards against potential security threats. PS4: I feel reassured that AI chatbots help manage risks to my financial information. PS5: I believe AI chatbots can help prevent financial losses through enhanced security.	(Al-Emran et al., 2021)	5
Confidentiality (C)	C1: I take proactive steps, such as using strong passwords and two-factor authentication, to protect my financial data when using AI chatbots. C2: I trust that AI chatbots maintain high standards of confidentiality and integrity for my financial information.	(Green et al., 2024)	4

	C3: I am confident AI chatbots prioritize security and privacy for sensitive financial data. C4: I feel empowered using AI chatbots as they respect my control over my personal financial information.		
Privacy (P)	P1: I trust AI chatbots to only collect essential information needed to enhance my experience. P2: I believe AI chatbots have sufficient safeguards to prevent unauthorized access to my data. P3: I trust AI chatbots to use secure methods for storing and managing my financial data. P4: I feel comfortable sharing financial information with AI chatbots because privacy concerns are adequately addressed.	(Mutimukwe et al., 2022)	4
Performance Expectancy (PE)	PE1: I believe AI chatbots simplify managing my personal finances. PE2: I feel AI chatbots make it easier to achieve my financial goals. PE3: I believe AI chatbots enable me to handle financial tasks more efficiently. PE4: I am confident AI chatbots significantly improve my financial productivity and decision-making.	(Venkatesh et al, 2012)	4

	PE5: I trust AI chatbots to provide accurate, up-to-date financial advice.		
Trust (T)	T1: I believe AI chatbots provide transparent and honest interactions. T2: I trust that AI chatbots prioritize my best financial interests. T3: I feel that AI chatbots communicate clearly and reliably with me. T4: I trust AI chatbots to deliver unbiased, accurate financial information.	(Venkatesh et al, 2012)	4
Facilitating Conditions (FC)	FC1: I have access to the resources and support I need to use AI chatbots for financial management. FC2: I am equipped with the knowledge and tools necessary to effectively use AI chatbots in my financial planning. FC3: I feel AI chatbots integrate smoothly with other financial technologies I use. FC4: I am confident I can readily find support if I encounter issues with AI chatbots.	(Venkatesh et al, 2012)	4
Intention To Use (IOU)	IOU1: I plan to regularly use an AI chatbot to manage my personal finances. IOU2: I intend to frequently use AI chatbots in the future for financial tasks.	(Venkatesh et al, 2012)	4

	IOU3: I am interested in incorporating an AI chatbot into my daily financial management in future. IOU4: I prefer using AI chatbots for routine financial services over human advisors.		

Source: Developed for research

3.5 Measurement Scales

The categorical and continuous data measurement scales are illustrated in Table 3.5 and Table 3.5.1. Measurement scales encompass four types: nominal, ordinal, interval, and ratio (Bhandari, 2023).

Table 3.5 Scale for Categorial Data

Constructs	Measurement	Coding
Screening Question: Are you living in Klang Valley, aged between 17 and 28?	Nominal	1=Yes 2=No
Gender	Nominal	1= Male 2= Female
Age (as in 2024)	Ordinal	1= 17-19 2= 20-22 3= 23-25 4= 26-28

Ethnicity	Nominal	1= Malay 2= Indian 3= Chinese 4= Others. ___________
Occupation	Nominal	1= Student 2= Working professional 3= Entrepreneur 4= Unemployed
Level of Education	Ordinal	1= STPM level/O-level 2 =Foundation/ A-Level 3= Diploma 4= Bachelor's Degree 5= Postgraduate
What is your disposable income level per month?	Ordinal	1= Below RM1500 2= RM1501 -RM 3000 3= RM3001 – RM4500 4= Above RM 4501
How often do you use online banking services?	Ordinal	1= Daily 2= Weekly 3= Monthly 4= Rarely 5= Never
Have you ever used a mobile payment app (e.g. GrabPay, Touch 'n Go, etc.)?	Nominal	1=Yes 2=No
Are you aware of any fintech companies in Malaysia (e.g., funding societies)?	Nominal	1=Yes 2=No

Are you aware of any digital investment and financial platforms (e.g. robo-advisors, cryptocurrency, etc.)?	Nominal	1=Yes 2=No
How familiar are you with AI chatbots in personal financial planning?	Ordinal	1= Very familiar 2= Somewhat familiar 3= Not very familiar 4= Not at all familiar
Have you ever used an AI chatbot for financial services (e.g. customer support, transaction inquiries, etc.)?	Nominal	1=Yes 2=No

Source: Developed for research

Table 3.5.1 Scale for Continuous Data

Constructs	Items	Measurement	Coding
Self-Efficacy (SE)	5	**Scale**	**1= Strong Disagree** **2= Disagree** **3= Neutral** **4=Agree** **5= Strongly Agree**
Response Efficacy (RE)	4		
Reponse Costs (RC)	4		
Perceived Vulnerability (PV)	5		
Perceived Severity (PS)	5		

Confidentiality (C)	4		
Privacy (P)	4		
Performance Expectancy (PE)	4		
Trust (T)	4		
Facilitating Conditions (FC)	4		
Intention To Use (IOU)	4		

Source: Developed for the Research

3.6 Pre-Testing and Pilot Test

Pretesting is running a small-scale version of the formal data collection process to identify potential issues with data collection instruments, procedures, and methods (Janelli & Lipnevich, 2021). The value of pretesting lies in its ability to detect errors related to cultural and linguistic differences, ambiguous wording, and weaknesses in the survey's measured variables. It also provides early warning of potential failures in large-scale research projects by revealing impracticalities or challenges in research protocols (Hurst et al., 2015).

This study conducted a pre-test on 10 entrepreneurs from different industries (financial planning, steel and welding) and 15 students from Tunku Abdul Rahman University, Sunway University and Taylor's University. This diverse feedback ensures that the survey is clear, relevant and appropriate for the target population.

Pilot studies are primarily designed to test the feasibility of the study design and recruitment process rather than to test hypotheses. Therefore, sample sizes for pilot studies are often not rigorously calculated. Some studies suggest a sample size of more than 30 participants per group, while others suggest that 12 participants per group may be sufficient (2017). A sample of 30 respondents was selected for this pilot test to assess the practicality and effectiveness of the research design.

This approach is particularly important as we examine Gen Z's intentions to use AI chatbots for personal financial planning. Pre-testing and pilot studies helped refine the survey instruments and methods, ensuring they effectively collected accurate and meaningful data from the target population in Klang Valley, Malaysia. Table 3.6 presents the reliability results for each variable based on the responses of the 30 participants.

Table 3.6: Pilot Test of Result

Constructs	**Alpha**	**Rho_a**	**Rho_c**	**AVE**
C	0.894	0.913	0.925	0.756
FC	0.911	0.913	0.938	0.790
IOU	0.903	0.906	0.932	0.775
P	0.877	0.902	0.916	0.732
PE	0.890	0.907	0.924	0.753
PS	0.941	0.960	0.955	0.809
PV	0.906	0.907	0.930	0.728
RC	0.900	0.903	0.931	0.773
RE	0.899	0.909	0.929	0.767

SE	0.885	0.886	0.917	0.691
T	0.934	0.939	0.953	0.835

Source: Develop for the research

3.7 Data Collection Procedure

Primary data is a valuable and cost-effective tool for researchers to quickly collect diverse opinions from individual consumers (Evans & Mathur, 2005). “Primary data” refers to information collected directly from respondents, usually through surveys and questionnaires. Additionally, supplementary data sources can enrich the primary data set (Hox & Boeije, 2005). Primary data is generally considered more reliable, authentic, and valid because it is collected first-hand and is less susceptible to external influences (Kabir, 2016).

In this study, primary data were collected through online surveys and physical methods, which have the advantages of speed, ease of data storage, and seamless data transfer for analysis (Lefever et al., 2007). Those combined methods were chosen to collect data from the wider Gen Z audience in Klang Valley, Malaysia.

3.8 Data Processing

3.8.1 Data Checking

After Primary Data Collection, ensuring the quality and accuracy of the data collected requires a thorough validation process. Questionnaire responses will be carefully reviewed for validity, and any incomplete or logically inconsistent entries will be excluded from the system. Valid data will be collected from the online survey and recorded in a structured format to ensure efficient organization and streamlined data management.

3.8.2 Missing Value

If there were any missing answers in the responses, and will analyzed the extent of missing data. Depending on the situation, this may delete responses with missing data, use averages to fill gaps or apply other methods to handle missing information that does not affect the results.

3.8.3 Outlier

Outliers are extreme values that may affect the results of a study (Cousineau & Chartier, 2010). This study will identify outliers by examining values much higher or lower than others. Once discovered, we will decide whether to remove, transform, or use statistical methods to minimize their impact on the analysis.

3.8.4 Response Bias

Response bias occurs when people give inaccurate answers because they do not fully understand the question or want to give socially ideal answers. This study will examine whether there are signs of this bias, such as patterns of extreme or inconsistent answers. Biased responses will be corrected or deleted.

3.8.5 Common Method Bias

Common method bias occurs when the way we collect data leads to errors (Kock et al., 2021). To check this, we will use a statistical test to see if one factor explains the majority of the variance. This study will also take steps during the survey design process, such as ensuring questions are clear and responses are anonymous, to reduce the possibility of this bias.

3.9 Data Analysis

Lastly, the collated data will be analyzed according to the methods outlined in Sections A, B, C, and D, and the data will be checked. Partial least squares structural equation modelling (PLS-SEM) has been chosen as the primary analytical method for the primary data investigation. PLS-SEM allows the performance of various statistical tests, including multiple linear regression analysis, reliability analysis, and Pearson correlation coefficient analysis. Once results are obtained, the findings are thoroughly interpreted and evaluated to draw well-supported conclusions based on the data.

3.9.1 Descriptive Analysis

The descriptive analysis immediately observes desired behaviour in natural settings without any experimental alterations. It aims to study relevant environmental factors and potential occurrences related to a specific target response. Descriptive analysis is a preliminary step before conducting experimental functional assessments of problematic behaviour (Sloman, 2010).

3.9.2 Multivariate Assumption Test

3.9.2.1 Normality Test

Descriptive statistics help summarize data effectively, so choosing an appropriate statistical method is crucial for effective hypothesis testing. The normality test is crucial for continuous data as it guides the selection of measures such as central tendency, dispersion, and appropriate parametric or nonparametric tests (Mishra et al., 2019). Two visual methods, such as histograms and Q-Q plots, are recommended to assess normality. Ensuring normal data distribution is also key when validating results to confirm that correct statistical techniques were used (Ghasemi & Zahediasl, 2012). Therefore, assessing the normality of the data is essential in this study to ensure that the data follows a normal distribution; appropriate statistical methods can be chosen for hypothesis testing, leading to more accurate and reliable results.

