DETERMINANTS OF THE INTENTION TO USE FINANCIAL ROBO-ADVISORY IN MALAYSIA

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FACULTY OF BUSINESS AND FINANCE
DEPARTMENT OF FINANCE

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DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our 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) Equal contribution has been made by each group member in completing the FYP.

(4) The word count of this research report is 18607.

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DEDICATION

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AVE	Average Variance Extracted
BI	Behavioural Intention
COVID-19	Coronavirus Disease
CR	Composite Reliability
DIM	Digital Investment Management
DIS	Discomfort
Fintech	Financial Technology
FRA	Financial Robo-Advisory
HTMT	Heterotrait-Monotrait Ratio of Correlation
INS	Insecurity
INV	Innovativeness
OPT	Optimism
PDPA	Personal Data Protection Act 2010
PLS-SEM	Partial Least Square Structural Equation Modelling
PU	Perceived Usefulness
SC	Security Commission Malaysia

Sdn Bhd	Sendirian Berhad - Private Limited Company
SEM	Structural Equation Modelling
TAM	Technology Acceptance Model
TRI	Technology Readiness Index
VIF	Variance Inflation Factors

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PREFACE

In year 2008, the world first public robo-advisory, Betterment was launched to help manage passive investments through a simple online platform. Since then, Financial Robo-Advisory (FRA) has slowly grow momentum in the increasing of users. The Covid-19 outbreak in year 2020 has accelerate the usage of FRA globally when the world is facing an economy and physical activity shut down at most of the country globally. The demand of financial technologies has boosted during the pandemic period, where banks move most of their services online, blockchain technology bloomed in cryptocurrency, and different sectors are looking their way to survive in the digital universe. Being an artificial intelligence based financial advisor, FRA eliminate the need of human intervention in providing personal financial investment advice. Investors could avoid human error and reduce behavioural bias when investing through the FRA platforms where every client have their unique choices of portfolio based on their personal preference implying with their risk attitude towards investments. Although it lacks human-to-human interaction and 2-way communication, FRA is available to assist 24 hours a day with a much lower cost compared to the traditional human financial advisory.

As the Malaysian regulators have created standards for FRA to be legally introduced in Malaysia in 2017, it provides Malaysians an easier way of investment. The Digital Investment Management (DIM) framework introduced by Securities Commission Malaysia plays a significant role in maintaining the standards of legal FRA services in Malaysia, where growing numbers of FRA providers are licenced under the framework to operate in Malaysia in this introductory stage. It is believed that more and more FRA providers will get into competition in the Malaysia market and boost up the number of individuals using FRA services due to its conveniency and affordability.

ABSTRACT

Financial Robo-Advisory (FRA) has been slowly taking over the market share of traditional human financial advisory in recent years, providing investors a platform to have customised investment suggestions without human intervention to avoid human errors and behavioural bias. As the introduction of FRA in Malaysia has been relatively slow compared to other countries, the factors that affect the intention to use FRA in Malaysia is needed to understand to improve the current situation of FRA development in Malaysia. This research is to study the determinants of intention to use FRA by 18-29 years-old Malaysians staying in the Klang Valley region of Malaysia. The Technology Readiness Model (TRI) is used as the main theoretical framework while Technology Acceptance Model (TAM) is used as the supporting theoretical framework for this study. The variables extracted from TRI model includes discomfort, insecurity, optimism, and innovativeness while variable from TAM model is the perceive usefulness.

An online questionnaire survey was performed with the targeted participants of 18-29 years old individuals staying at Klang Valley region of Malaysia. Questions based on the variables was asked in the questionnaire and feedback were collected through Likert Scale and analysed using SmartPLS software. The result of this study shows that optimism, innovativeness insecurity and perceived usefulness have a significant relationship with the behavioural intention to use FRA in Klang Valley, Malaysia within the 18-29 years old range. However, discomfort was found insignificant in affecting the behavioural intention to use FRA in this study. Implications of this study are made for the academia, policy makers (regulators and government) and stakeholders (FRA providers and investors) for them to have a clearer picture of the factors affecting the intention to use FRA in Malaysia.

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

As compared to traditional financial advisory which depends on human advisors, Financial Robo-Advisory (FRA) is an automated and technology-driven technique for offering financial advice and investment management services. Regarding this, the main purpose of this study was to look into the determinants of the intention to use FRA by focusing on optimism, innovativeness, discomfort, insecurity, and perceived usefulness towards the residents between 18 and 29 in Klang Valley, Malaysia. Research background, development of FRA in Malaysia and problem statement of this study will be covered in this chapter. In addition, this study will cover the objectives, questions, significance of the research and conclusion. The entire research is laid out and summarised in this chapter.

1.1 Research Background

1.1.1 Evolution of Financial Technology (Fintech)

As the latest technological term in the globalisation era, Financial Technology (Fintech), is a cutting-edge financial service that evolved in line

with the development of new technology. According to Zavolokina et al. (2017), the term "Fintech" illustrates the convergence of finance and information technology to develop new and innovative ways for offering financial services. It includes the adoption of digital technologies by the financial industry, enabling them to drive innovation and enhance their operations. It has revolutionized the entire financial industry by introducing disruptive changes to nearly every aspect of financial services (Goldstein et al., 2019). By combining information technology and financial services, Fintech involves the development of cutting-edge business models, software programs, workflows, and other products. These advancements aim to provide individuals and businesses with more effective, convenient, accessible, and efficient risk management options, along with new and improved financial services and products (Alaassar et al., 2022; Hua et al., 2019).

According to Hua et al. (2019), start-ups and technology firms are driving the expansion of Fintech, encompassing a diverse array of applications that include robo-advisors, mobile payments, cryptocurrency, marketplace financing, peer-to-peer lending, smart contracts, and decentralized autonomous organizations (DAO). In recent years, the Fintech industry has experienced tremendous growth and has drawn significant interest and investment from professionals, investors, regulators, consultants, and academics. They are interested in how these cutting-edge technology and innovations may affect organisations and even the broader financial system (Hua et al., 2019). Fintech is a game-changing innovation in the financial sector. For example, Fintech improves interactions with financial services by eliminating intermediaries, transforming how the financial advisory industry creates and delivers their offerings with the help of online brokers and trading platforms. Additionally, Fintech expands business opportunities and stimulates inclusive economic growth (Anshari et al., 2022).

1.1.2 Emergence of Financial Robo-Advisory (FRA)

History of FRA

During recent decades, digitalization forces investors to adopt digital services, there are few changes occurring in the financial advisory industry, as shown in figure 1.1. According to Jung et al. (2018a), a dramatic change in which financial services were made accessible occurred in the 1970s. This happened when online brokers and trading platforms became available, making financial guidance more affordable for the United States middle class. In contrast to traditional financial advisors, online brokers did not offer investment advice but instead executed buy and sell orders for clients at lower commissions. A key driver in the financial advisory industry's transformation was the World Wide Web's emergence in the 1990s and its significantly enhanced connectivity and accessibility. As a result, a broader group of investors, including high net worth people, wealthy investors, and even retail investors who maintained their own portfolios, were able to engage in online trading.

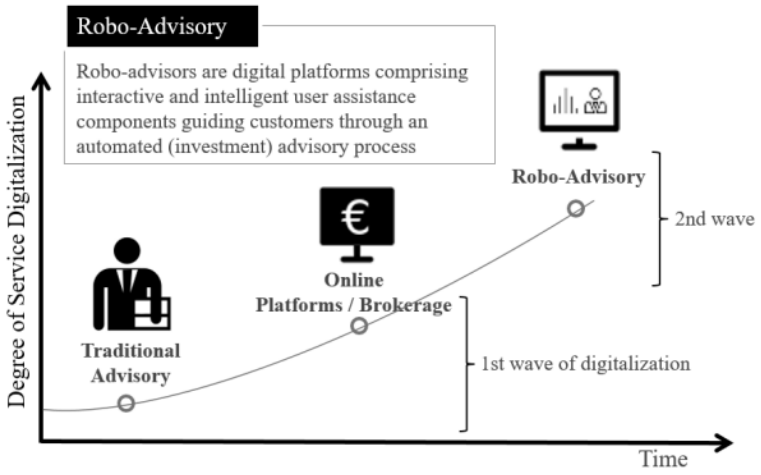

Figure 1.1. Digitalization of the financial advisory industry. Adapted from Jung, D., Dorner, D., Glaser, F., & Morana, S. (2018). Robo-Advisory: Digitalization and Automation of Financial Advisory. Institute of Information Systems and Marketing (IISM), *Karlsruhe Institute of*

Technology, 60(1), pg 81 - 86 ; Jung, D., Glaser, F., & Köpplin, W. (2019). Robo-advisory: opportunities and risks for the future of financial advisory. *Advances in Consulting Research: Recent Findings and Practical Cases*, 405-427.

According to Jung et al. (2018a), algorithmic trading gained popularity in the years that followed. It developed fully automated investment techniques, giving investors new opportunities. These developments opened the door for new market participants who attempted to alter it by providing efficient user experiences, cheaper prices, and innovative investing techniques. They are also known as "robo-advisors" in the industry. Algorithmic trading gained popularity in the years that followed. It developed fully automated investment techniques, giving investors new opportunities. These developments opened the door for new market participants who attempted to alter it by providing efficient user experiences, cheaper prices, and innovative investing techniques. They are also known as "Financial Robo-Advisory (FRA)" in the industry.

The developments in Artificial Intelligence (AI) have led to the creation of innovative services in various industries, including the financial sector. FRA acts as an AI-based advising system, have become prominent examples because it excludes the human from the process, empowers the services and increases the scalability (Tauchert & Mesbah, 2019). FRA rapidly substitutes traditional advisory methods for retail customers by offering fully automated investment and financial planning services. FRA which was first offered in 2010 by Wealthfront and Betterment. With minimal human involvement, this disruptive technology continuously assesses market trends, modifies portfolios, delivers personalised risk assessments, and offers real-time service changes. FRA uses AI to reduce human error and bias in judgement, increase prediction reliability and precision, and make

financial information, advice, goods, and services widely accessible to the public at a cheaper cost (Jung et al., 2018a; Zhang et al., 2021).

Mechanisms of FRA

A Financial Robo-Advisory (FRA) develops a digital platform to carry out customer self-evaluation and portfolio management by applying artificial intelligence and other advanced technologies. FRA aids investors by guiding their investment decisions based on factors such as their individual financial objectives, tolerance for risk, and current financial circumstances (Nguyen et al., 2023). By understanding the underlying process and components of the FRA system can provide valuable insights into how these systems operate and guide investment decisions. The step-by-step process flow that presents how the FRA assists investors in optimizing their portfolios and achieving their financial goals as illustrated in figure 1.2.