3.9.2.2 Linearity Test

This study used the linearity test to assess whether a linear relationship exists between the independent and dependent variables (Schneider et al., 2010). In this study, which explores Gen Z's intentions to use AI chatbots for financial planning in Klang Valley, Malaysia, ensuring linearity is crucial for accurately modelling the factors that influence these intentions. Visual tools, such as scatter plots, help evaluate the linearity assumption, while statistical tests like correlation analysis can further confirm the strength of these relationships (Bewick et al., 2003). Therefore, Ensuring linearity is essential for selecting the appropriate statistical methods and enhancing the accuracy of predictions in this study.

3.9.3 Reliability Test

Reliability and validity are fundamental concepts in research methods and provide a framework for understanding the robustness of research results. Reliability refers to the stability and consistency of the results, and validity refers to the accuracy and authenticity of the research results (Altheide & Johnson, 1994). Ensuring reliability and validity requires careful examination of data collection methods. This review is critical for interpreting scores from psychometric tools such as symptom scales, questionnaires, educational tests, and observer ratings in various fields, including clinical practice, research, education, and management.

In research, reliability and validity are critical to improving assessment accuracy (Tavakol & Dennick, 2011). Ignoring these concepts can lead to measurement errors that distort theoretical relationships. Therefore, using various data collection methods is critical to collecting reliable and valid data for this research. To help resolve this issue, Table 3.9.1 guides the interpretation of Cronbach's alpha, a common measure of reliability.

Table 3.9.1: Rules of Thumb for Reliability Test

Cronbach's alpha	**Internal consistency**
$\alpha \geqslant 0.9$	Excellent
$0.9 > \alpha \geqslant 0.8$	Good
$0.8 > \alpha \geqslant 0.7$	Acceptable
$0.7 > \alpha \geqslant 0.6$	Questionable
$0.6 > \alpha \geqslant 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Source: Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

3.9.4 Correlation

Correlation measures the association between variables. When data are correlated, the changes in one variable are related to changes in another variable, either positively (positive correlation) or negatively (inverse correlation). The term is commonly used to describe a linear relationship between two continuous variables represented by the Pearson product-moment correlation coefficient. Several ways of interpreting correlation coefficients exist, often classifying them as “weak”, “moderate”, or “strong” (Schober et al., 2018).

Although it is generally accepted that coefficients below 0.1 indicate a very weak relationship and above 0.9 a very strong relationship, the interpretation of values in between remains controversial; for example, a correlation coefficient of 0.65 might be labelled "good" or "moderate," depending on the rule of thumb chosen. Assigning terms such as "weak" or "moderate" to coefficients such as 0.39 versus 0.40 seems arbitrary and inconsistent. It is also important to note that covariance is affected by the scale at which the variable is measured, which makes its absolute magnitude difficult to interpret or compare across studies.

To improve interpretability, the Pearson correlation coefficient is widely used. This dimensionless measure of covariance is scaled between -1 and +1, providing a standardized understanding of the strength and direction of the relationship between variables. According to Table 3.9.2, the rules of thumb for interpreting correlation coefficients are provided.

Table 3.9.2: The Rules of Thumb about Correlation Coefficients.

Size of Correlation	Interpretation
0.90 to 1.00 (-0.90 to -1.00)	Very high positive (negative) correlation
0.70 to 0.90 (-0.70 to -0.90)	High positive (negative) correlation
0.50 to 0.70 (-0.50 to -0.70)	Moderate positive (negative) correlation
0.30 to 0.50 (-0.30 to -0.50)	Low positive (negative) correlation
0.00 to 0.30 (0.00 to -0.30)	Negligible correlation

Source: Jaadi, Z. (2019). Everything you need to know about interpreting correlations. Medium. https://towardsdatascience.com/eveything-you-need-to-know-aboutinterpreting-correlations-2c485841c0b8

3.9.5 Partial Least Square Structural Equation Modeling

This study will eventually employ the use of Partial Least Squares Structural Equation Modeling (PLS-SEM) through the use of SmartPLS software in the study of relationships between independent and dependent variables. The SEM combines latent variables and structural relationships, and PLS-SEM is a variance-based multivariate analysis tool, especially useful in testing complex causal models (Cepeda-Carrion et al., 2018).

As stated by the research by Zeng et al. (2021) regarding the power of PLS-SEM as an alternative to covariance-based SEM (CB-SEM), the latter suits confirmatory analysis more, while PLS-SEM optimally serves exploratory research and sample sizes or with formative constructs that are relatively small. Its major goal is causal prediction under the premise of maximizing the variance explained in the dependent variable, which refers to various logical reasoning frameworks. PLS-SEM is therefore especially important for theory development and exploration in the early stages of the field, whereas CB-SEM is shown to be more beneficial for theory validation (Hair et al., 2020).

PLS-SEM during the process features two major stages. The first stage covers the evaluation of the measurement model with reference to its reliability and validity. Unlike Cronbach's Alpha, PLS-SEM uses composite reliability to assess internal consistency (Hair et al., 2017). Convergent validity is evaluated using the average variance extracted (AVE), and discriminant validity is estimated through the heterotrait-monotrait (HTMT) ratio. The second stage involves an examination of the structural model, with an emphasis on hypothesis testing regarding the relationships between variables and checking whether the model is able to predict any future results or out-of-sample fits. Indicator reliability is tested using external loadings, which gives information on the reliability of the individual indicators.

PLS-SEM is particularly relevant for this study as it provides a comprehensive framework for analyzing the complex relationships between various factors and Generation Z's intention to use AI chatbots for personal financial planning in Klang Valley, Malaysia. Its ability to handle intricate causal models makes it well-suited for exploring the key drivers behind the intention of use AI chatbot in financial planning.

3.9.5.1 Measurement Assessment

3.9.5.1.1 Factor Loadings

In this study, factor loadings will be examined to assess the contribution of each indicator to its respective construct. Cheung et al. (2023) recommend reporting composite reliability (CR) when analyzing latent constructs because CR takes into account different factor loadings between indicators. Typically, the CR value should not be lower than 0.7, with 0.8 being the preferred threshold. If the upper limit of the 90% confidence interval (CI) of CR exceeds 0.8, it indicates that the construct has reached a satisfactory level of reliability in this study.

3.9.5.1.2 Composite Reliability & Convergent Validity

This study will employ composite reliability to assess the internal consistency of constructs related to intentions to use artificial intelligence chatbots for personal financial planning among Generation Z in Klang Valley, Malaysia. Composite reliability ensures that each item consistently reflects the construct it measures, such as trust in artificial intelligence or financial literacy. Hair et al. (2020) suggested that the acceptable CR range is between 0.7 and 0.95, which is suitable for the reflectance measurement model used in this study. This helps ensure that key indicators, such as willingness to use AI for financial planning, remain stable and free of random errors.

Additionally, convergent validity will be assessed using average variance extracted (AVE), a method that verifies whether the items in each construct accurately represent the underlying concept they are intended to measure. AVE is calculated as the squared mean of indicator loadings, reflecting shared variance within the construct. A minimum AVE of 0.50 is required, indicating that the construct explains at least half of the variance in its indicator (Hair et al., 2021).

By confirming composite reliability and convergent validity, this study ensures that the construct measuring Gen Z’s intention to use artificial intelligence chatbots for financial planning in the Klang Valley is reliable and valid. This enhances the credibility of the findings and provides insights into the factors that influence decision-making. Table 3.9.3 summarizes the combined idea of composite reliability.

Table 3.9.3 Idea of composite reliability

CR Value	Degree of Reliability
>0.95	Excellent
0.7-0.9	Good
0.6-0.7	Acceptable
<0.6	Unacceptable

Source: Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24.

3.9.5.1.3 Discriminant Validity

Discriminant validity assesses how distinct a construct is from other constructs in a model, ensuring that it measures uniqueness compared to other constructs. It confirms that constructs are more strongly correlated with their indicators than other constructs in the PLS path model (Hair et al., 2022). Henseler et al. (2015) suggested using the heterogeneity-to-unitarity (HTMT) ratio to assess discriminant validity. HTMT values below 0.85 are considered acceptable, especially in variance-based SEM methods such as partial least squares (PLS), indicating that the structures are sufficiently differentiated. Therefore, this study will use the HTMT ratio to assess discriminant validity.

3.9.5.2 Structural Assessment

Once reliability and validity are established, construct evaluation will focus on assessing the relationships between constructs in the model and the extent to which the model explains the underlying theoretical framework. The evaluation included checking for multicollinearity, analyzing path coefficients, determining the coefficient of determination (R^2), and measuring the effect size (f^2). These components are critical to validate the structural model and ensure the robustness of PLS-SEM results.

3.9.5.2.1 Multicollinearity

In order to resolve any potential multicollinearity issues, a multicollinearity test must be conducted. The researcher Daoud (2017) recommended evaluating bivariate correlation coefficients between predictors and variance inflation factors (VIFs) while closely monitoring changes in coefficient estimates, standard errors, and VIF values. Therefore, this study will perform VIF analysis on each construct. Interpretation of VIF values will follow the guidelines outlined in Table 3.9.4.

Table 3.9.4 Guidelines of VIF

VIF - value	Conclusion
VIF = 1	Not correlated
1< VIF <= 5	Moderately Correlated
VIF > 5	Highly correlated

Source: Daoud, J. I. (2017). Multicollinearity and regression analysis. *Journal of Physics Conference Series*, *949*, 012009.

3.9.5.2.2 Path coefficient

Path coefficient means that the strength and direction of the relationship between the dependent and independent variables are directly determined by the path coefficients in the construct's elaboration. These coefficients provide a means of describing hypothesized links between constructs based on standardized regression weights. A higher path coefficient means that one variable has a greater impact on another variable (Hair et al., 2021). In this work, SmartPLS version 4 will determine t-values and p-values to provide evidence of the intrinsic importance of the relationship being developed. Analysis of path coefficients will shed more light on the interactions between constructs. Model.