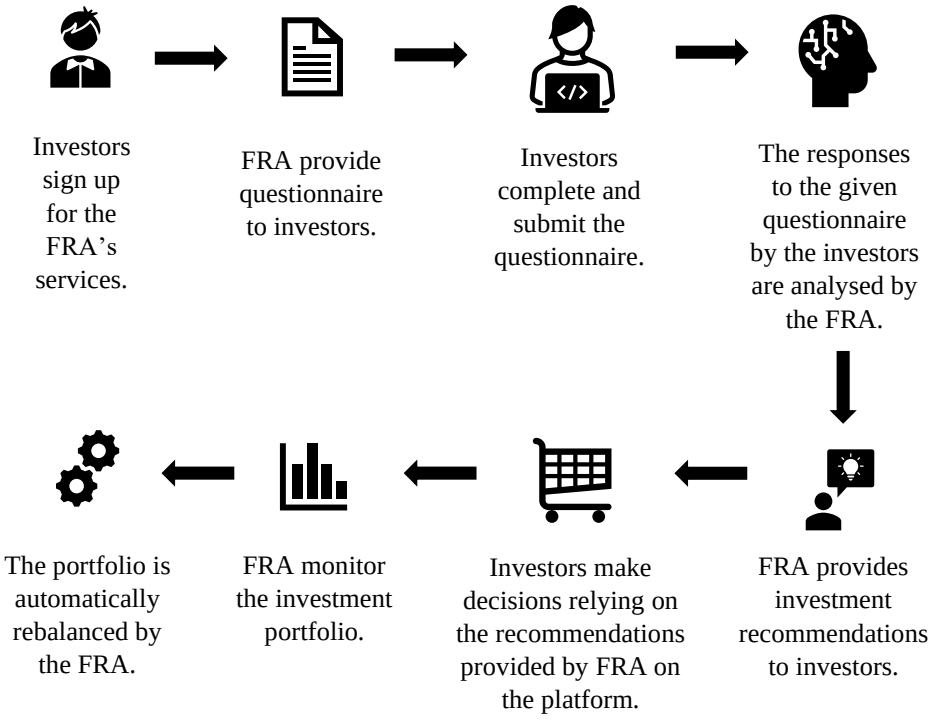

Figure 1.2. The typical process by which Financial Robo-Advisory operates. Adapted from Hoya, T.N. (2019). Development of Investor-Facing Robo-Advisors in Indonesia.

Once a potential investor has registered on the website and expresses an interest in investing by using FRA, the initial step of interaction involves evaluating factors such as their financial objectives, tolerance for risk, and current financial circumstances. Through this evaluation procedure, FRA is more effective to understand the investor's particular financial circumstances and preferences. FRA can create a customized investment portfolio plan tailored to the investor's unique needs and objectives by carefully evaluating these aspects (Jung et al., 2019). Therefore, investors are required to respond to a predefined questionnaire consisting of three main categories, each containing several subcategories. For instance, these categories may include basic information (with subcategories such as occupation, income and amount invested), risk capacity (with subcategories like income forecast, investment timeline and liabilities), and risk tolerance (with subcategories such as choice of portfolio risk level and comfort level with stock investment) (Tertilt & Scholz, 2018).

According to Jung et al. (2019), every FRA utilizes distinct methods to select suitable asset classes based on each investor's unique profile. For example, stocks, bonds, currencies, and commodities. The selection process relies on the responses provided in the questionnaire to align with the investor's specific requirements. Once the appropriate asset classes have been identified, the next step is to determine the right portfolio weights for each asset class. Portfolio weights show the proportion of each asset should be included in the target portfolio in relation to the other assets. "Algorithmic rebalancing" is crucial for maintaining stable portfolio weights and risk levels after the investment has been made. According to Jung et al. (2019), it accomplishes this by adjusting investments across asset classes to restore their specified long-term risk equilibrium, enabling investors an efficient way to deal with market volatility and stay in line with their investment goals (Jung et al, 2019).

Popularity of FRA

The development of Financial Robo-Advisory (FRA) has benefited investors significantly. FRA makes personalised and cost-effective services available with lower fees and minimum expenditure. Opportunities have now become available for those who were previously underserved, such as low-income people who were not normally served by traditional financial advisory firms. FRA platforms' access to low-cost solutions has increased the accessibility of investing for a broader range of people, including less wealthy investors (Gan et al., 2021). Even wealthy investors are starting to look at these digital platforms as viable alternatives since they have the potential to maximise earnings through lower costs while maintaining a high level of service (Jung et al., 2019). This shift is driven by the belief that FRA can offer cost-effective investment solutions that are efficient and effective, opening financial advice to a larger market (Fisch et al., 2019).

According to Jung et al. (2019), FRA also allowed investors to make decisions with reduced emotional influence which is one of the key strengths of FRA services. Increased robot interaction in investment processes helps humans avoid being affected by emotions (Figà-Talamanca et al., 2022). During market declines, average investors frequently act hastily because of fear and panic, selling their holdings to limit losses. However, the performance of long-term investments can be harmed by this impulsive behaviour. By utilizing FRA, investors can overcome these emotional habits, avoid missing out on potential price gains, and benefit from trading algorithms that prevent hasty reactions to market fluctuation upturns (Jung et al., 2019). This enhances overall investment performance and enables investors to keep their attention on their long-term objectives.

Referring to Abraham et al. (2019), FRA plays a valuable role in mitigating behavioral biases commonly observed in financial advisory services. Subjectivity, potential biases towards commission-based products, the inability to simultaneously monitor many assets, a propensity to concentrate on domestic securities, and other biases can all affect traditional financial advisors. However, FRA can address and decrease these biases by switching the decision-making process from humans to automated algorithms.

When compared to conventional services that rely on traditional financial advisors, the ease of access of FRA is one benefit of using them. FRA gives clients a platform that is easily accessible online or through mobile applications, making it convenient for investors to manage their finances from anywhere at any time with a network connection (Abraham et al., 2019). According to Fisch et al. (2019), FRA gives their clients unlimited access which brings a level of ease that was not previously possible. The younger, tech-savvy generation is especially drawn to this improved accessibility and finds it to be quite exciting.

1.2 Development of FRA in Malaysia

Digital Investment Management Framework

Malaysia only implemented this invention in 2017 when the Securities Commission Malaysia announced the "Digital Investment Management" framework, known as DIM. DIM framework which facilitates the licence and regulation of fund management companies that engage in Financial Robo-Advisory (FRA) services. They use cutting-edge technologies to provide investors with automated discretion portfolio management services (Securities Commission Malaysia, 2017). To promote a defined scope of regulated activity inside the DIM framework, as stated

by the Securities Commission Malaysia, the word DIM is employed in Malaysia instead of FRA (Securities Commission Malaysia, n.d.). The DIM framework implies that the services provided by the DIM company must incorporate automation of fundamental elements of portfolio management, such as risk profiling, suitability assessment, asset allocation, and rebalancing (Securities Commission Malaysia, n.d.).

Refer to Table 1.1, Securities Commission Malaysia has approved 8 companies with FRA license under DIM framework (Securities Commission Malaysia, 2023).

Table 1.1

8 Licensed Operators under Digital Investment Management (DIM)

No	Company Name
1	Akru Now Sdn Bhd
2	BH Global Fintech Solutions Sdn Bhd
3	GAX MD Sdn Bhd
4	Raiz Malaysia Sdn Bhd
5	StashAway Malaysia Sdn Bhd
6	UOB Asset Management Bhd
7	Wahed Technologies Sdn Bhd
8	Kenanga Investment Bank Berhad

Note. Adapted from Securities Commission Malaysia. (2023). *Digital Initiatives.*

Based on the DIM framework published by Securities Commission Malaysia, the key fund management activities that need to be performed by the FRA licensed operators as illustrated in the following figure 1.3. Exploring the key fund management activities reveals the essential steps that drive investment strategies of FRA. The DIM company aims to emulate the core activities typically performed by traditional fund managers through online access.

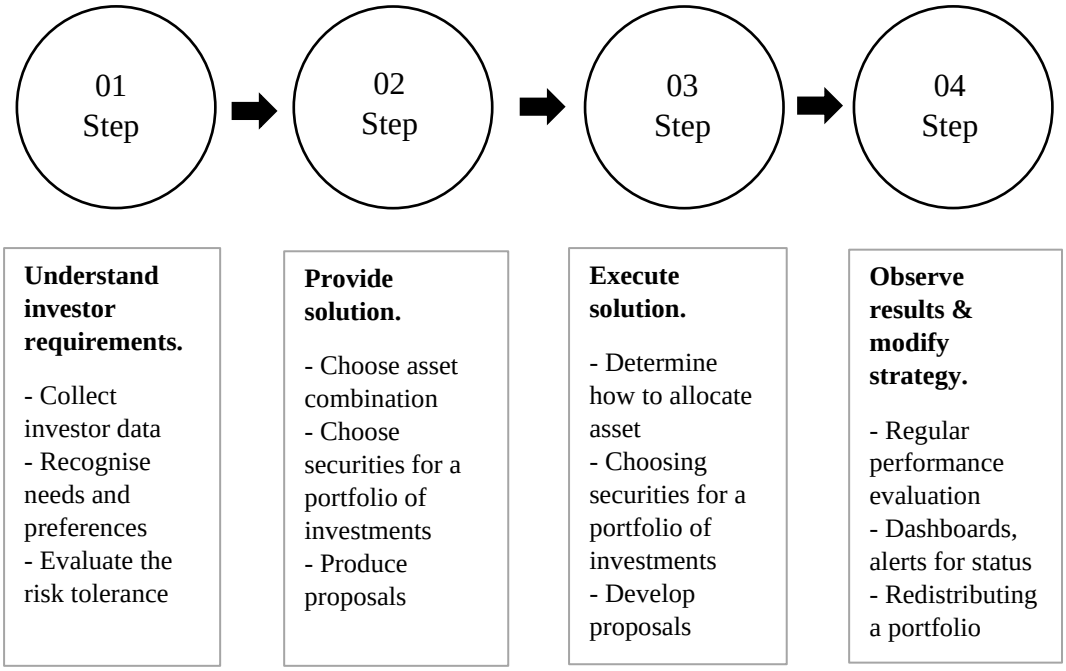

Figure 1.3. Key fund management activities of DIM company. Adapted from Securities Commission Malaysia. (2023). *Digital Initiatives.*

In 2020, the global Covid-19 outbreak has driven financial advisors to switch from physical to online interactions, and this has accelerated the digital technology adoption including FRA. In the upcoming years, the Malaysia FRA market is expected to continue to grow in terms of both assets under management and number of users (Nguyen et al., 2023). According to Statista (2023a), the FRA market in Malaysia is projected to increase at a rate of 11.78% per year, with assets under management reaching US$33.39 billion as illustrated in Figure 1.4 and number of users reaching 2.2 million as illustrated in Figure 1.5 by 2027.

Figure 1.4. Asset under management in Malaysia's Financial Robo-Advisory sector. Adapted from Statista. (2023a). *Robo-advisors- Malaysia.*

Figure 1.5. Number of Users in Malaysia's Financial Robo-Advisory sector. Adapted from Statista. (2023a). *Robo-advisors- Malaysia.*

1.3 Problem Statement

As introduced in the previous part, the Covid-19 pandemic accelerated the growth of Financial Robo-Advisory (FRA) globally. According to Nguyen et al. (2023), the global implementation of movement controls during the COVID-19 outbreak

caused significant disruptions to various businesses, including financial advisory services. Concerns regarding the need of personal financial planning for Malaysians are raised by the fact that such behaviours have not altered much since November 2019 and were obviously noticeable during the pandemic (Gan et al., 2021). As a result, traditional financial advice providers were obstructed in acquiring new clients due to the lack of price competitiveness and biases, prompting a shift to virtual meetings. FRA platforms have emerged as a substitute of traditional advisors for investors seeking guidance during these challenging times. This situation has expedited the adoption of FRA platform. It eliminates human intervention in automated processes, in conform to the recommendation by the World Health Organization as part of the digital technology response to the COVID-19 pandemic (Gan et al., 2021).

However, few research shows that investors that have used traditional financial advisory usually do not use FRA as they need interactions with humans to make financial decisions. According to Jung et al. (2017), the adoption of the automated investment advisory was not as fast as expected. A survey brought out by Rossi and Utkus (2020) shows 60% of traditionally advised respondents prefer to talk to an experienced advisor before investing, and 33% of them do not trust FRA in managing their investment portfolio. Question arises in methods to build confidence and trust when machines take over the task in providing services to the customers in the financial sector that used to be providing humanised services (Nourallah et al., 2022). This explained the situation of the increment of FRA users slowing down in several countries, especially in the US. With the data from Statista (2023b), although the United States has the highest number of recorded users of 12.622 million (Figure 1.6), and penetration rate of 3.8% (Figure 1.7), the future estimated numbers show slowing growths in both data.

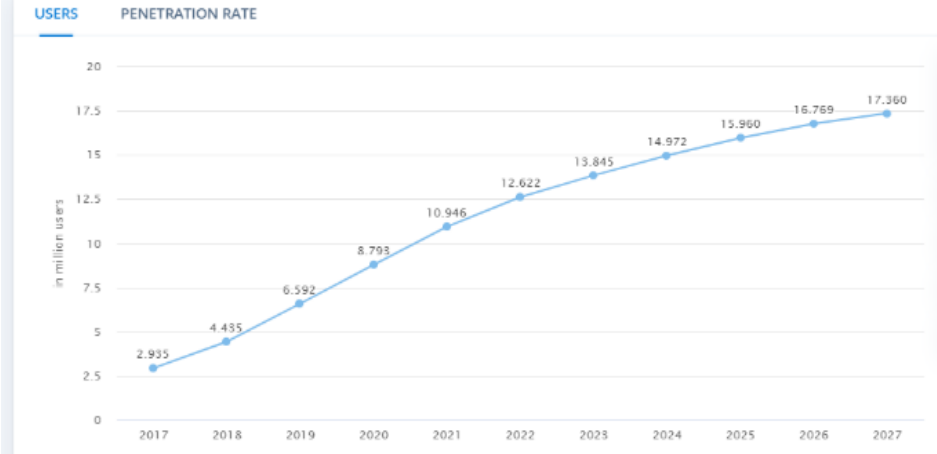

Figure 1.6. Number of users of Financial Robo-Advisory in the US. Adapted from Statista. (2023b). *Robo-advisors- United States.*

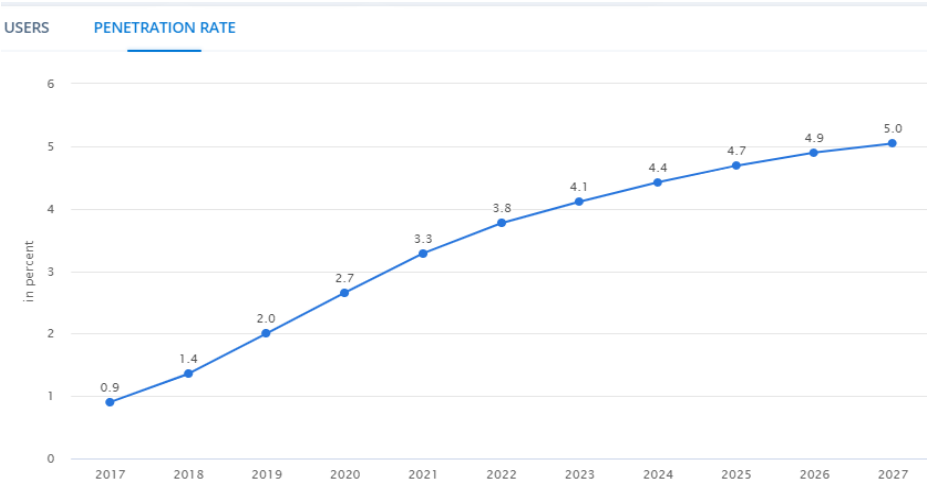

Figure 1.7. The penetration rate of Financial Robo-Advisory in the US. Adapted from Statista. (2023b). *Robo-advisors- United States.*

The situation is worse in Malaysia, as the number of users and penetration rate are unacceptably lower than most of the country. A study by Nourallah et al. (2022) compared Malaysia with Sweden on the adoption of FRA, as they think that both countries have stable banking sectors and are both making their way to a cashless society. Sweden recorded a 3.6% penetration rate (Figure 1.8), while Malaysia only had 0.582 million FRA users (Figure 1.9) with a penetration rate of 1.8% in 2022 (Figure 1.10). Moreover, a survey held by The Star in 2022 studies the preferences

of Malaysian investors. Among 1068 respondents, 63% of them prefer investing in Malaysia's equity market. However, more investors prefer directly investing into the stock market rather than using an FRA compared to the previous year (The Star, 2022).

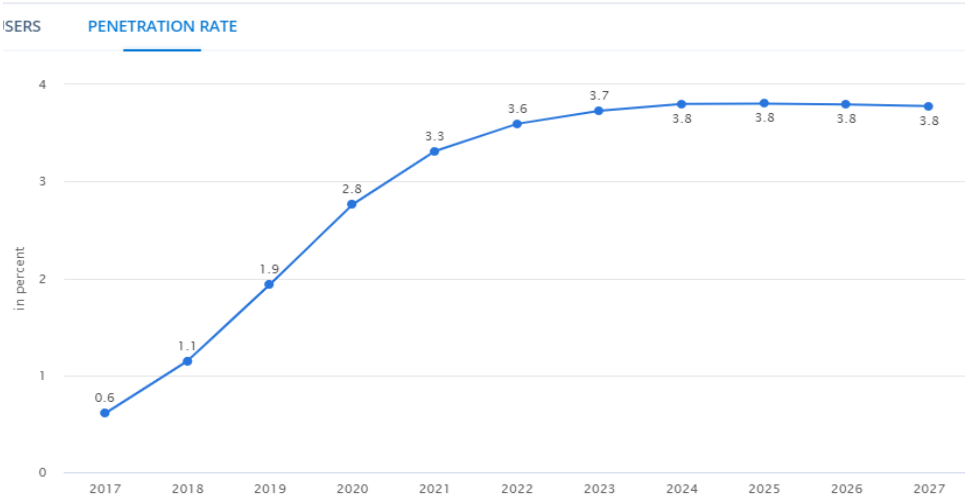

Figure 1.8. The penetration rate of Financial Robo-Advisory in Sweden. Adapted from Statista. (2023c). *Robo-advisors- Sweden.*

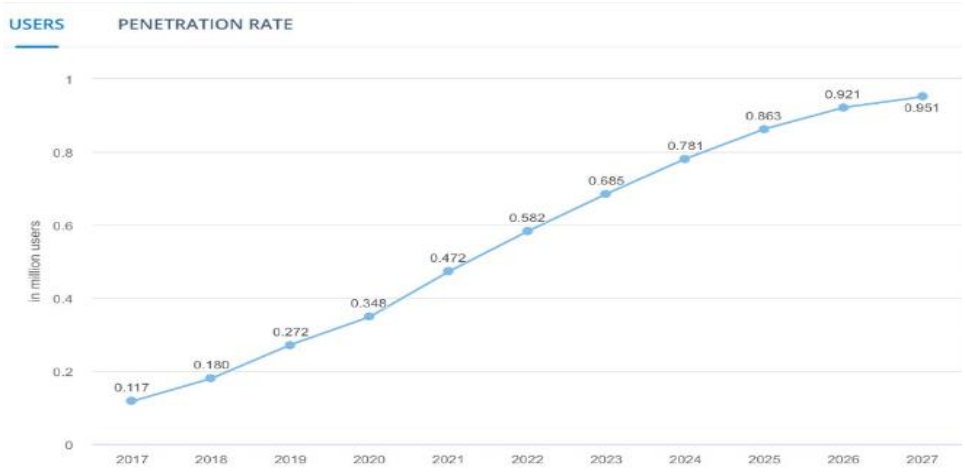

Figure 1.9. The number of Financial Robo-Advisory users in Malaysia. Adapted from Statista. (2023a). *Robo-advisors- Malaysia.*

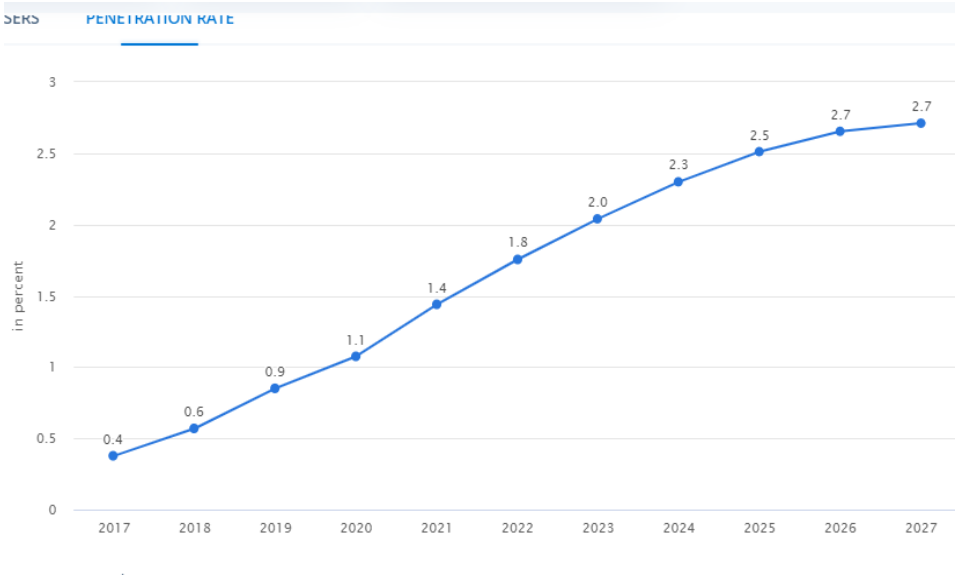

Figure 1.10. The penetration rate of Financial Robo-Advisory in Malaysia. Adapted from Statista. (2023a). *Robo-advisors- Malaysia.*

The low penetration rate of FRA in Malaysia compared to other countries raises our eagerness to conduct this study as using FRA is a solution to many known investing problems in Malaysia, including Behavioural Bias and Money Game Schemes. As introduced previously, FRA could bring several benefits to the individuals with investment desire and experienced investors. In Malaysia, one of the common problems of young investors is investing with behavioural bias. According to Nourallah (2022), FRA firms usually target young retail investors as their main customers as the age group (18-29 years old) were neglected by human financial advisors because they are low in income, lack investment ability and do not have the financial ability to hire an advisor. However, they are the people who need financial guidance because they have little experience making financial decisions.

Studies have proved that FRA helps individuals become healthy investors by lowering risk through automated portfolio diversification and removing behavioural bias (Bai, 2021). Young investors now have access to low-cost services as well as the chance to interact with and influence the stock markets with the automated services offered by FRA. When young and inexperienced retail investors make

investments on their own, their decision will be affected by some behavioural biases, including herding effect, disposition effect and overconfidence bias. They become less rational in making investment decisions when influenced by behavioural bias, which causes them to incur losses in the market (Bihari et al., 2022).