3.9.5.2.3 Coefficient of Determinant (R2)

According to Chicco et al. (2021), the coefficient of determination (R^2) is a measure reflecting the percentage of the variation in the dependent variable which is explained by independent variables in the model. The coefficient provides a measure of the explanatory power of the model, with 0 representing a very weak explanatory power and 1 indicating a perfect fit in explanation. In PLS-SEM, R^2 values of 0.75, 0.50, and 0.25 define strong, moderate, and weak prediction models, respectively (Hair et al., 2014). This study will evaluate the R^2 for each of the endogenous constructs to assess how well the model predicts the dependent variables.

3.9.5.2.4 Effect Size (f2)

Effect Size (f2) is beyond one to discuss, since these are the very measures that help put the final restraints on other measures. In other words, effect size embodies the degree of contribution of an independent variable to a dependent variable by measuring how much R^2 changes on the addition or deletion of a single construct in the model (Cohen, 2013). This last calculation reveals to which entirely construct accordingly to signifying variance from the dependent variable. Cohen (2013) describes f^2 values as small when $f^2 = 0.02$, medium as $f^2 = 0.15$, and large when $f^2 = 0.35$. In this study, the f^2 values will be analyzed to identify the individual contributions of predictor variables to the overall explanatory power of the model.

3.10 Chapter Summary

This chapter outlines the research methodology, detailing key components such as construct measurement, target population, data analysis techniques, sample size determination, and research instruments, including the development and pilot testing of the questionnaire. It also elaborates on sampling techniques, data collection methods, and the processes for analyzing questionnaire data. The chapter concludes with an explanation of the descriptive, reliability, and inferential statistical methods used for data analysis.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter presents and analyzes the data gathered from 387 Gen Z respondents in the Klang Valley. The data underwent processing and preparation, including filtering, cleaning, and outlier detection, before being analyzed. Descriptive analysis was conducted using Jamovi, while inferential statistical analysis was carried out with SMARTPLS 4.0.

4.1 Data Screening and Data Cleaning

Data screening and cleaning are important to avoid invalid data analysis in the future. Apart from this, 12 respondents answered no in the screening question, which means they are not targeted in this study. Therefore, there are 375 remaining data to conduct data analysis for this study.

4.1.1 Outliers Detection

A data review revealed that 21 respondents provided unreliable or untrue answers. Therefore, these 21 responses were excluded from the data set. As a result, 354 valid responses were retained for final data analysis.

4.2 Common Method Bias

4.2.1 Full Collinearity Test

This study has conducted a full collinearity test, and values were calculated for all constructs to assess the presence of multicollinearity, which may indicate common method bias. The VIF values for all constructs were below the generally accepted threshold of 3.3, as shown in e 4.1, and

Table 4.1 Full Collinearity Test

Constructs	Full Collinearity VIF
C >IOU	2.37
FC >IOU	2.71
P >IOU	1.79
PE >IOU	2.77
PS >IOU	2.59
PV >IOU	1.92
RC >IOU	2.87
RE >IOU	2.03
SE >IOU	2.82
T >IOU	2.92

Source: Develop for the research

4.2.2 Harman Single Factor Test

Harman's one-factor test was conducted to examine common method bias. The results, shown in Table 4.3, indicate that a single factor explained 50.7% of the total variance. In addition, complete collinearity tests were performed and no issues were found. Since the variance explained by a single factor is close to the 50% threshold and there are no problems with the perfect collinearity test, it can be concluded that common method bias does not present a serious problem in this study.

Table 4.2 Harman Single Factor Test

Harman Single Factor Test
% of Variance
50.7

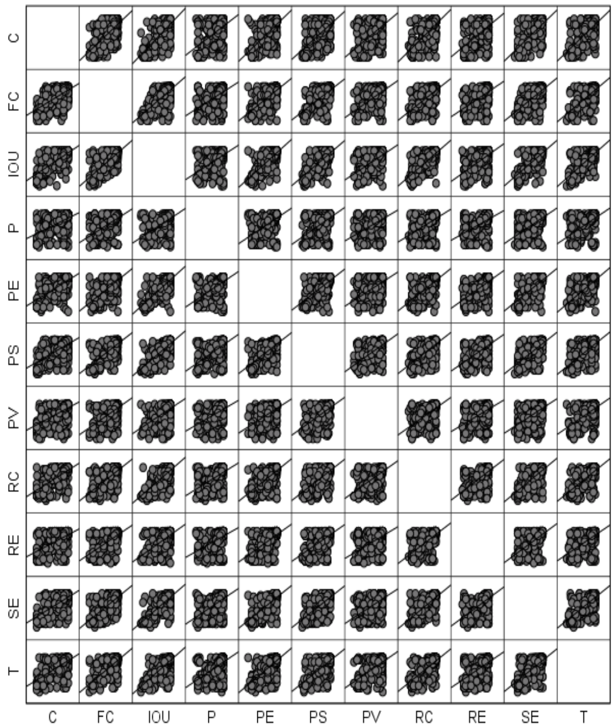
Source: Develop for the research

4.2.3 Linearity Test

As Bewick et al. (2003) highlighted, visual tools such as scatterplots are highly effective in assessing linearity assumptions, while statistical tests can further confirm the strength and nature of these relationships. In this study, a scatterplot matrix was employed to visually examine the constructs' linearity. The matrix displays pairwise relationships, helping to determine whether the data conforms to linearity assumptions.

As shown in Table 4.2, the scatterplot matrix indicates that most variables exhibit linear relationships, with no significant deviations or non-linear trends detected. These findings confirm that the assumption of linearity has been satisfied, supporting the suitability of the dataset for regression analysis. This ensures the validity and reliability of the study's results.

Table 4.3 Linearity Test



Source: Develop for the research

4.3 Descriptive Data Analysis

This section will analyse the demographic of respondents. Financial habits and familiarity with AI chatbot features expected from an AI chatbot, and concerns about using AI chatbots.

4.3.1 Respondent Profile

This section analyzes the demographics of the 354 respondents and discusses their intentions towards using AI chatbots for personal financial planning. Tables 4.4 and 4.4.1 overview the demographics, digital financial habits, and familiarity with AI chatbots.

Table 4.4 Demographics of Respondents

Constructs	Frequency	Percentage
Gender		
Male	199	56.21%
Female	155	43.79%
Age		
23-25	186	52.54%
20-22	109	30.79%
26-28	41	11.58%
17-19	18	5.08%
Ethnicity		
Chinese	196	55.37%
Malay	100	28.25%
Indian	58	16.38%
Current Occupation		
Working professional	210	59.32%
Student	78	22.03%
Entrepreneur	55	15.54%
Unemployed	11	3.11%
Level of Education		
Bachelor’s Degree	189	53.39%
Diploma	68	19.21%
Foundation/ A-Level	67	18.93%
STPM level/O-level	22	6.21%
Postgraduate	8	2.26%
Income Level		
RM3001 – RM4500	151	42.66%
RM1501 -RM 3000	136	38.42%
Above RM 4501	41	11.58%
Below RM1500	26	7.34%

Source: Develop for the research

According to Table 4.4, the sample comprises 199 male respondents (199 respondents) and 155 female respondents (43.79%), reflecting a balanced representation of genders for this study. Next, Most respondents (52.54%) fall within the 23–25 age range, followed by 20–22 years (30.79%). A smaller proportion (16.66%) is distributed among younger (17–19) and older (26–28) age groups. Moreover, The majority of respondents are Chinese (55.37%), with Malays accounting for 28.25% and Indians 16.38%. This distribution reflects the multicultural population of Klang Valley, Malaysia.

The respondents were mainly professionals, accounting for 59.32% of the sample, followed by students, accounting for 22.03% of the sample. Among the respondents, 15.54% were entrepreneurs, and 3.11% were unemployed. Regarding education level, the majority of respondents had a bachelor's degree (53.39%), with 19.21% and 18.93% having completed a diploma or foundation/A-Level, respectively. A small percentage (2.26%) hold graduate degrees. Regarding income level, most respondents earned between RM3001 – RM4500 (42.66%) or RM1501 – RM3000 (38.42%). Meanwhile, 11.58% of respondents earned more than RM4,501, and 7.34% earned less than RM1,500.

Table 4.4.1 Financial Habits and Familiarity with AI Chatbots

Constructs	Frequency	Percentage
i) How often do you use online banking services?		
Weekly	213	60.17%
Monthly	76	21.47%
Daily	35	9.89%
Rarely	27	7.63%
Never	3	0.85%
ii) Have you ever used a mobile payment app (e.g. GrabPay, Touch 'n Go, etc.)?		
Yes	351	99.15%

No	3	0.85%
iii) Are you aware of any fintech companies in Malaysia (e.g., funding societies)?		
Yes	272	76.84%
No	82	23.16%
IV) Are you aware of digital investment and financial platforms (e.g., robo-advisors, cryptocurrency, etc.)?		
Yes	262	74.01%
No	92	25.99%
v) AI Chatbot in Personal Financial Planning: How familiar are you with AI chatbots in personal financial planning?		
Somewhat familiar	222	62.71%
Very familiar	89	25.14%
Not very familiar	32	9.04%
Not at all familiar	11	3.11%
vi) Have you ever used an AI chatbot for financial services (e.g. customer support, transaction inquiries, etc.)?		
Yes	317	89.55%
No	37	10.45%

Source: Develop for the research

Table 4.4.1 showcases the financial habits and knowledge of AI chatbots among Generation Z respondents. The majority of respondents (60.17%) employ online banking services once a week; a smaller portion does so either once a month (21.47%) or daily (9.89%). A small fraction of respondents exhibited rarely or never use of these services at 7.63% and 0.85%, respectively. This trend thus suggests that online banking is widely practised in this group. Almost all respondents (99.15%) have used mobile payment applications such as GrabPay or Touch 'n Go, which are big indicators of users' wide acceptance of digital payment technologies.

The large proportion (76.84%) of people familiar with fintechs established in Malaysia indicates substantial awareness of financial technologies available in the domestic market. As a parameter, knowledge of advanced financial tools such as robo-advisors and cryptocurrency platforms by 74.01% of respondents indicates moderate familiarity with such cutting-edge services.

On the side of respondents, AI chatbots are familiar to over 87% of respondents. Among them, 62.71% consider themselves to be "somewhat familiar with" and 25.14% are"; as for familiarity punctuated, 12.15% are "not very familiar" or "not at all familiar". Also, 89.55% use AI chatbots for financial services such as customer care or transaction inquiries, indicating some real-world experience using chatbot applications in finance.

Therefore, it can be concluded that these findings are in accordance with the widespread use of digital finance tools and services by Generation Z respondents in general and considerable awareness and practice of chatbot technology in financial management.