In addition, FRA provides inexperienced retail investors an option to make passive income, avoiding them into "money game" schemes that are well known in Malaysia. Money games usually trick people by using the propaganda term "high return investments", when individuals lose their capital in money games, they lose interest in making investments (Loanstreet, 2019). This causes a huge impact in the Malaysia equity market as the reducing number of investors may cause a reduction in market liquidity. Individuals have trauma on investing and hence keep their excessive income by themself. The lack of liquid cash flow limits the size and the growth of the Malaysian financial market, hence reduces the economic welfare in Malaysia when the growth of the equity market is slow.

To conclude, the purpose of this research is to study the determinants that affect the intention to use FRA in Malaysia, namely optimism, innovativeness, discomfort, insecurity and perceived usefulness due to the low penetration rate. These vital factors could encourage the financial market participants, especially those that are young and inexperienced to understand more about the market, increase their return on investments and learn to make the right investment decision at a lower cost.

1.4 Research Objective

General Research Objective

- To examine the determinants affecting the intention to use Financial Robo-Advisory (FRA).

Specific Research Objectives

- To study the relationship between discomfort and the intention to use FRA.
- To study the relationship between insecurity and the intention to use FRA.
- To study the relationship between innovativeness and the intention to use FRA.
- To study the relationship between optimism and the intention to use FRA.
- To study the relationship between the perceived usefulness and the intention to use FRA.

1.5 Research Questions

- What is the relationship between discomfort and the intention to use Financial Robo-Advisory (FRA) in Malaysia?
- What is the relationship between insecurity and the intention to use FRA in Malaysia?
- What is the relationship between innovativeness and the intention to use FRA in Malaysia?
- What is the relationship between optimism and the intention to use FRA in Malaysia?
- What is the relationship between perceived usefulness and the intention to use FRA in Malaysia?

1.6 Significance of study

The purpose of this research is to investigate the factors that influence the intention to use Financial Robo-Advisory in Malaysia. The findings have the potential to give significant insights and contributions to parties such as academia, regulators, and stakeholders.

1.6.1 Academia

This research might help academics that are looking into themes like Financial Robo-Advisory (FRA), Artificial Intelligence (AI), and Financial Technology (Fintech) by providing insights, comprehensive information and extensive knowledge. It focuses on investigating the reasons behind the low penetration rate of FRA usage in Malaysia and comparing it to other countries where FRA has gained more traction by incorporating Technology Readiness Index (TRI) and Technology Acceptance Model (TAM). Understanding this gap is crucial for identifying the barriers and challenges that prevent widespread adoption of FRA in Malaysia. It also has the potential to add to the academic literature on fintech and provide useful insights into customer behaviour and decision-making in the context of FRA.

1.6.2 Regulators and Government (Policy makers)

This research aimed to assist regulators and policy makers by providing the advanced knowledge and insights of the usage of the Financial Robo-

Advisory (FRA) in the financial industry. It facilitates information for regulators to recognise the existing condition of the FRA and the difficulties that individuals face if they want to adapt to the FRA. Therefore, the regulators and policymakers can take the research as reference in order to better facilitate policy decisions, promote consumer protection, foster market development, encourage competitiveness and innovation. As a result, this proactive approach in actively managing and monitoring the FRA can foster a conducive environment for FRA growth and contribute to Malaysia's overall financial sector development.

1.6.3 Stakeholders

The findings can provide several insights and contributions to stakeholders such as financial institutions, for example, it brings insights to financial institutions on how they can better design and market the Financial Robo-Advisory (FRA) to meet consumers' needs and preferences by identifying the relationship between technology and financial decision making. According to Blut & Wang (2020), Technology Readiness Index was able to provide the marketers with information on the clients who are most likely going to use particular technologies. Therefore, the financial institutions can develop various financial instruments or financial plans by using FRA to fulfill different needs.

1.7 Conclusion

Chapter 1 provided an overview of the foundation for the in-depth investigation of the determinants of the intention to use the Financial Robo-Advisory (FRA) in Malaysia. The background and context emphasised the emergence of Fintech which drove the development of FRA, highlighting the need for a greater comprehension of the factors that influence people's decisions to adopt financial robo-advisory and

its implications. FRA is the fully automated investment technique which aims to provide efficient user experiences, cheaper prices, and innovative investing techniques. Throughout the technique, FRA also has employed Artificial Intelligence (AI) into the automated financial management process to minimize human error, enhance prediction reliability and precision, and make financial information, advice, goods, and services easily accessible to the public at a lower cost.

Besides, the problem statement identified the current research gap, underlining the need for a detailed investigation of the low penetration rate of FRA use in Malaysia. This research has taken the United States and Sweden as the peer countries in comparison to the FRA penetration rate in Malaysia, while the United States has a 3.8% penetration rate, Sweden has a 3.6% penetration rate, and Malaysia has a 1.8% penetration rate. Thus, the research objective has been identified in order to provide a roadmap for our research, which is to examine the determinants affecting the intention to use FRA.

The significance of this study is also being discussed in this chapter. It brings comprehensive knowledge and extensive knowledge to academia, access the existing conditions of the FRA to policy makers, and provide FRA market's insights to stakeholders to better design and market the FRA as a product. Furthermore, the details of the variables and literature review will be discussed in the next chapter.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter will discuss the theories involved, Technology Readiness Index (TRI) and Technology Acceptance Model (TAM) in detail. Besides, the relationship between the independent variables, optimism, innovativeness, discomfort, insecurity and perceived usefulness are also being discussed towards the dependent variable, which is the intention to use Financial Robo-Advisory. Then, the conceptual framework will disclose a clearer relationship between the independent and dependent variables.

2.1 Theoretical Framework

2.1.1 Technology Readiness Index (TRI)

Technology Readiness Index was proposed by Parasuraman & Colby (2015) with the support of Rockbridge Associates to comprehend attitudes and behaviours of individuals associated with technology and observe the technology behavior trend. According to Parasuraman (2000), TRI was developed by considering the technology eight paradox established by Mick and Fournier (1998) based on the qualitative study on people's attitudes to technology. From the eight-paradox technology, Parasuraman concludes the eight paradoxes to two aspects, which are stimulators or inhibitors.

TRI is an individual-level trait that does not shift suddenly in response to a stimulus or vary in the short term. Higher Technology Readiness levels are associated with more utilization of cutting-edge technology, higher adoption rates, and higher perceived ease of use (Parasuraman & Colby, 2015). It analyses consumers' mental readiness for technology, positively or negatively (Parasuraman & Colby, 2015). The four dimensions of technology readiness are two motivators, optimism and innovativeness, and two inhibitors, discomfort and insecurity (Flavián et al., 2021).

Optimism is a positive view on technology and believing it provides individuals with more control, flexibility, and efficiency in their life. While innovativeness is a tendency of being an innovator and thought leader in technology is a trait of innovation. In terms of two inhibitors, discomfort means the perception of a lack of control over it in a sense of technological overwhelm, and insecurity means a mistrust of technology that is caused by scepticism about its reliability and worries about any potential negative effects. Optimism and innovativeness are "motivators," helping to TRI, while discomfort and insecurity are "inhibitors," diminishing from it (Parasuraman & Colby, 2015).

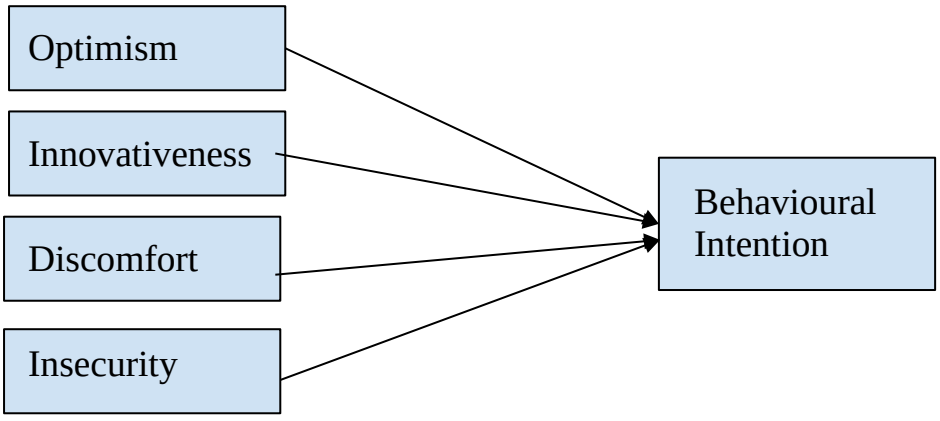

Figure 2.1. Technology Readiness Index. Adapted from Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of service research*, *18*(1), 59-74.

2.1.2 Technology Acceptance Model (TAM)

TAM is the model that is being developed by Davis (1989) aims to describe the behavioral intention of potential users to utilize the advanced technology. The model was being established on the theory of reasoned action (TRA), the psychological theory that attempts to interpret human behaviour. According to Marangunić & Granić (2015), Davis updated his model throughout later experimental rounds in order to add new variables and adjust the linkages that were first created. Similarly, other scholars have applied and proposed a number of changes to TAM.

TAM may significantly explain customer acceptance of a variety of technologies, making it one of strongest frameworks for analysing customers' behaviours towards technical developments (Belanche et al., 2019). The model consists of two dimensions which are perceived usefulness and perceived ease of use. According to Davis (1989), perceived usefulness is the individual's belief that employing new technology would increase or improve his or her performance while perceived ease of use refers to the degree to which a person thinks utilising a specific technology would be effortless. The perceived usefulness, one of the variables from the theory, is being incorporated as additional independent variables for this framework. This characteristic may have a favourable impact on behavioural intentions towards Financial Robo-Advisory (FRA).

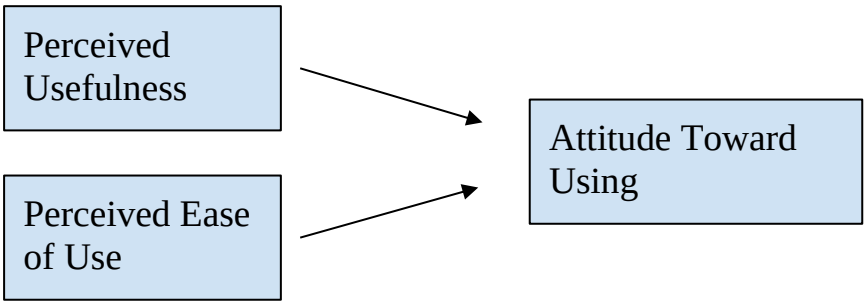

Figure 2.2. Technology Acceptance Model. Adapted from Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology).

2.2 Literature Review on Dependent Variable

Intention to Use Financial Robo-Advisory (FRA)

Literally, intention refers to the underlying purpose or motive behind an action or decision. Intention to use FRA, refers to the motivation to encourage an individual's willingness to use FRA. In order to assess the intention to use FRA, a lot of past studies have been conducted to identify the predictors of the intention to use Artificial Intelligence (AI) related services and explain the relationship between the predictors and the intention to use. A number of AI adoption researchers have recommended the Technology Readiness Index (TRI) as a workable framework, hitherto unexplored in this innovative environment (Mende et al, 2019; Flavián et al., 2021; Ma et al., 2022; Gao et al., 2022; Yin et al., 2023). Besides, according to Belanche et al. (2019), Technology Acceptance Model (TAM) is also being recognised as one of the greatest frameworks to investigate users' reactions to technological innovation as it can simply explain and considerably extend consumers' intention behaviour (Lee et al., 2020; Zhong et al, 2022; Lim & Zhang, 2022; Sohn & Kwon, 2020).

2.3 Literature Review on Independent Variable

2.3.1 Discomfort

Discomfort is the perceived lack of control over technology and the feeling of being overpowered by it (Walczuch et al., 2007). Discomfort was defined as the degree of the technology's distrust, resulting from doubts about its functionality and worries about its negative effects (Flavián et al., 2021). A sense of a lack of control or ability in dealing with technology might lead to the rejection of innovations (Flavián et al., 2021).

In summary, the majority of the studies shows that discomfort can reduce the intention to use Financial Robo-Advisory (FRA) or any related Financial Technology (Fintech) services. Walczuch et al. (2007) mentioned that people who have a high level of discomfort believe technology to be more complicated and consequently more difficult to employ. In short, people who score high in discomfort tend to not adopt the new technology as they may feel suffering. Shirahada et al. (2019) has carried out studies in the United Kingdom and Japan on the impact of discomfort towards the intention to use self-service products like FRA and the result showed the increase of the level of discomfort can decrease the intention to use. Salim et al. (2022) also developed the same result as Shirahada et al. (2019), indicating high discomfort normally caused by people's bias on the new technology when they are dealing with complex and difficult advanced technology. While Alharbi & Sohaib (2021) mentioned that individuals may experience uncertainty in using Fintech related services, in fact, information feedback may make technology easier to use.

However, Flavián et al. (2021) has carried out studies on impact of discomfort towards the intention to use FRA on communities in North

America and the result shows that discomfort did not negatively affect the intention to use but it is positively related. Discomfort was being categorized as inhibitors which means the high levels of discomfort will reduce the using intention. Yet, in the research carried out by Flavián et al. (2021), discomfort was positively associated with the intention to use. They provided the explanation on the result, that the individuals who experience greater degrees of technological discomfort may embrace Artificial Intelligence (AI) systems more enthusiastically since automation eliminates the need for learning and dealing with difficult technological procedures.

2.3.2 Insecurity

Insecurity was being defined as the distrust in technology and scepticism about its capacity to function effectively (Parasuraman, 2000). It means that the individuals with high insecurity are worried about technology and its capacity to operate. Similarly, insecure persons are less inclined to explore new experiences and are more likely to struggle with self-efficacy and self-esteem. When presented with new obstacles such as learning a new kind of technology, people are more subject to encounter troubles or just desire to avoid something new entirely. (Akhtar & Khawaja, 2018).

All of the related research studies on insecurity towards intention to use Financial Robo-Advisory (FRA) or Financial Technology (Fintech) related technology are showing significant negative relationships. Flavián et al. (2021) studies explained that the basic knowledge of Artificial Intelligence (AI) is one of the factors contributing to the level of insecurity. While similar research also being conducted by Shirahada et al. (2019) applied on online public self-service technologies, mentioned that the feelings of insecurity drive by low confidence level towards the new technology and worries of other parties stealing their personal information. Similar result

shown on the indication on the intention to use on Fintech products. Alharbi & Sohaib (2021) further add on the reason of high insecurity may be resulted from the issues of insecurity and privacy. Salim et al. (2022) also explained that the feeling of insecurity oftenly being arise from anxiety as well as pessimism. It begins by predicting the harm that might be produced by using this new technology, and it has a negative impact on its perceived value and benefit.

2.3.3 Innovativeness

Innovativeness has been defined as the degree of the innovativeness of the customers on the view of technology performance. Innovative customers usually have a positive view of technology performance even when its prospective value is uncertain (Flavián et al., 2021). According to Lu et al. (2005), they described that highly innovative people are constantly on the lookout for fresh ideas as well as fresh and new technology. While Hu et al. (2019) defined innovativeness as individuals' willingness to explore new goods, technology, or services. Individuals that are highly inventive can tolerate a high level of uncertainty and have a more favourable desire to implement the invention. In other words, they are less sensitive to identify hazards and more open to technological advancement. Setiawan et al. (2021) also described technology innovativeness in relation to Fintech as an ambition to try new technologies, to be a pioneer in using the latest technology, and to experiment with Fintech services.

Most of the research has developed a result of innovativeness that tends to have a positive relationship with the intention to use. According to Cruz-Cárdenas et al. (2021), innovativeness is a kind of attitude that encourages an individual to act as the first one to use the new technology. In other words,

in order to be an early adopter of technical goods and services, the individual must be the first one to recognise the technology's advantages. Same result goes to Salim et al. (2022) finding, they further explained the early adopters of new technology, they also inspire and influence others to do the same which is attributed to innovativeness characteristics. Highly innovative individuals oftenly like to discuss and even offer advice regarding the particular new technology as well as attracting others to purchase new products and services using advanced technology. Alharbi & Sohaib (2021) have investigated the relationship between the Fintech product, the cryptocurrencies with the user intention to adopt. They stated that early adopters of technology appreciate innovation, even though it doesn't immediately seem to have any advantages.

But Flavián et al. (2021) gets a different result other than significant. Their result showed that the individual's level of innovation has no significant effect on their use intentions on financial robo-advisory. The reason behind was being provided, that is the growing number of robo-advisors is not primarily driven by clients' technological innovation. Perhaps, in such a changing economy, the most innovative customers are seeking for even more creative investing options, such as cryptocurrency and/or crowdsourcing. Because robo-advisors diminish clients' participation through technology, they may attract less innovative clients.

2.3.4 Optimism

Optimism, as the driver of TRI, is the degree of the favourable opinion on the specific technology and the perception that it gives users more control, flexibility, and efficiency over their lives (Parasuraman, 2000; Flavián et al., 2021). In short, optimism is "the predisposition to trust that one will

typically have beneficial life results" (Peter et al., 2010). Peter et al. (2010) also summarized that high optimism tends to increase positive affect and well-being, more resistance to uncertainty events and better health. A technology optimist believes that new technologies will provide individual with greater control, flexibility, and efficiency in their life (Parasuraman, 2000), which indicates that they have a predetermined favourable perspective of new technology before being exposed to it (Acheampong et al., 2017).

This concept may be used in Artificial Intelligence as people may view it as either "heaven" or "hell" (Kaplan & Haenlein, 2020). According to Flavián et al. (2021), they conducted research on North American-based potential customers showing that the optimistic technology users perceive FRA as a functional and trustworthy method, ignoring the potential bad consequences. Besides, based on Oehler et al. (2021) research towards undergraduate students, the individuals that with high degree of optimism tend to have high intention of willingness to use FRA. It is also mentioned in the research of Salim et al. (2022) on the intention to adopt blockchain technology, stating that optimism has also been connected to productivity, optimistic technology users are frequently convinced that new technologies will help them accomplish their work faster or with less effort, which encourages adoption.

2.3.5 Perceived Usefulness

Perceived usefulness was developed from technology acceptance models and can be defined as the degree to which a person believes that using a particular system would enhance his or her job performance (Davis, 1989).

In summary, the majority of research came to the conclusion that perceived usefulness has a favourable effect on an individual's willingness to use Financial Robo-Advisory (FRA) or Financial Technology (Fintech) related services. Flavián et al. (2021) mentioned that potential users should view robo-advisors as simple to use as well as helpful to their financial management. Chung et al. (2023) studies also explained that perceived usefulness is the crucial variable in predicting the user's intention. Seiler & Fanenbruck (2021) also developed the results pointing to perceived usefulness being the most important drivers of the intention to use a financial robo advisory.

However, the opposite result by Belanche et al. (2019) revealed that perceived usefulness has no significant impact on influencing the user' intention. The reason behind is the research also included individuals who have no prior experience with FRA. There are many past studies that revealed that the perceived usefulness is much higher after the individuals accept the technology (Bhattacherjee, 2001; Casaló et al., 2010; Mou et al. 2017; Daneji et al., 2019).

2.4 Conceptual Framework

The conceptual framework is constructed with reference to the investigations done by Flavián et al. (2021) and Belanche et al. (2019). Flavián et al. (2021) has conducted research to investigate the factors which will influence the individual's intention to use analytical Artificial Intelligence (AI) investment services in North America. The factors being investigated include optimism, innovativeness, discomfort, and insecurity. Besides, Belanche et al. (2019) also conducted research on the intention to use Financial Robo-Advisory (FRA) with other determinants which is perceived usefulness in North America, British and Portuguese. The

researchers hypothesized a significant relationship between each of the five parameters and individuals' intention to use FRA.

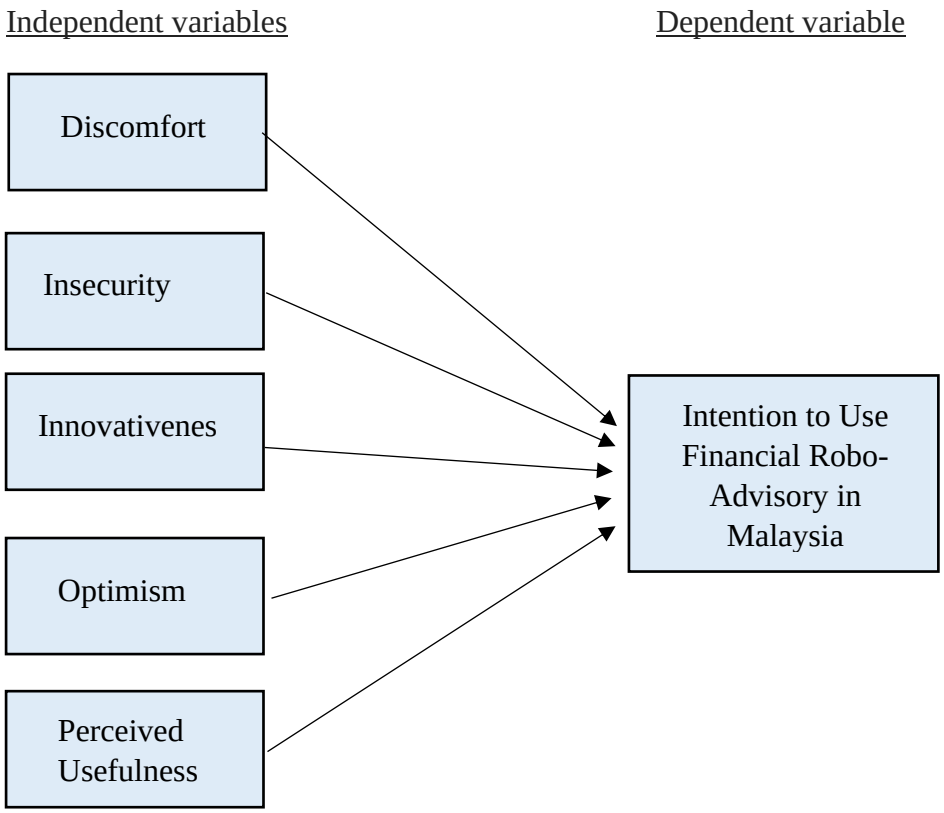

Figure 2.3. Conceptual Framework. Develop by the authors.

2.5 Hypothesis Testing

Upon the introduction of the relationship between the dependent variable and the independent variables, the hypothesis was developed in order to test the significance of the relationship between the dependent variable and the independent variables.