4.3.2 Multiple Responses Analysis

Table 4.4.2 Features Expected from an AI Chatbot

What features would you expect from an AI chatbot for personal financial planning?

Constructs	**Frequency**	**% of responses**
Budgeting and expense tracking	271	25.96
Investment advice and portfolio management	271	25.96
Bill payments and reminders	265	25.38
Credit score monitoring and reporting	237	22.70
Total	1,044	100

Source: Develop for the research

Table 4.4.3 Concerns About Using AI Chatbots

What are your most concerns about using an AI chatbot for personal financial planning?		
Constructs	**Frequency**	**% of responses**
Security and data privacy	217	16.58
Lack of human interaction and empathy	215	16.42
Limited functionality and capabilities	211	16.12
Dependence on technology	204	15.59
Response efficacy and performance expectancy	192	14.67
Facilitating conditions	144	11.00
Trust	126	9.63
Total	1,309	100

Source: Develop for the research

According to Table 4.4.2, features expected from an AI chatbot showed that respondents placed equal emphasis on budgeting and expense tracking (271 responses, 25.96%) and investment advice and portfolio management (271 responses, 25.96%). These were slightly higher than bill payments and reminders (265 responses, 25.38%), which many saw as useful and effort-saving features. Credit score monitoring and reporting (237 responses, 22.70%) ranked slightly lower, indicating a moderate but interconnected interest in the ability to assess financial usage.

Respondents expressed mixed concerns about using AI chatbots for personal financial planning. The top three concerns were security and data privacy (217 responses, 16.58%), human interaction and empathy (215 responses, 16.42%), and limited functionality and capabilities (211 responses, 16.12%). These reflect anxieties about the technical reliability and the emotional connection AI solutions offer.

According to Table 4.4.3, the reliance on digital technology was also a notable concern, with dependence on technology (204 responses, 15.59%) alongside insufficient response efficacy and performance expectations (192 responses, 14.67%). These findings highlight doubts about the reliability and usefulness of artificial intelligence in personal finance. Concerns about facilitating conditions (144 responses, 11.00%) and trust (126 responses, 9.63%) were less prominent but remain important as they underline perceived barriers to technology acceptance and trustworthiness.

Overall, the survey results indicate that while respondents believe AI chatbots can assist with critical financial tasks, fundamental concerns about security, functionality, and trust need to be addressed to increase acceptance and confidence in the technology.

4.4 Partial Least Square Structural Equation Model

This section explores the application of the Partial Least Squares Structural Equation Model (PLS-SEM) to analyze the relationships between constructs and assess the reliability and validity of the proposed model.

4.5 Measurement Model Assessment

4.5.1 Convergent Validity

This section evaluates the convergent validity of the model, ensuring that the indicators effectively measure their corresponding constructs. Table 4.4 shows the results:

Table 4.5 Convergent Validity Test

Constructs	F.L	Alpha	rho_a	rho_c	AVE
C	0.884	0.909	0.91	0.936	0.786
	0.893				
	0.887				
	0.883				
FC	0.862	0.901	0.902	0.931	0.771
	0.883				
	0.884				
	0.883				
IOU	0.88	0.898	0.898	0.929	0.765
	0.88				
	0.867				
	0.873				
P	0.872	0.904	0.905	0.933	0.777
	0.883				
	0.888				
	0.884				
PE	0.889	0.905	0.905	0.933	0.778
	0.882				
	0.869				
	0.888				
PS	0.876	0.918	0.919	0.938	0.753
	0.855				
	0.882				
	0.862				
	0.861				
PV	0.871	0.919	0.922	0.939	0.755
	0.844				
	0.873				
	0.873				
	0.882				

RC	0.897	0.905	0.906	0.934	0.779
	0.862				
	0.882				
	0.889				
RE	0.893	0.914	0.916	0.939	0.794
	0.898				
	0.885				
	0.889				
SE	0.859	0.913	0.914	0.935	0.742
	0.853				
	0.872				
	0.864				
	0.859				
T	0.895	0.912	0.913	0.938	0.791
	0.888				
	0.892				
	0.881				

Source: Develop for the research

Table 4.5.1 Full Factor Loading Test

Constructs	C	FC	IOU	P	PE	PS	PV	RC	RE	SE	T
C1	**0.884**	0.54	0.624	0.426	0.561	0.51	0.495	0.564	0.488	0.559	0.557
C2	**0.893**	0.563	0.632	0.491	0.579	0.525	0.502	0.582	0.47	0.584	0.572
C3	**0.887**	0.578	0.619	0.46	0.587	0.595	0.529	0.626	0.505	0.6	0.603
C4	**0.883**	0.574	0.611	0.452	0.575	0.524	0.469	0.586	0.499	0.557	0.56
FC1	0.541	**0.862**	0.606	0.441	0.562	0.546	0.488	0.561	0.491	0.585	0.609
FC2	0.535	**0.883**	0.639	0.447	0.581	0.581	0.484	0.598	0.485	0.586	0.608

FC3	0.568	**0.884**	0.658	0.484	0.615	0.59	0.535	0.584	0.486	0.619	0.639
FC4	0.588	**0.883**	0.656	0.504	0.607	0.563	0.549	0.585	0.518	0.609	0.612
IOU1	0.599	0.627	**0.88**	0.473	0.659	0.642	0.486	0.635	0.523	0.619	0.642
IOU2	0.59	0.669	**0.88**	0.49	0.689	0.619	0.46	0.623	0.517	0.627	0.686
IOU3	0.633	0.637	**0.867**	0.47	0.662	0.586	0.464	0.647	0.514	0.66	0.644
IOU4	0.629	0.617	**0.873**	0.479	0.645	0.65	0.537	0.637	0.539	0.622	0.617
P1	0.451	0.437	0.465	**0.872**	0.49	0.503	0.413	0.468	0.398	0.511	0.481
P2	0.445	0.463	0.477	**0.883**	0.493	0.52	0.39	0.448	0.433	0.497	0.48
P3	0.498	0.503	0.497	**0.888**	0.502	0.532	0.475	0.486	0.433	0.509	0.534
P4	0.424	0.479	0.487	**0.884**	0.499	0.505	0.44	0.435	0.399	0.473	0.503
PE1	0.567	0.604	0.677	0.503	**0.889**	0.556	0.441	0.578	0.541	0.608	0.626
PE2	0.598	0.588	0.678	0.487	**0.882**	0.562	0.471	0.6	0.528	0.617	0.613
PE3	0.569	0.589	0.655	0.457	**0.869**	0.564	0.497	0.592	0.503	0.572	0.609
PE4	0.556	0.595	0.666	0.537	**0.888**	0.607	0.502	0.601	0.541	0.586	0.647
PS1	0.49	0.54	0.604	0.474	0.537	**0.876**	0.47	0.54	0.469	0.552	0.592
PS2	0.517	0.539	0.596	0.5	0.531	**0.855**	0.519	0.561	0.493	0.535	0.558
PS3	0.569	0.604	0.673	0.574	0.626	**0.882**	0.561	0.623	0.554	0.629	0.629
PS4	0.504	0.548	0.596	0.484	0.544	**0.862**	0.506	0.562	0.497	0.583	0.563
PS5	0.548	0.581	0.62	0.497	0.57	**0.861**	0.537	0.539	0.503	0.561	0.573
PV1	0.487	0.495	0.476	0.413	0.445	0.499	**0.871**	0.507	0.412	0.465	0.494
PV2	0.444	0.483	0.432	0.384	0.446	0.49	**0.844**	0.469	0.381	0.458	0.436
PV3	0.514	0.521	0.519	0.467	0.464	0.539	**0.873**	0.56	0.479	0.515	0.545
PV4	0.505	0.498	0.467	0.409	0.487	0.524	**0.873**	0.508	0.407	0.445	0.505
PV5	0.489	0.542	0.512	0.44	0.505	0.545	**0.882**	0.535	0.484	0.488	0.521
RC1	0.588	0.588	0.654	0.495	0.612	0.618	0.537	**0.897**	0.618	0.627	0.62
RC2	0.556	0.576	0.625	0.41	0.567	0.548	0.49	**0.862**	0.552	0.588	0.586
RC3	0.624	0.624	0.664	0.476	0.626	0.573	0.541	**0.882**	0.573	0.629	0.607
RC4	0.576	0.549	0.62	0.455	0.564	0.563	0.533	**0.889**	0.528	0.596	0.571

RE1	0.463	0.475	0.54	0.42	0.498	0.492	0.439	0.57	**0.893**	0.528	0.496
RE2	0.537	0.525	0.572	0.455	0.562	0.553	0.46	0.589	**0.898**	0.569	0.519
RE3	0.462	0.509	0.506	0.398	0.504	0.489	0.43	0.569	**0.885**	0.551	0.487
RE4	0.506	0.499	0.51	0.405	0.572	0.536	0.454	0.567	**0.889**	0.561	0.519
SE1	0.565	0.572	0.648	0.464	0.595	0.554	0.453	0.608	0.534	**0.859**	0.577
SE2	0.525	0.584	0.614	0.485	0.559	0.57	0.428	0.598	0.515	**0.853**	0.587
SE3	0.568	0.593	0.597	0.503	0.603	0.577	0.473	0.563	0.55	**0.872**	0.582
SE4	0.567	0.57	0.597	0.456	0.542	0.571	0.483	0.609	0.531	**0.864**	0.565
SE5	0.568	0.622	0.652	0.521	0.609	0.573	0.517	0.601	0.54	**0.859**	0.604
T1	0.568	0.654	0.682	0.513	0.638	0.591	0.493	0.62	0.505	0.637	**0.895**
T2	0.577	0.616	0.637	0.504	0.603	0.578	0.52	0.588	0.478	0.579	**0.888**
T3	0.589	0.62	0.675	0.532	0.66	0.647	0.535	0.617	0.557	0.632	**0.892**
T4	0.566	0.607	0.637	0.465	0.613	0.576	0.509	0.576	0.475	0.557	**0.881**

Source: Develop for the research

According to Table 4.4, all of the indicator's factor loadings are more than 0.7 and between 0.8 and 0.9, which is recommended by researchers Cheung et al. (2023). Moreover, each construct's Cronbach Alpha and Composite Reliability are valid and fulfil the recommended number by researcher Hair et al. (2021). Next, each construct's AVE is above 0.5, which is also valid and fulfils the recommended number by researcher Hair et al. (2021). Lastly, as shown in Table 4.5, each item's outer loading on its associated construct was greater than its loading on other constructs, and no high cross factor between other indicators. Therefore, the Convergent Validity of this study is valid to establish.