H_0: There is no relationship between discomfort and intention to use Financial Robo-Advisory (FRA) in Malaysia.

H_1: There is a relationship between discomfort and intention to use FRA in Malaysia.

The level of discomfort serves as an inhibitor which can affect the intention to use FRA in Malaysia as it refers to a sense of being out of control of technology and being overpowered by it (Parasuraman & Colby, 2015). It is expected that there will be a negative relationship between discomfort and intention to use FRA. Innovative systems may be rejected because of a lack of control or technological competence. People who feel anxious or uncomfortable using robots for investment decisions may reject or avoid FRA services. (Flavián et al., 2021).

H_0: There is no relationship between insecurity and intention to use FRA in Malaysia.

H_1: There is a relationship between insecurity and intention to use FRA in Malaysia.

Insecurity of the individuals serves as an inhibitor as it negatively affects the intention to use FRA. It is expected that there will be a negative relationship between insecurity and intention to use FRA. According to Parasuraman and Colby (2015), it refers to distrust of technology, resulting from doubts about its functionality and worries about its negative effects. People are less inclined to accept the technology if they are more uncertain about the threats of FRA services.

H_0: There is no relationship between innovativeness and intention to use FRA in Malaysia.

H_1: There is a relationship between innovativeness and intention to use FRA in Malaysia.

The willingness to explore new technology is referred to as innovativeness. It is expected that the positive relationship between innovativeness and intention to use FRA in Malaysia will be significant. Innovative individuals have a greater tendency to use FRA services and other new financial technologies. People who are highly innovative tend to have open-mindedness and a willingness to adopt cutting-edge

products and services even if it has an uncertain future usefulness (Flavián et al., 2021).

H_0: There is no relationship between optimism and intention to use FRA in Malaysia.

H_1: There is a relationship between optimism and intention to use FRA in Malaysia.

A person's level of confidence in their ability to use technology is referred to as optimism. It is anticipated that optimism and intention to use FRA would be positively correlated. Optimistic consumers have positive attitudes towards new technology, while passionate investors seek innovative investment options in the financial sector. (Flavián et al., 2021). Confident technology users are more likely to use FRA services efficiently.

H_0: There is no relationship between perceived usefulness and intention to use FRA in Malaysia.

H_1: There is a relationship between perceived usefulness and intention to use FRA in Malaysia.

Perceived usefulness refers to the extent to which the individual believes the technology. It is expected that perceived usefulness will positively affect the intention to use FRA. An individual is more likely to have a favourable attitude towards using the FRA service and be more eager to utilise it if they believe that it would be helpful, and vice versa (Shahzad et al., 2022).

2.6 Conclusion

In conclusion, Chapter 2 of this research has delved deeply into the theoretical framework used, literature review on the variables and also development of the hypothesis. This chapter firstly has provided the solid foundation on the development of the conceptual framework by reviewing the theoretical framework which is Technology Readiness Index (TRI) and Technology Acceptance Model (TAM). The conceptual framework consisted of these 5 variables which are optimism, innovativeness, discomfort, insecurity, and perceived usefulness. Secondly, the literature review and the definitions on the dependent variable, intention to use Financial Robo-Advisory (FRA) and the independent variables, optimism, innovativeness, discomfort, insecurity, and perceived usefulness were also being investigated to identify and highlight the relationship between them.

Lastly, the hypothesis was being developed to drive research investigation by incorporating the sign of the relationship. In summary, the optimism, innovativeness, perceived usefulness will have positive relationship with the intention to use FRA in Malaysia, while discomfort and insecurity will give negative relationship with the intention to use FRA in Malaysia.

This chapter sets the stage for the empirical investigation that follows in future chapters by contextualizing the research within the larger academic discussion, and the next chapter will discuss the methodology of this study.

CHAPTER 3: METHODOLOGY

3.0 Introduction

In this chapter, the authors will outline the specific research design, sampling design, research instrument, and proposed analytic technique that will be utilized to answer the research questions mentioned in Chapter 1. Above all, this chapter is primarily concerned with gathering, processing, and analysing the data to determine the relationship between the variables.

3.1 Research Design

Research design is the blueprint to execute a study, consisting of an overall approach to test the hypothesis and answer specific research questions through data collection, interpretation, analysis, and discussion (Jaiswal, 2023). In this study, the quantitative method was used to acquire numerical data for statistical analysis in order to quantify and summarise the findings (Bhandari, 2022a). In accordance with Gaille (2019), quantitative research provides reliable insight into decision-making because the results can be tailored to specific requirements.

3.2 Data Collection Method

Primary data, also known as unprocessed information, comprises information obtained directly from the source in a non-threatening manner (Kabir, 2016). In this research, primary data will be collected from the sample population via survey questionnaire. As mentioned by Khuc & Tran (2021), this result is more pertinent because the unmediated information acquired was collected specifically for research purposes, as opposed to secondary data derived from existing sources. This method has been utilised extensively in financial robo-advisory research (Flavián et al., 2021; Salim et al., 2022; Belanche et al., 2019; Yi et al., 2023).

3.3 Sampling Design

Sampling design is the roadmap for choosing a representative survey sample from a population of interest for statistical analysis (Rashid, 2022). In addition, Stephanie (2023) asserts that sampling design is a mathematical function that provides the probability that any particular sample is being selected. Sampling design is crucial because it ensures the sample can conclude the overall population (Survey Monkey, n.d.). In the upcoming subsection, a comprehensive explanation of the sampling technique, targeted respondents, sampling location, and the determined sample size of this study will be discussed further.

3.3.1 Sampling Technique

This study will be conducted using a probability sampling method. Using this method, authors are able to derive statistically sound conclusions that accurately represent the entire population by randomly selecting small

samples from a large existing population (McCombes, 2023). In accordance with this probability sampling technique, the questionnaire will be distributed using a simple random sampling method. A simple random method suggests selecting the sample from the entire population at random. Without favouritism, each member of the population has an equal opportunity to be selected (Fleetwood, 2023). Although this method is easy to implement and highly representative of the population, it takes longer to collect a large sample size (Glen, 2021).

3.3.2 Targeted Respondents

The participants of this study consist of individuals who are Malaysian citizens and now reside in the Klang Valley region. The age range of the respondents is between 18 and 29 years. According to the Department of Statistics Malaysia (2020), approximately 25 percent of Malaysia's population age falls between 15 and 29, contributing to the second-largest age group in Malaysia (Appendix 3.1). Specifically, statistics indicate that people aged 18 to 34 make up the largest proportion of early tech adopters ("YouGov analysis," 2020), people aged 20 to 30 make up the largest group of internet users (Statista, 2022a), people aged 24 to 34 have the highest level of trust in robo-advisors (Statista, 2022b), and people aged 15 to 29 make up that 45 percent of total population owns a smartphone (Malaysian Communications and Multimedia Commission, 2021).

The first reason this research decided to frame the age range between 18 and 29 is that, according to Nourallah et al. (2022), young individuals aged between 18 and 29 with limited investment experiences will most likely use financial robo-advisory. Secondly, the Security Commission of Malaysia

(SC) requires that investors should be at least 18 years old to establish a financial robo-advisory (FRA) trading account (Nguyen et al., 2023). Above all, Nourallah (2021), Aggarwal et al. (2023), and Nourallah et al. (2022) also focus on this age group in their fintech-related research in Malaysia.

3.3.3 Sampling Location

Klang Valley was selected as a sampling location because, according to Siva (2021), this city is projected to become a global technology centre on account of its robust infrastructure and vast talent pool. Due to its large population of early-tech adopters, this city plays a crucial role in functioning as a laboratory for innovators to demonstrate their innovations. Specifically, the majority of robo-advisor service providers have set up headquarters in this city. Accordingly, an investor can directly visit the office whenever an error or problem arises on the platform.

Besides, according to Aman (2023), Kuala Lumpur and Selangor have the most advanced technology, with 5G network coverage exceeding 90 percent in the popular region. Internet network coverage is essential because it enables investors to receive prompt responses. Furthermore, more than one-fifth of Malaysia's population resides in Klang Valley, making it one of the most developed regions in Malaysia (Lau et al., 2020).

3.3.4 Sampling Size

Sample size refers to the minimum number of the target respondent involved in research to represent the whole population. In line with (Faber & Fonseca, 2014), determining an accurate minimum sample size is crucial because it will directly influence research findings. Generally, a larger sample may help in determining a more precise result. However, if the minimum sample size is too large, it may waste resources and be time-consuming. Whereas if the minimum sample size is too small, the result may become unscientific and unethical since it may underestimate the effect (Andrade, 2020).

Based on Boomsma (1985), for Structural Equation Modelling (SEM) analysis, it is recommended to use a heuristic minimum sample size of 100 to 200 samples. Since the population of the target respondent contributes to one over four of the entire population, hence, the minimum sample size of this research is account to 200, which is close to (Shaikh et al., 2020; Rahman et al., 2018; Alwi et al., 2021).

3.4 Research Instrument

Research instruments refer to any specific tools used by the researcher in obtaining, measuring, and analysing the data in the research of interest. In this study, quantitative data is processed using an online survey questionnaire (Google Form) since it is timesaving, cost-effective, and capable of reaching participants anywhere (Wright, 2006).

Using a Google form, a self-administered questionnaire will be distributed to collect first-hand, sincere opinions. The questionnaire contains seven sections in total. Before answering the questionnaire, participants will be provided with a concise explanation of the automated algorithm of financial robo-advisory and an acknowledgment notice of the Personal Data Protection Act (PDPA). Section A will consist of questions regarding age and gender. Section B relates to the dependent variable, whereas Sections C through G correspond to the independent variable. Both independent and dependent variables will be measured using a 5-point Likert scale that ranges from 1 (Strongly disagree) to 5 (Strongly agree). Contrarily, demographic questions are answered using multiple-choice and short-answer formats.

The modified questions are based on the Technology Readiness Index (TRI) developed by Parasuraman (2000) and Parasuraman & Colby (2015) and the Technology Acceptance Model (TAM) developed by Davis in 1989. To ensure that respondents can make accurate judgements, clear and straightforward language will be used. From 1 June to 30 June 2023, the online Google Form will be distributed via multiple social media channels, including WhatsApp, Facebook, Instagram, Telegram, and Facebook Messenger. A pilot study will be conducted to ensure that the questionnaire is reliable and ready to answer the research questions.

3.5 Measurement Scales

In statistics, levels of measurement are used to classify, define, and measure the nature of the data. It plays a vital role in data collection, analysis, and presentation because it aims to provide a framework for understanding the properties and relationships between various types of data. According to Mishra et al. (2018), different types of recording tools during data collection and statistical tools during

data analysis may change according to the different data types. The proper and appropriate use of measurement scales is crucial because it enables researchers to obtain the most valid and reliable results (Reading Craze, 2017) and makes it easier for the researcher to present the summary of the findings simultaneously. As Stevens (1946) proposed, there are four widely recognized measurement scales: nominal, ordinal, interval, and ratio. This study will classify data using only nominal, ordinal, and ratio scales.

3.5.1 Nominal Scale

This study's demographic questions, including gender, age, and yes or no questions, are measured using a nominal scale. A nominal scale provides information regarding non-numerical data based on an identifier. It aids in identifying the specific characteristics of a variable without assigning a numerical value to the variable (Kumar, 2023). In most instances, it is used to designate and classify variables, groups, or classes without any inherent order implied for descriptive comparison (Reading Craze, 2017). Typically, gender, religion, ethnicity, nationality, and marital status are the most prevalent examples. In particular, a researcher usually designates the gender as either 0 or 1; 1 indicates male, and 0 indicates female vice versa. However, 1 does not demonstrate superiority over 0, and 0 does not imply inferiority over 1. Both 1 and 0 represent distinct categories in this instance.

3.5.2 Ordinal Scale

This study measures education level, dependent variable, and independent variable using an ordinal scale. The ordinal scale identifies and classifies the data in a particular order. Although the value is ranked or rated, there is no information regarding the distance between any two values. In other words, this scale does not classify values according to fixed intervals (Reading Craze, 2017). Similar to the ordinal variable, this scale's values cannot be added, subtracted, multiplied, or divided, nor can the difference between each value be quantified. The most common examples are frequency, degree of agreement, and satisfaction. In this particular situation, it is evident that one value is greater and superior to another. This scale, however, cannot determine if the distance between 2 and 3 is equal to the distance between 3 and 4.

3.5.3 Ratio Scale

Absolute scales, also known as ratio scales, contain all the characteristics of four measurement scales. In this study, income is measured using a ratio scale. With an actual zero point on a uniform interval scale, the ratio scale can provide meaningful information about the magnitude of differences compared to other scales. The zero point signifies that the data has no value and represents the absence of the measured attribute (Bhandari, 2022b). Ratio scale data enable any mathematical calculations and advanced statistical techniques in analysis. Weight, height, and income are the finest variables that can be measured on a ratio scale due to their absolute zero point and inability to attain negative values.

3.6 Pilot Test

Prior to finalizing the preliminary research questionnaire, the purpose of the pilot study is to determine the reliability of the rephrased questionnaire and identify any areas of perplexity. It is essential because it helps ensure that the research is on the right track and identifies potential issues prior to actual data collection. For instance, correct the grammatical error, rearrange the question order, and restructure the sentences to be more transparent and direct. By conducting this test, researchers may acquire experience in data processing and be able to rectify any potential flaws in the actual study (In, 2017). Several analyses, including Outer loadings, Average variance extracted (AVE), Cronhach's alpha, and Composite reliability (CR), will be conducted to determine the reliability of the questionnaire. In order to acquire an instantaneous result, 30 pilot test respondents will be collected as a considerable ratio from the people surrounding the researchers.

3.7 Proposed Data Analysis Technique

This study will conduct the Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis with Smart PLS software. PLS-SEM is a proper statistical technique for evaluating complex theoretical cause-effect relationships between multiple constructs in a structural model and assessing the model's capacity to explain the target constructs (Hair & Alamer, 2022). In this study, the researchers aimed to assess both the latent and observable variables in order to ascertain the magnitude of the associations between the target constructs and test the research

hypotheses concurrently. This approach is generally considered because it does not necessitate normally distributed data. Thus, researchers can still obtain reliable results and insights despite the small data size without transforming it. Second, PLS-SEM is particularly valuable when small sample sizes are involved. This is helpful because it allows this study to gather a small sample within one month. Lastly, PLS-SEM is also easily adaptable to composite instruments. In other words, PLS-SEM can combine all individual items to measure the constructs accurately. This enables researchers to obtain a more comprehensive view of the construct under study, as this research consists of five constructs and eight items per construct (Hair et al., 2014). Under this method, measurement model analysis will be utilized to test the measurement model, while structural model analysis will be used to measure the structural model.

3.7.1 Descriptive Analysis

Descriptive analysis is a technique for summarising, describing, and visualizing the primary characteristics of a raw numerical dataset that represents either a small sample or a whole population. It provides a clear and concise overview of the data by converting the raw data into graphical information to generate valuable research insight. Histograms, bar charts, and pie charts are data's most familiar visual representations. Thus, the researcher and audience can readily interpret, communicate, conclude, and comprehend a specific dataset's distribution, tendency, and variability (Hayes, 2023). In this study, a descriptive analysis will be used primarily to determine the distribution of gender, income level, education level, and other demographic variables by number and percentage.

3.7.2 Measurement Model Analysis

Measurement model analysis refers to assessing the reliability and validity of each items to represent or measure the construct in a structural equation modeling (SEM) study. Generally, there are two types of measurement models, namely, reflective and formative. In this study, a reflective model has been employed since the construct manifests all the items. Compared to the formative model, the reflective items are interchangeable and must be highly correlated since they share a common theme. To ensure that the construct can contribute a meaningful conclusion to the path model, all the reflective items will go through a reliability and validity assessment, including indicator reliability, convergent validity, internal consistency reliability, and discriminant validity (Hanafiah, 2020).

Outer Loadings

The Outer loadings measure an indicator's reliability to represent its constructs. A high Outer loadings value may indicate that the indicator is reliable. In contrast, a low Outer loadings value may suggest that the indicator does not adequately represent the construct in the measurement model. Based on Yana et al. (2015), an ideal Outer loadings value should be 0.7 and above, however, values 0.6 to 0.7 are acceptable. On the other hand, as founded by Hair et al. (2021), any value greater than 0.708 is deemed an endorsed value because it indicates that the specific construct can account for 50% of the variance of each indicator. Conversely, any indicator with an Outer loadings value below 0.40 should immediately be eliminated from the model. Indicators between 0.40 and 0.708 will be temporarily removed from the model in preparation for a recalculation. If the removed indicator demonstrates a substantial increase in Average Variance Extracted (AVE) or Composite Reliability (CR), it may be necessary to remove the indicator; otherwise, it may not.

Average Variance Extracted (AVE)

Average Variance Extracted (AVE) is a common measurement of convergent validity. According to Benitez et al. As indicated by Hair et al. (2021), AVE is the average value of the squared Outer loadings of the construct-related items. As Sarstedt et al. (2017) stated, an AVE value equal to or exceeding 0.5 demonstrates that the construct can explain a minimum of 50% of the variance in the items. In other words, a high AVE may suggest that the indicators measure the same construct, showing a high convergent validity.

Cronbach's Alpha

Cronbach's Alpha is a widely recognised measure of internal consistency reliability developed by Cronbach (1951). According to Tavakol & Dennick (2011), Cronbach's Alpha typically ranged from 0 to 1. A greater Cronbach's Alpha value may indicate that the item is of superior quality and reliability when measuring the same construct. According to the rule of thumb of Cronbach's Alpha developed by (George & Mallery, 2003), an Alpha value greater than 0.90 suggests excellent internal consistency, whereas any value below 0.50 is unacceptable and should be revised or eliminated. On the other hand, Hair et al. (2021) assert that an idea's Cronbach's Alpha should lie between 0.8 and 0.9, and the minimum should be at least 0.7 or 0.6 in exploratory research.

Composite Reliability (CR)

Composite reliability (CR) is a widely employed measurement for assessing the internal consistency reliability in Partial Least Squares Structural Equation Modelling (PLS-SEM), which was initially devised by Joreskog in 1971 (Hair et al., 2019). Comparable to Cronbach's Alpha, it evaluates

the consistency of an item to determine the reliability of the items. Composite reliability is typically between 0 and 1. The higher the values, the greater the reliability. According to (Hair et al., 2021), any value between 0.70 and 0.90 is considerable. Values above 0.95 are problematic and may compromise the validity. Therefore, a value of 0.7 or greater is permissible in this research.

Heterotrait-Monotrait Ratio of Correlation (HTMT)

By estimating the strength of correlations between constructs, discriminant validity in Structural Equation Modelling (SEM) examines whether a construct is legitimately distinct from another. Heterotrait-monotrait ratio of correlation (HTMT) is computed in line with Hair et al. (2019) by comparing the mean value of the indicators measured on the same construct to the average correlation of indicators across different constructs. In keeping with Henseler et al. (2015), when accessing HTMT in a variance-based SEM, the researcher can either compare to a threshold or construct a confidence interval. If the constructs are similar, any HTMT value greater than the 0.90 threshold in the first method indicates that discriminant validity does not exist. In contrast, if the constructs are not similar, Hair et al. (2019) suggest a threshold of 0.85. In the second method, researchers can construct a 95% confidence interval of HTMT to determine if the upper bound is substantially less than a predetermined threshold, such as 1, 0.90, or 0.85. The HTMT value is close to or greater than 1, indicating a potential discriminant validity issue. As proposed by Henseler et al. (2015), HTMT is a superior alternative when measuring discriminant validity because Fornell-Larcker and Cross loadings have a low sensitivity to uncover discriminant validity problems due to their characteristics.

Cross Loadings

The Cross loadings is another liberal measure of discriminate validity in factor analysis. As stated by Henseler et al. (2015), Cross loadings refers to the relationship of each item in measuring with different constructs. Ideally, the Outer loading value of each item of its particular underlying construct must be higher than all another construct. In other words, once the Outer loading value is higher than the cross value, the discriminate validity is established, showing that the items are measuring its underlying construct.

3.7.3 Structural Model Analysis

The purpose of structural model analysis is to identify the connection between constructs. This information will be obtained via a non-parametric bootstrap procedure facilitated by Smart PLS. By implementing bootstrapping for Partial Least Squares Structural Equation Modelling (PLS-SEM), researchers can obtain statistical information such as the path coefficient and R-squared value associated with its significance level (Ringle et al., 2022).

Collinearity (Variance Inflation Factor)

Collinearity in statistics refers to any strong correlation between two independent variables, either positive or negative, making it difficult to estimate the result accurately. In accordance with Hair et al. (2021), collinearity should be identified before determining the path coefficient to ensure that the result is not biased. A Variance Inflation Factor (VIF) value less than 3 is the ideal value to indicate that collinearity is absent. Whereas any value greater than 5 shows collinearity between independent variables.

A value falling between 3 and 5 is acceptable but still consists of potential collinearity.

Path Coefficient

According to Hair et al. (2021), the path coefficient measures how much a change of 1 unit of standard deviation in the predictor construct will alter the endogenous construct's standard deviation, all else being equal. In other words, a path efficient reveals the strength and direction of the association between variables. Typically, a path coefficient falls within the range of -1 to 1. Any value outside this range may indicate an unacceptable problem. As the value approaches -1, a robust negative relationship is indicated, whereas any value approaching +1 indicates a strong positive relationship. The significance of the relationship will be determined using p-value thresholds. When the p-value is lower than 0.05, it is appropriate to reject the null hypothesis, suggesting a statistically significant association between the variables. Conversely, when the p-value exceeds 0.05, it is not appropriate to reject the null hypothesis, indicating the absence of a statistically significant association between the variables.

3.8 Conclusion

In summary, Chapter 3 outlines the planned approach for conducting this research, focusing on the aspects of the type of research design, data collection method, research instrument, and proposed data analysis technique. For this study, a quantitative research method was employed to collect the numerical data for statistical analysis. The primary focus is to gather first-hand information from a minimum of 200 Malaysian individuals, aged between 18 and 29, residing in Klang Valley area.

To achieve this, a five-point Likert scale survey questionnaire will be administered via online Google Form. The distribution will follow a simple random sampling method through multiple social media channels. The collected data will be analysed by using Smart PLS version 4.0.9.3 software. The analysis encompasses measurement and structural model analysis, including assessment of the reliability and validity of the items, collinearity between constructs, and the path coefficient.