4.5.2 Disciminant Validity

Table 4.6 HTMT Criterion Test

Construct	C	FC	IOU	P	PE	PS	PV	RC	RE	SE	T
C											
FC	**0.702**										
IOU	0.776	**0.809**									
P	0.568	0.591	**0.606**								
PE	0.716	0.746	0.842	**0.622**							
PS	0.663	0.712	0.785	0.64	**0.71**						
PV	0.614	0.642	0.611	0.533	0.593	**0.65**					
RC	0.732	0.733	0.805	0.575	0.742	0.714	**0.651**				
RE	0.606	0.621	0.659	0.517	0.659	0.633	0.543	**0.707**			
SE	0.711	0.752	0.797	0.621	0.743	0.72	0.595	0.76	**0.678**		
T	0.71	0.774	0.817	0.623	0.778	0.734	0.629	0.742	0.62	**0.74**	

Source: Develop for the research

According to Table 4.6, showing the HTMT value of the construct, all of the constructs are below 0.85 and valid to the recommendation by the researcher (Hair et al. 2017) .This means that there are no high correlation issues between each construct. Therefore, the Discriminant Validity of this study is valid to establish.

4.6 Structural Model Assessment

Table 4.7 Collinearity Statistics

Construct	VIF
H1: SE -> IOU	2.822
H2: RE -> IOU	2.026
H3: RC -> IOU	2.875
H4: PV -> IOU	1.917
H5: PS -> IOU	2.588
H6: C -> IOU	2.366
H7: P -> IOU	1.786
H8: PE -> IOU	2.774
H9: T -> IOU	2.917
H10: FC -> IOU	2.707

Source: Develop for the research

According to the result of Table 4.7, all of the constructs are valid to the threshold below 3.3, which Vacheva et al. (2016) recommend. This result means that there is no multicollinearity issue in the construct. Therefore, it can be concluded that it can continue addressing the model assessment of this study.

4.6.1 PLS Estimation

This study used 10,000 bootstrap and two-tailed settings, as recommended. Therefore, the results are shown in Table 4.8

Table 4.8 Path Coefficient and Hypotheses Testing

Hypotheses	Path Coefficient (β)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1: SE -> IOU	0.114	0.114	0.053	2.164	0.031	Supported
H2: RE -> IOU	**-0.004**	**-0.004**	**0.045**	**0.083**	**0.934**	**Unsupported**
H3: RC -> IOU	0.142	0.141	0.049	2.879	0.004	Supported
H4: PV -> IOU	**-0.048**	**-0.048**	**0.043**	**1.104**	**0.27**	**Unsupported**
H5: PS -> IOU	0.164	0.161	0.05	3.258	0.001	Supported
H6: C -> IOU	0.136	0.134	0.048	2.865	0.004	Supported
H7: P -> IOU	**-0.025**	**-0.023**	**0.04**	**0.614**	**0.539**	**Unsupported**
H8: PE -> IOU	0.23	0.231	0.065	3.514	0	Supported
H9: T -> IOU	0.144	0.145	0.059	2.424	0.015	Supported
H10: FC -> IOU	0.151	0.15	0.056	2.686	0.007	Supported

Source: Develop for the research

According to Table 4.8, the results of the path coefficients and hypothesis testing for this study are detailed below. A hypothesis is supported if the t-statistic is greater than 1.96 (Hair et al., 2019), the p-value is less than 0.05 (Lohmöeller, 1989), and the path coefficient is sufficiently strong.

H1 evaluates self-efficacy in relation to intention to use. The final statistic results show a β value of 0.114, with a t-value of 2.164 and a p-value of 0.031. This suggests a significant relation, thereby accepting the hypothesis and confirming that SE positively influences IOU.

H2 treats the relation between RE and IOU. The testing resulted in a β value of -0.004, a t-value of 0.083, and a p-value of 0.934, suggesting no significance. For this reason, H2 is disconfirmed.

H3 assesses the role of RC in IOU. The results show a β value of 0.142, with a t-value of 2.879 and a p-value of 0.004, establishing a significant positive relationship: this supports H3.

H4 evaluates the relation of PV and IOU. The final result discloses a β value of -0.048, a t-value of 1.104, and a p-value of 0.27, suggesting no significance. So H4 is rejected.

H5 assesses the role of PS in IOU. The final statistic results show a β value of 0.164, with a t-value of 3.258 and a p-value of 0.001. These results confirm a positive relationship in the means.

H6 investigates the relationship between confidentiality and IOU. The final statistic results are a β value of 0.136, t-value of 2.865, and a p-value of 0.004. Therefore, it was concluded that the relationship was meaningful and thus supported H6.

H7 investigates the relationship between privacy and IOU. The final statistic results show a β value of -0.025, while t-value is 0.614, yielding a p-value of 0.539; since this p-value exceeds the 0.05 confidence level, H7 is not supported.

H8 explores the relationship between performance expectancy (PE) and IOU. The analysis indicates a β value of 0.23, a t-value of 3.514, and a p-value of 0.000, showing a strong positive connection and supporting H8.

H9 examines how trust (T) influences IOU. With a β value of 0.144, a t-value of 2.424, and a p-value of 0.015, the results confirm a significant link, supporting H9.

H10 assesses the role of facilitating conditions (FC) in shaping IOU. The findings, with a β value of 0.151, a t-value of 2.686, and a p-value of 0.007, show a significant positive impact, supporting H10.

4.7 Coefficient of Determination (R2)

Table 4.9 Coefficient of Determination

Constructs	R-square	R-square adjusted
IOU	0.747	0.739

Source: Develop for the research

According to Table 4.9, the R^2 value is 0.747, which indicates strong explanatory power. This suggests that the independent variables collectively have a significant impact on intention to use an AI chatbot for personal financial planning. The remaining 25.3% of the variance can be attributed to model external factors or random error. R^2 values range from 0 to 1, indicating the model's ability to explain variation, with higher values indicating greater explanatory strength (Hair et al., 2014).

4.8 Effect Size (F2)

Table 4.10 Effect Size (f^2) Results for Variables Influencing IOU

Constructs	f-square
C -> IOU	0.031
FC -> IOU	0.033
P -> IOU	0.001
PE -> IOU	0.075
PS -> IOU	0.041
PV -> IOU	0.005
RC -> IOU	0.028
RE -> IOU	0
SE -> IOU	0.018
T -> IOU	0.028

Source: Develop for the research

The researcher Cohen (2013), describes f^2 values as small when $f^2 = 0.02$, medium as $f^2 = 0.15$, and large when $f^2 = 0.35$. According to Table 4.10, this is the effect size (f^2) results for variables influencing IOU

Variables such as C (0.031), FC (0.033), PE (0.075), PS (0.041), RC (0.028), and T (0.028) demonstrated small but statistically significant effects on the intention to use (IOU). Among these, PE stands out with the strongest influence, showing an effect size of 0.075, which approaches a medium effect. This indicates that PE plays a critical role in shaping IOU and suggests that it should be prioritized in strategies aimed at enhancing the adoption of AI chatbots.

In contrast, variables such as P (0.001), PV (0.005), and SE (0.018) show small effects, indicating minimal influence on IOU. Furthermore, RE (0) has no measurable effect. These findings suggest that these variables are less significant in influencing IOU within the context of this study.

Overall, the interpretation of these results aligns with the threshold of f^2 effect size guidelines (Cohen, 2013). Effect sizes below 0.02 are deemed negligible, which explains the limited impact of P, PV, SE, and RE. Conversely, variables with effect sizes exceeding 0.02, such as PE, underscore their meaningful contributions. These insights highlight the importance of considering these influential variables when exploring factors that drive IOU.

4.9 Chapter Summary

This chapter provides an overview of the key findings, including descriptive analysis, measurement model assessment, structural model assessment, and hypothesis testing based on data from 354 respondents. The results provide insights into the relationship between independent and dependent variables, revealing the proposed research framework.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATION

5.0 Introduction

In Chapter 5, a comprehensive summary will be crafted based on the content covered in Chapters 1 through 4 of this study. The summarization will encompass demographic details, data presentation, and recommendations and suggestions for future studies exploring this topic.

5.1 Discussion of Major Finding

This section contextualizes the findings with existing literature, comprehensively understanding their implications.

Table 5.1 Discussion of Major Finding Results

Hypotheses	P values	Decision
H1: SE -> IOU	0.031	Supported
H2: RE -> IOU	**0.934**	**Unsupported**
H3: RC -> IOU	0.004	Supported
H4: PV -> IOU	**0.27**	**Unsupported**
H5: PS -> IOU	0.001	Supported
H6: C -> IOU	0.004	Supported
H7: P -> IOU	**0.539**	**Unsupported**
H8: PE -> IOU	0	Supported
H9: T -> IOU	0.015	Supported
H10: FC -> IOU	0.007	Supported

Source: Develop for the research

5.1.1 Self-Efficacy and Intention to Use

According to Table 5.1, Self-efficacy (SE) had a significant effect on the intention to use AI chatbots in personal financial planning, with a p-value of 0.031 indicating support for the hypothesis accepted. Such findings relate well to the theory of protection motivation (PMT), in which those with self-efficacy center higher confidence in managing risk. These results complement researcher Him et al. (2019), who reported that self-efficacy positively influences technology intention by bolstering users' competence in financial matters, making financial tasks appear less threatening. Similarly, authors Hoffman and Plotkina (2021) support this concept, illustrating how past success with financial management can improve self-efficacy, consequently leading to a higher intention level.

However, stands in contrast to the findings of Muslichah (2018), which found no significant relationship between self-efficacy and the willingness to adapt technologies. Certain discrepancies between the two studies may be attributed to differences that each group embodies. For the Gen-Z population in Klang Valley of Malaysia, the belief that they could effectively use AI chatbots permitted them to take on these tools to enable better financial decisions. Fostering acceptance toward AI chatbots entails harnessing treatment to sell self-efficacy and increase the intention rate.

5.1.2 Response Efficacy and Intention to Use

The hypothesis related to RE is rejected as it does not significantly predict intention to use an AI chatbot in personal financial planning ($p = 0.934$), according to Table 5.1. This further suggests that Gen Z’s primary motivation for adopting AI chatbots is not to mitigate financial risk. It is reasonable to assume that Gen Z, as digital natives, may have completed the foundation of trust through technology and its capabilities, which will reduce the importance of response efficiency as a decisive factor. Tool efficiency may be a gamble rather than a key motivating factor for this population. Instead, respondents said user experience, convenience and social impact played a greater role in developing their intentions.

Otherwise, while AI chatbots are still a novel concept for financial advice in the Klang Valley, many users require more experience or tangible evidence of their efficacy in improving financial outcomes. There is little empirical knowledge or collaborative examples to demonstrate that these tools can achieve piloting of their capabilities without the internal risk of ineffective operation due to one or two perceived failures within self-imposed time frames.

This finding aligns with previous research. Warkentin et al. (2016) claimed that response efficacy did not significantly affect the continued use of anti-malware software, suggesting that users are generally willing to support simpler or easier-to-use programs over efficacy. In contrast, Vedadi and Warkentin (2020) argued that response efficiency is a key motivator for the continued use of password protection tools, while Al-Emran et al. (2021) proposed a significant positive relationship between response efficiency and smartwatch intention. Therefore, all these differences seem to emphasize that the weight of response effects can vary significantly depending on technology type, context, and user familiarity.

5.1.3 Response Cost and Intention to Use

According to Table 5.1, Response cost (RC) significantly influenced the intention to use AI chatbots ($p = 0.004$), supporting the hypothesis. This aligns with PMT, which suggests lower perceived costs associated with protective behaviors enhance intention. High response costs, such as complex interfaces or financial burdens, can deter users from adopting new technologies (Hanus & Wu, 2018).

For example, Hanus and Wu (2018) found that perceived time-consuming and inconvenient aspects of complying with information security measures reduced intention rates among Finnish employees. Similarly, Rodrigues et al. (2023) observed that high response costs, including the effort required to implement security measures, lowered students' engagement with information security practices. Conversely, Fischer-Preßler et al. (2022) noted that response costs were less significant during initial intention but became more relevant for continued usage. This suggests that while initial adopters may overlook response costs, they become critical for sustained use.

As a result of this study, response costs are an essential consideration for GenZ in Klang Valley. If the perceived complexity or time investment required to use AI chatbots is too high, intention rates may decline despite the potential benefits, such as personalized financial advice and convenience. Therefore, simplifying chatbot interfaces, reducing associated costs, and offering user-friendly onboarding processes could mitigate these barriers and encourage broader intention among this demographic.

5.1.4 Perceived Vulnerability and Intention to Use

According to Table 5.1, the hypothesis regarding perceived vulnerability (PV) was unsupported ($p = 0.27$), indicating that Gen Z’s intention to use AI chatbots for personal financial planning is not significantly influenced by their assessment of financial threats. This result contrasts with findings from prior research, such as Park et al. (2024). They highlighted the central role of perceived vulnerability in shaping attitudes toward technology intention. Their study emphasized that vulnerability and severity are critical components of threat appraisal, surpassing coping mechanisms like self-efficacy and response efficacy in influencing user attitudes.

Similarly, Bauer and Bernroider (2015) noted that perceived vulnerability is limited in scenarios where users either feel confident managing risks or underestimate potential threats. For example, their study on information security awareness programs revealed that while these initiatives enhanced perceptions of severity and efficacy, they had a negligible effect on perceived vulnerability.

In Klang Valley's Gen Z context, the lack of significant influence of perceived vulnerability on chatbot intention could stem from several factors. First, this demographic may not perceive financial risks as severe or immediate enough to warrant using AI chatbots. Alternatively, they may view such risks as manageable through conventional means, reducing the perceived need for technological intervention. The supporting studies by Hanus and Wu (2016) and Martens et al. (2019) also demonstrated that heightened awareness of risks does not necessarily correlate with increased perceptions of vulnerability.

Therefore, these findings suggest that service providers must address the gap by emphasizing the relevance of financial risks and uncertainties to this target group. Educating users on the potential consequences of inadequate financial planning and showcasing AI chatbots as effective tools for mitigating these risks could increase the salience of perceived vulnerability. By doing so, service providers may enhance the perceived importance of AI chatbots in addressing financial challenges and encourage their intention among Klang Valley's Gen Z population.

5.1.5 Perceived Severity and Intention to Use

The hypothesis regarding perceived severity (PS) was accepted, with results shown in Table 5.1, which showed a significant influence on the intention to use AI chatbots ($p = 0.001$). This underscores perceived severity as a key element of threat appraisal. According to PMT, individuals who perceive a threat as severe are more likely to adopt protective measures, including technologies designed to mitigate risks. Gen Z's awareness of the potential consequences of financial mismanagement may drive them to adopt AI chatbots. Recognizing the seriousness of financial risks, they may view these chatbots as practical and easy-to-use solutions to safeguard their financial well-being. This reflects consistent findings across domains where perceived severity significantly affects user behavior.

Previous studies support this finding. For instance, Sukeri et al. (2020) and Wei et al. (2020) demonstrate that heightened awareness of significant financial risks motivates users to adopt innovative solutions, such as AI chatbots. These tools are perceived as effective in addressing critical financial challenges. Similarly, Sreelakshmi and Prathap (2021) found that perceived severity during crises, such as the COVID-19 pandemic, was pivotal in adopting protective technologies like mobile payments and health apps. Likewise, Daragmeh et al. (2021) highlighted that increased awareness of risks accelerates the intention of digital tools to mitigate those threats.

To capitalize on this, service providers should highlight the serious consequences of poor financial planning and the unique advantages that AI chatbots offer in mitigating these risks. Campaigns highlighting the urgency and impact of financial threats may further engage Gen Z’s attention and increase their motivation to use these tools. Providers can increase intention and effectively meet user needs by showcasing AI chatbots as valuable resources for solving financial challenges.

5.1.6 Confidentiality And Intention To Use

According to Table 5.1, confidentiality and its influence on the intention to use AI chatbots was supported with p-values ($p = 0.004$), emphasizing that there is a critical role in fostering confidentiality and encouraging intention, particularly in the domain of financial management. When users trust that their sensitive information will remain secure, they are more inclined to adopt AI chatbots for managing financial tasks.

This finding aligns with previous research. For instance, Chai and Zolkipli (2021) demonstrated a strong positive relationship between confidentiality and users' intention to adopt AI chatbots, highlighting the importance of secure information handling in influencing trust. This is particularly relevant for Gen Z, a demographic that is both tech-savvy and highly aware of data privacy concerns. Confidentiality reassures them that their personal and financial information is safe, significantly impacting their willingness to interact with AI-driven solutions.

Similarly, Normalini et al. (2019) found that confidentiality positively impacts customer retention in online banking services. Their study concluded that accurate and secure data management fosters continued use, reinforcing that confidentiality is essential in trust-dependent environments like financial services. Additionally, Suh and Han (2003) emphasized the criticality of confidentiality in e-commerce, noting the risks posed by potential breaches during data transmission. These findings underscore the universal importance of confidentiality across various digital platforms.

Therefore, Gen Z users in Klang Valley are more likely to adopt AI chatbots if confidentiality measures are perceived as reliable. Service providers can leverage this by highlighting their use of advanced security technologies and transparent data management practices. Demonstrating commitment to confidentiality builds trust and positions AI chatbots as secure and dependable tools for financial management.

5.1.7 Privacy And Intention To Use

The privacy (P) hypothesis was unsupported despite results showing a significant influence on the intention to use AI chatbots ($p = 0.539$). This outcome suggests that privacy is a crucial factor in technology intention, but its impact in this specific context may be more nuanced than anticipated. Privacy concerns typically revolve around how personal data is collected, stored, and shared, especially in sensitive areas such as financial management. However, the findings indicate that privacy concerns alone are not a primary driver of intention for Gen Z in Klang Valley.

This result starkly contrasts previous research that emphasized the critical role of privacy in shaping user intentions. For example, Lutz and Tamò-Larrieux (2021) highlight how privacy concerns can significantly impact the intention of emerging technologies such as AI chatbots. Additionally, the "privacy paradox," in which users express privacy concerns but still choose to adopt a technology, suggests that privacy concerns do not always serve as a direct barrier to technology intention. This is especially true unless the user considers the risks or consequences serious. Yao et al. (2024) similarly point out that while privacy concerns may be decisive in some cases, their impact may be weakened if users perceive sufficient benefits or guarantees of data security.

In financial applications, privacy issues are more prominent due to the sensitivity of information required for personalized services. The study by Martinez-Navarone et al. (2023) and Sebastian (2023) highlights the importance of privacy-enhancing technologies (PETs) that increase user trust by ensuring greater control over personal data. Despite these findings, the unsupported hypothesis here may suggest that Gen Z in the Klang Valley considers existing privacy measures adequate or prioritises other factors, such as convenience or functionality, over privacy concerns.

To address this, service providers can proactively mitigate privacy concerns by implementing robust safeguards like encryption and transparent data practices. Educating users about these measures and demonstrating their effectiveness can build trust and encourage intention. By aligning privacy protections with user expectations, providers may enhance the role of privacy in influencing intention decisions for AI chatbots.

5.1.8 Performance Expectancy And Intention To Use

Table 5.1 supports the hypothesis that performance expectancy significantly affects the intention to use AI chatbots with a p-value = 0. Performance expectancy refers to the belief that technology will enhance efficiency or productivity (Venkatesh et al., 2003). This aligns with findings from Camilleri (2024), who observed a positive relationship between performance expectancy and users' intentions to adopt ChatGPT, showing that the perceived benefits of improving task performance are a strong motivator. Similarly, Chen et al. (2022) found that users who believe that fintech services can improve their financial tasks are more likely to adopt these technologies.

Apart from this, Gen Z in Klang Valley may perceive significant performance benefits, such as enhanced financial decision-making and time savings. Syakinah (2024) further reinforces this notion, showing that higher performance expectations correlate with greater willingness to use AI services. Therefore, this suggests that AI chatbots' tangible advantages in financial planning drive their intention among this demographic.

5.1.9 Trust And Intention To Use

According to Table 5.1, the hypothesis that trust significantly affects intention to use an AI chatbot was also supported with p-values = 0.015. Trust is defined as confidence in a system's ability to deliver reliable and secure results, and it is a key factor in technology intention. This study supports researcher Zhong et al. (2022), who emphasized that trust can positively impact behavioral intentions, especially in contexts involving emerging technologies. Furthermore, researcher Miltgen et al. (2013) identified trust as the strongest predictor of iris scanning AI intention, emphasizing its critical role in user decision-making.

Beyond this, trust in the accuracy, security, and reliability of AI chatbots or the service providers who manage these tools plays a crucial role in the effectiveness of the intention process. Financial planning inherently involves sensitive data, and ensuring that this information is handled securely increases the likelihood of using such tools. Therefore, this reflects broader findings across multiple domains where trust in technology positively impacts intention behavior.

5.1.10 Facilitating Condition And Intention To Use

According to Table 5.1, the hypothesis that facilitating conditions significantly affect the intention to use AI chatbots is supported with a p-value of 0.007, highlighting the importance of infrastructure and resources in driving technology intention. Facilitating conditions encompass user-friendly interfaces, reliable technical support, and seamless integration into daily routines, collectively enabling smooth intention and usage (Abbad, 2021).

The study by Rahim et al. (2022) showed that adequate support infrastructure, especially when combined with existing technical assistance, can positively impact willingness to adopt chatbots. Similarly, Chatterjee and Bhattacharjee (2020) highlighted that enabling facilities such as ease of use and convenience can facilitate the intention of AI technologies by reducing user effort and complexity. These findings highlight the critical role of supportive environments in promoting adaptive behaviors.

It can be concluded that convenience is particularly important in shaping their willingness to use AI chatbots for personal financial planning. Elements such as intuitive interfaces, reliable internet connections, and the ability to seamlessly integrate AI tools into daily life can address practical barriers and make these technologies more attractive. These features simplify the user experience and increase trust and ease of use, thereby increasing the likelihood of intention.

By delivering powerful convenience, service providers can position AI chatbots as practical, easy-to-use, and indispensable financial management tools. Therefore, this highlights the need to invest in infrastructure and user-centred design to optimize intention among digitally savvy users such as Generation Z.

5.2 Implications of the Study

5.2.1 Theoretical Implication

The study makes significant theoretical contributions by integrating PMT and UTAUT into Generation Z's intention to use AI chatbots for personal financial planning. Traditionally, these two models have been practically applied to study either psychological or technological behaviors. By integrating PMT's understanding of the threat and coping appraisals with UTAUT's technology acceptance factors, this research provides a robust framework for exploring intention behaviors in digital finance.

Moreover, the PMT model underexplored threat and coping appraisals, especially the manner in which these influence Gen Z's decision about AI chatbot intention. This study provides insight into perceived vulnerability, severity, self-efficacy, and response costs in Generation Z's decision-making process. To enhance the theoretical, adding the UTAUT model can overcome the weakness of PMT model, which are important considerations in determining how AI systems are effective and reliable.

In conclusion, This study fills an important gap in the literature by placing this combined model within a Malaysian context, wherein studies on AI chatbot intention for personal financial planning seem rare. Additionally, the study extends earlier work on PMT and UTAUT because it considers privacy and confidentiality, which are becoming much more pertinent in the digital age. Furthermore, the findings will extend beyond Malaysia and lay a foundation for similar research in other emerging markets. Therefore, the research contributes to our understanding of the intention of AI in varied contexts by setting out ways in which psychological and technological factors may work together.

5.2.2 Practical Implication

Policy recommendations based on this research may include actions by financial institutions, policymakers, and educators regarding Gen Z’s intention of AI chatbots for personal financial planning. The findings demonstrate key factors in the intention of AI chatbots and provide a basis for developing approaches suitable for specific populations.

Moreover, since performance expectancy influences intention, chatbots must offer concrete advantages, like personalized financial analysis, complete budgeting tools, and sales-oriented insights. Features such as gamification, predictive analytics, and financial goal monitoring would engage the Gen Z generation more effectively. To mitigate the large impact of response costs on intention, financial institutions should erect any apparent barriers to action, namely complexity, time, and effort. These barriers can be eliminated through user-friendly interfaces, intuitive onboarding, and customer support. Providing users with the necessary support and resources remains critical. Informative FAQs, robust customer service, and access to tutorial materials can significantly enhance users' ability to leverage chatbot capabilities in financial planning.

While privacy concerns do not affect intentions, policymakers should enforce Personal Data Protection Act 2010 to raise trust in AI systems. Practices strengthened with transparent data usage and regular audits can give enough assurance to the users concerning the safety of their personal information. Policymakers can offer tax breaks or grants to encourage the development of AI chatbots in financial institutions and fintech firms focused on user security and technological advancements. Partnerships between private and governmental institutions may speed up the design of Gen Z-centric solutions. Educating the public on using AI chatbots and safety features will remove misconceptions and pave the way toward acceptance. The awareness campaign can be on success stories and demonstrate how chatbots ease financial planning.

Lastly, educational institutions and consumers can take charge of training users on how to use AI chatbots efficiently. The educational system can create curricula wherein Gen Z is taught how to use AI applications for budgeting, saving, and investment planning; workshops with hands-on participation would instil confidence in users about adopting the technology. To counter their fear of hesitation, live demonstrations and testimonials showing the successful use of AI chatbots can be offered by one or more funding institutions in partnership with educators. These initiatives create comfort against fears associated with high severity and boost trust.

In conclusion, this study provides a roadmap for financial institutions, policymakers, and educators to improve the intention of AI chatbots for financial planning. Addressing performance expectancy, trustworthiness, and confidentiality as significant predictors and conciliating response costs can encourage the environment for GenZ to grab AI chatbots as an essential tool for personal financial planning.

5.3 Limitations of The Study

This study reveals the usage of artificial intelligence chatbots among Gen Z consumers in Klang Valley, Malaysia; however, it provides portions of this study to explain some limiting factors that may affect the results.

First, the study area is limited to Gen Z consumers in the Klang Valley. While this precise focus can provide insights into specific market segments, the generalizability of the results will bypass other age groups, i.e. Millennials or Baby Boomers, or different geographic regions. Cultural, economic and technological differences across regions are most likely to change the acceptance of AI chatbots. Needs further elaboration.

Second, there are also potential limitations to relying on self-reported survey data. Participants may have provided responses they believed were socially desirable rather than accurately reflecting their true opinions or behaviors. This response bias may affect the validity and reliability of the study results.

Another shortcoming involves the technical background of the study. The findings are based on the development of artificial intelligence chatbot technology at the time of the study. Given continued advances in artificial intelligence fields such as natural language processing or further enhancements in personalized user experiences, the rapidly changing technology environment may make many of the results of this study irrelevant in the future.

Additionally, surveys rarely consider other external factors such as internet access, digital literacy levels, and the impact of marketing on users. These are important aspects that may influence user behavior and perception but were excluded from the scope of this study. Addressing these variables in future research could provide a comprehensive understanding of the factors influencing the intention to use AI chatbots.

5.4 Recommendation for Future Study

This research has its limitations, as knowledge about the intention to use AI chatbots continues to grow. In addition to the research already presented, this study also provides recommendations for future research.

Firstly, future research could explore generational differences in AI chatbot intention by expanding the generational alignment studied to include Millennials and Baby Boomers. It could also shed light on unique generational preferences, guiding principles for each group, and barriers worth discussing when using AI chatbots. Further research could be extended to other geographical areas in Malaysia or anywhere in the world to assess whether cultural and economic factors influence users' behavioral paradigms. Differences in the perspectives of rural and urban users may reveal additional barriers and facilitators inherent to different socioeconomic backgrounds with different intentions to use AI chatbots for personal financial planning.

As AI technology advances, it will be difficult for future studies examining user trust and AI intention to ignore emerging capabilities such as natural language processing and sentiment analysis. Recent advances can enhance user experience by reducing barriers that can harm real-world user experience, such as misunderstood communication or lack of personalization. The study's findings may help guide developers and policymakers on how best to enable AI chatbot capabilities to meet user expectations.

Lastly, future research could examine qualitative methods, including focus groups and in-depth interviews, to better understand the perceptions, experiences, and motivations behind users. This mode of inquiry may be useful in understanding complex issues and behavioral nuances often overlooked in quantitative surveys. Such qualitative surveys can also address user concerns about data security or point out needs that quantitative surveys might miss.

By addressing these recommendations, future research can build upon the foundation established in this study. Expanding demographic inclusivity, exploring the impact of technological advancements, and integrating qualitative approaches. These insights will be instrumental in informing strategies and provide a more comprehensive understanding of factors influencing the intention to use AI chatbots for developers, financial institutions, and other stakeholders aiming to optimize chatbots for public use.

5.5 Chapter Summary

In summary, this research has demonstrated a significant and positive relationship between all independent variables, representing the influencing factors and the dependent variable. Each independent variable exhibited statistical significance, contributing valuable insights into the factors influencing the intention to use AI Chatbot among Gen Z’s personal financial management in the Klang Valley, Malaysia. It is important to consider the identified limitations for future studies to delve deeper into the intricacies of this subject.

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APPENDICES

Appendix A Ethical Clearance and Online Survey Questionnaire

UKMZ3016 RESEARCH PROJECT

FINAL YEAR PROJECT (FYP)

BACHELOR OF INTERNATIONAL BUSINESS (HONS)

Research project title:	**Intention to use AI Chatbot in GenZ' personal financial planning**
FYP No:	
Student's name:	**LIM KEAN CHUAN**
Student's ID:	**2005724**
Supervisor's name:	**Dr. Tang Kin Leong**

Dear Participant,

I'm Lim Kean Chuan from the Bachelor of International Business (HONS) of Universiti Tunku Abdul Rahman (UTAR). Welcome to the survey Intention to use AI Chatbot in GenZ' personal financial planning. Your participation in this research is highly valued and will contribute to a better understanding of the perceptions and knowledge of AI in financial planning.

The main objective of this survey is to assess the level of attitudes from your in Klang Valley towards AI Chatbot in personal financial planning. Your input will help us identify areas of improvement, potential concerns, and opportunities for integrating AI-focused financial education.

Your responses will remain completely confidential and will be used solely for research purposes. Your individual responses will not be shared or linked to your identity. By proceeding with this survey, you are providing your informed consent to participate.

This questionnaire consists of a series of questions. Please answer each question to the best of your knowledge and beliefs. There are no right or wrong answers; we are interested in your honest opinions.

Completing this survey should take approximately in 15 minutes. We kindly request that you allocate some uninterrupted time to provide well-considered responses. Thank you for your participation, which is a valuable contribution to our research on AI intention in personal financial planning among undergraduates in Klang Valley, Malaysia.

If you have any questions or concerns, please feel free to contact us. Thank you!

Your sincerely,

Lim Kean Chuan

016-5570940
chuanchuan2123@1utar.my

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. The purposes for which your personal data may be used are inclusive but not limited to:-

- For assessment of any application to UTAR
- For processing any benefits and services
- For communication purposes
- For advertorial and news
- For general administration and record purposes
- For enhancing the value of education
- For educational and related purposes consequential to UTAR
- For the purpose of our corporate governance
- For consideration as a guarantor for UTAR staff/ student applying for his/her scholarship/ study loan

2. 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.

3. 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.

4. 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 **chuanchuan2123@1utar.my**

1. Acknowledgement of Notice

- 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.

UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT

BACHELOR OF INTERNATIONAL BUSINESS (Honours)

Section A: Screening Question

1.Are you living in Klang Valley and aged between 17-28 years old?

- ◻ Yes, procced to Section A
- ◻ No, thank you. (end of the survey, not target)

<u>Section B: Demographic Questions</u>

1. Gender ◻ Male ◻ Female
2. Age (as in 2024) ◻ 17-19 ◻ 20-22 ◻ 23-25 ◻ 26-28
3. Ethnicity ◻ Malay ◻ Indian ◻ Chinese ◻ Others. ____________
4. Occupation: ◻ Student ◻ Working professional ◻ Entrepreneur ◻ Unemployed

5. Level of Education □ STPM level/O-level □ Foundation/ A-Level □ Diploma □ Bachelor’s Degree □ Postgraduate
6. What is your disposal income level per month? □ Below RM1500 □ RM1501 -RM 3000 □ RM3001 – RM4500 □ Above RM 4501

Section B: Fintech Landscape with demographic

1. How often do you use online banking services? □ Daily □ Weekly □ Monthly □ Rarely □ Never
2. Have you ever used a mobile payment app (e.g. GrabPay, Touch 'n Go, etc.)? □ Yes □ No
3. Are you aware of any fintech companies in Malaysia (e.g. Funding Societies etc.)? □ Yes □ No
4. Have you aware of any digital investment and financial platforms (e.g. robo-advisors, cryptocurrency, etc.)? □ Yes □ No
5. AI Chatbot in Personal Financial Planning

How familiar are you with AI chatbots in personal financial planning?

- ◻ Very familiar
- ◻ Somewhat familiar
- ◻ Not very familiar
- ◻ Not at all familiar

6. Have you ever used AI chatbot for financial services (e.g. customer support, transaction inquiries, etc.)?

- ◻ Yes
- ◻ No

7. What features would you expect from an AI chatbot for personal financial planning? (Select all that apply)

- ◻ Budgeting and expense tracking
- ◻ Investment advice and portfolio management
- ◻ Bill payments and reminders
- ◻ Credit score monitoring and reporting
- ◻ Others (please specify)

8.What most concerns do you have about using an AI chatbot for personal financial planning? Please rank.

- ◻ Security and data privacy
- ◻ Lack of human interaction and empathy
- ◻ Limited functionality and capabilities
- ◻ Dependence on technology
- ◻ Response efficacy and performance expectancy
- ◻ Facilitating conditions
- ◻ Trust

Section D: Survey Questionnaire

This section is to obtain opinion of respondents about Intention to use AI Chatbot among GenZ' personal financial planning.

Please indicate how much you agree or disagree with each of the following statements based on a scale ranging from 1 (strongly disagree) to 5 (strongly agree).

1- Strongly disagree
2- Disagree
3- Neutral
4- Agree
5- Strongly agree

i	**Self-Efficacy (SE)** **Definition: Self Efficacy refer how confident you feel in using AI chatbots to manage your finances?**	**SD**	**D**	**N**	**A**	**SA**
1	**SE1:** I feel comfortable using AI chatbot to manage my personal finances	1	2	3	4	5
2	**SE2:** I can easily navigate and operate AI chatbot on my personal financial management.	1	2	3	4	5
3	**SE3:** I feel comfortable using AI chatbot for my own financial management even when I'm alone and don't have anyone to guide me.	1	2	3	4	5
4	SE4: I believe I can effectively use AI chatbot to manage my personal finances	1	2	3	4	5
5.	SE5: I have the skill to explore and utilize AI chatbots for diverse applications.	1	2	3	4	5

(Mosavian et al., 2023)

ii	**Response Efficacy (RE)** **Definition: How effective you believe AI chatbots are at protecting your data and preventing security issues in financial?**	**SD**	**D**	**N**	**A**	**SA**
1	RE1: I believe AI chatbots offer strong security measures to protect my financial data from unauthorized access.	1	2	3	4	5
2	RE2: I feel secure and confident using AI chatbots to manage my personal financial information.	1	2	3	4	5
3	RE3: I trust that AI chatbots help minimize security risks associated with managing financial data.	1	2	3	4	5
4	RE4: I confident the AI chatbot to follow strict security protocols to protect my financial information.	1	2	3	4	5

(Al-Emran et al., 2021)

iii	**Response Costs (RC)** **Definition: How much do you think it costs in terms of financial management when you are using AI chatbots?**	**SD**	**D**	**N**	**A**	**SA**
1	RC1: I believe the benefits of using an AI chatbot for personal financial management outweigh any associated costs.	1	2	3	4	5
2	RC2: I feel the advantages of an AI chatbot justify any required setup or maintenance expenses.	1	2	3	4	5
3	RC3: I am concerned that AI chatbots may involve additional, unforeseen expenses, such as data security fees.	1	2	3	4	5
4	RC4: I believe following AI chatbot security protocols is manageable and improves the overall experience.	1	2	3	4	5

(Al-Emran et al., 2021)

iv	**Perceived Vulnerability (PV)** **Definition: How likely do you think you are to be affected by changes or risks associated with AI technology?**	SD	D	N	A	SA
1	PV1: I feel that using AI chatbots could expose my financial data to potential security risks.	1	2	3	4	5
2	PV2: I believe there is a possibility of unauthorized access to my financial data when using AI chatbots.	1	2	3	4	5
3	PV3: I am concerned that technical issues in AI chatbots might compromise my financial security.	1	2	3	4	5
4	PV4: I think my reliance on AI chatbots increases the risk of data breaches.	1	2	3	4	5
5	PV5: I feel AI chatbots may make my financial information more vulnerable to cyber threats compared to traditional methods.	1	2	3	4	5

(Mosavian et al., 2023)

v	**Perceived Severity (PS)** **Definition: How likely do you think you are to be impacted by the changes or risks associated with AI technology for your personal financial management?**	SD	D	N	A	SA
1	PS1: I am confident that AI chatbots include features designed to secure my financial data.	1	2	3	4	5
2	PS2: I believe using AI chatbots can improve both my financial security and productivity.	1	2	3	4	5
3	PS3: I trust AI chatbots to offer strong safeguards against potential security threats.	1	2	3	4	5
4	PS4: I feel reassured that AI chatbots help manage risks to my financial information.	1	2	3	4	5
5	PS5: I believe AI chatbots can help prevent financial losses through enhanced security.	1	2	3	4	5

(Al-Emran et al., 2021)

vi	**Confidentiality (C)** **Definition: How much do you trust AI chatbots to protect your personal financial data and respect your privacy?**	**SD**	**D**	**N**	**A**	**SA**
1	C1: I take proactive steps, such as using strong passwords and two-factor authentication, to protect my financial data when using AI chatbots.	1	2	3	4	5
2	C2: I trust that AI chatbots maintain high standards of confidentiality and integrity for my financial information.	1	2	3	4	5
3	C3: I am confident AI chatbots prioritize security and privacy for sensitive financial data.	1	2	3	4	5
4	C4: I feel empowered using AI chatbots as they respect my control over my personal financial information.	1	2	3	4	5

(Green et al., 2024)

vii	**Privacy (P)** **Definition: How concerned are you about the personal information AI chatbots collect and how it is used in the context of financial planning?**	**SD**	**D**	**N**	**A**	**SA**
1	P1: I trust AI chatbots to only collect essential information needed to enhance my experience.	1	2	3	4	5
2	P2: I believe AI chatbots have sufficient safeguards to prevent unauthorized access to my data.	1	2	3	4	5
3	P3: I trust AI chatbots to use secure methods for storing and managing my financial data.	1	2	3	4	5
4	P4: I feel comfortable sharing financial information with AI chatbots because privacy concerns are adequately addressed.	1	2	3	4	5

(Mutimukwe et al., 2022)

viii	**Performance Expectancy (PE)** **Definition: How much do you believe AI chatbots can improve your financial management and help you achieve your financial goals?**	**SD**	**D**	**N**	**A**	**SA**
1	PE1: I believe AI chatbots simplify managing my personal finances.	1	2	3	4	5
2	PE2: I feel AI chatbots make it easier to achieve my financial goals.	1	2	3	4	5
3	PE3: I believe AI chatbots enable me to handle financial tasks more efficiently.	1	2	3	4	5
4	PE4: I am confident AI chatbots significantly improve my financial productivity and decision-making.	1	2	3	4	5

(Venkatesh et al., 2012)

ix	**Trust (T)** **Definition: How much do you trust AI chatbots to provide accurate and reliable financial information?**	**SD**	**D**	**N**	**A**	**SA**
1	T1: I believe AI chatbots provide transparent and honest interactions.	1	2	3	4	5
2	T2: I trust that AI chatbots prioritize my best financial interests.	1	2	3	4	5
3	T3: I feel that AI chatbots communicate clearly and reliably with me.	1	2	3	4	5
4	T4: I trust AI chatbots to deliver unbiased, accurate financial information.	1	2	3	4	5

(Source: Venkatesh et al, 2012)

x	**Facilitating Conditions (FC)** **Definition: Do you have the resources, knowledge, and support to use an AI chatbot effectively for personal financial planning?**	SD	D	N	A	SA
1	FC1: I have access to the resources and support I need to use AI chatbots for financial management.	1	2	3	4	5
2	FC2: I am equipped with the knowledge and tools necessary to effectively use AI chatbots in my financial planning.	1	2	3	4	5
3	FC3: I feel AI chatbots integrate smoothly with other financial technologies I use.	1	2	3	4	5
4	FC4: I am confident I can readily find support if I encounter issues with AI chatbots.	1	2	3	4	5

(Source: Venkatesh et al, 2012)

xi	**Intention to Use (IOU)** **Definition: How likely are you to use AI chatbots for financial management in the future?**	SD	D	N	A	SA
1	IOU1: I plan to regularly use an AI chatbot to manage my personal finances.	1	2	3	4	5
2	IOU2: I intend to frequently use AI chatbots in the future for financial tasks.	1	2	3	4	5
3	IOU3: I am interested in incorporating an AI chatbot into my daily financial management in future.	1	2	3	4	5
4	IOU4: I prefer using AI chatbots for routine financial services over human advisors.	1	2	3	4	5

(Source: Venkatesh et al., 2012)