Notably, a pilot study will be conducted to examine the reliability of the questionnaire. The outcome of both the pilot and actual study will be comprehensively discussed in the following Chapter 4.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter presents the outcomes of the pilot test, which involved the evaluation of reliability and validity through the selection of 30 eligible respondents from the questionnaire. Next, data analysis was performed based on the results obtained from the questionnaire and software. Respondents' demographic profile was examined by conducting descriptive analysis. In this study, Smart PLS 4.0.9.3 software was employed to identify the determinants of the intention to use Financial Robo-Advisory (FRA) in Malaysia. To provide a more thorough understanding of the research findings, a detailed explanation of the Partial Least Squares Structural Equation Modelling (PLS-SEM) results will be provided in this chapter to provide better understanding.

4.1 Result of Pilot Study

A pilot study aimed to ensure the items' reliability before the preliminary study. Several assessments have been conducted, including Outer loadings, Average Variance Extracted (AVE), Cronbach's Alpha, and Composite reliability (CR). The assessment outcome indicates the reliability of all the items, as the result consistently meets the criteria.

Outer Loadings

Outer loadings, an assessment of indicator reliability, examines how well the items measure the same construct. A strong Outer loading indicates that the items are answering the research needs. Table 4.1 shows a comprehensive result of the Outer loadings of the pilot study.

Table 4.1 shows that the Outer loadings value ranges from 0.712 to 0.939, meeting the criteria of 0.6 acceptable level proposed by Yana et al. (2015). As a result, none of the items will be removed from the model since all the items are able to show a high reliability.

Table 4.1:

Outer Loadings (Pilot study)

Items	BI	DIS	INS	INV	OPT	PU
1	0.894	0.930	0.908	0.916	0.860	0.813
2	0.889	0.725	0.861	0.739	0.809	0.866
3	0.823	0.782	0.827	0.755	0.820	0.797
4	0.729	0.800	0.853	0.712	0.878	0.832
5	0.779	0.841	0.730	0.713	0.826	0.893
6	0.817	0.872	0.779	0.805	0.825	0.769
7	0.747	0.823	0.843	0.797	0.808	0.845
8	0.830	0.902	0.860	0.939	0.815	0.781

Note. Developed by the authors.

Based on Table 4.1, the Outer loadings value ranges from 0.712 to 0.939, meeting the criteria of 0.6 acceptable level proposed by Yana et al. (2015). As a result, none of the items will be removed from the model, since all the items are able to show a high reliability.

Average Variance Extracted (AVE), Cronbach's Alpha, Composite Reliability (CR)

The Average Variance Extracted (AVE) is an assessment of the convergent reliability, whereas Cronbach's Alpha and Composite Reliability (CR) is an assessment of internal consistency reliability. All of these three assessments aimed at checking how well the items work together with each other in measuring the same construct. Table 4.2 shows a comprehensive AVE, Cronbach's Alpha, and CR result.

Table 4.2

Reliability Test (Pilot study)

Constructs	Average Variance Extracted (AVE)	Cronbach's Alpha	Composite Reliability (CR)
Behavioural Intention	0.665	0.927	0.940
Discomfort	0.700	0.938	0.949
Insecurity	0.696	0.937	0.948
Innovativeness	0.642	0.918	0.934

Optimism	0.690	0.936	0.947
Perceived Usefulness	0.681	0.933	0.945

Note. Developed by the authors.

Based on Table 4.2, the convergent validity is achieved where the AVE value ranges from 0.642 to 0.700, meeting the 0.5 criteria. Specifically, discomfort (0.700) has the highest convergent validity, followed by insecurity (0.696), optimism (0.690), perceived usefulness (0.681), behavioural intention (0.665), and innovativeness (0.642).

Besides, Table 4.2 also demonstrates that all variables meet the 0.7 thresholds, with Cronbach's Alpha ranging between 0.918 and 0.938. In other words, it implies that the variable exhibits a substantial degree of internal consistency and can be relied upon for preliminary research. The variable with the highest degree of reliability is discomfort (0.938), followed by insecurity (0.937), optimism (0.936), perceived usefulness (0.933), behavioural intention (0.927), and innovativeness (0.918).

Composite Reliability is another internal consistency reliability indicator. Results of Table 4.2 reveal that all variables meet the 0.7 acceptance level, with the Composite Reliability value ranging from 0.934 to 0.949. Specifically, it indicates a solid internal consistency and suggests that all variables are reliable for preliminary research. As indicated by Cronbach's Alpha, discomfort is the most reliable construct (0.949), followed by insecurity (0.948), optimism (0.947), perceived usefulness (0.945), behavioural intention (0.940), and innovativeness (0.934).

4.2 Data Collection & Data Screening

A total of 534 responses were obtained for this study using Google form surveys distributed on an online platform. Based on the first and second screening question in the questionnaire regarding the location and age, a total of 35 responses had been removed from this survey since it is out of the sample. As a result, there are 499 responses that have been used for data analysis to provide accurate results.

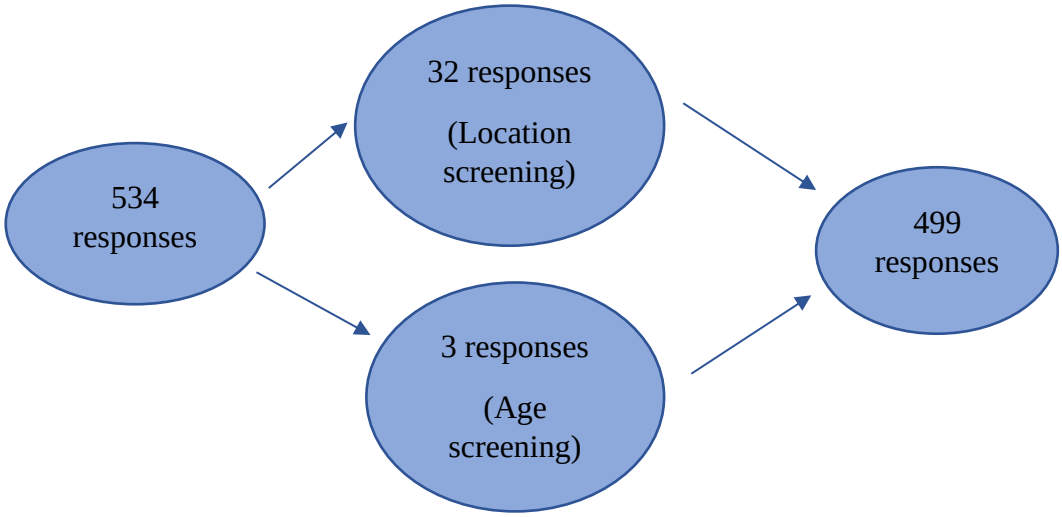

Figure 4.1. Data Collection and Data Screening. Developed by the authors.

4.3 Descriptive Analysis

Descriptive analysis entails summarizing and presenting the collected data provided by the respondents from the survey in a clear and organized manner. This section was mainly about the demographic information of the respondents, which was collected in Section A of the questionnaire.

4.3.1 Gender

Figure 4.2 displays the gender distribution of 499 respondents who participated in the survey, showing in number and percentage. There are 230 female respondents (46%) and 269 male respondents (54%) in the survey. In such, male respondents were more than female respondents in 39 people (7.3%) in total.

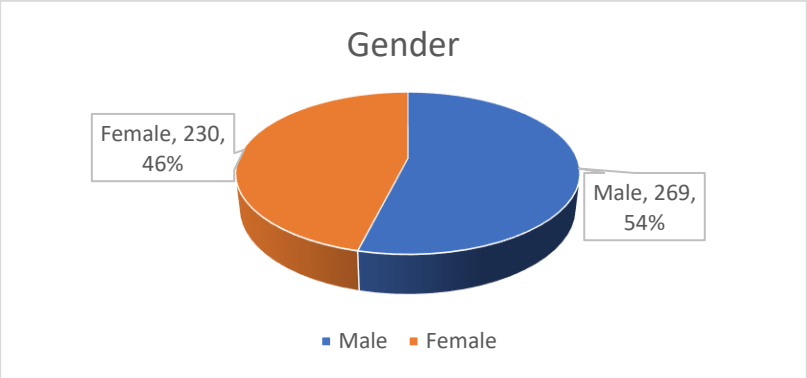

Figure 4.2. Statistics of Gender. Developed by the authors.

4.3.2 Education Level

Figure 4.3 shows the education level of 499 respondents who participated in the survey, showing in number and percentage. There are 5 categories of education level in this survey. Based on the obtained results, most of the respondents, totaling 238 individuals, are pursuing a bachelor's degree, accounting for 48% of the chart's data. Next, 89 respondents (18%) are pursuing a diploma certificate, while 64 respondents (13%) are pursuing a master's degree. Additionally, 65 respondents (13%) are pursuing SPM or

O-level, and 43 of them (8%) are pursuing STPM, UEC or A-level. There are no respondents who indicated pursuing a PHD and professional paper level of education.

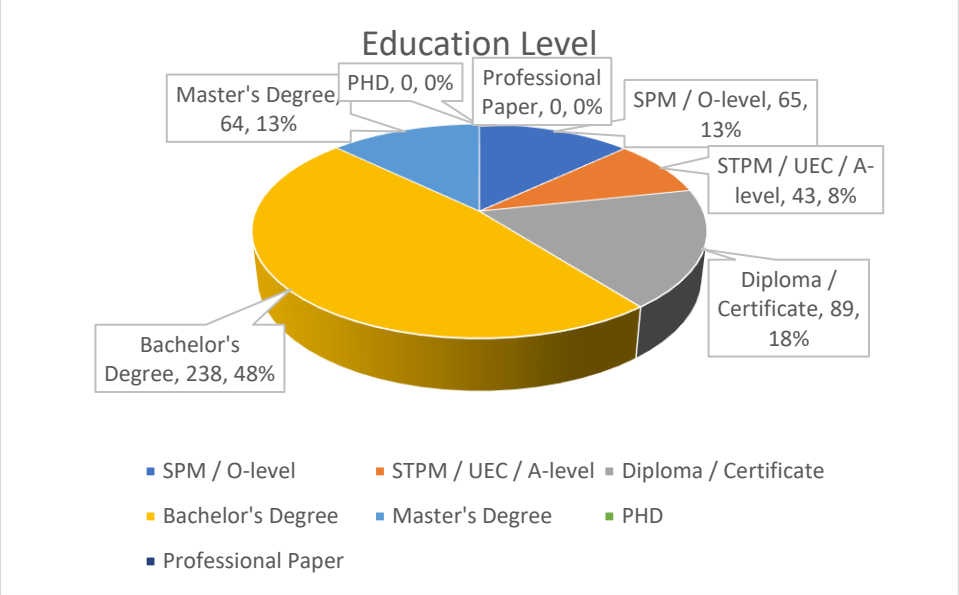

Figure 4.3. Statistics of Education Level. Developed by the authors.

4.3.3 Income Level

Figure 4.4 reveals the income level group of 499 respondents in this survey, there are 3 groups of income level. Most respondents, a total of 304 individuals, are earning an income level below RM4,849, contributing 61% of the chart's data. Additionally, income level of RM 4,850 to RM10,959, of which 156 respondents accounted for 31% and RM10,960 and above which had 39 respondents accounted for 8%. The number of respondents decreased as the income level increased.

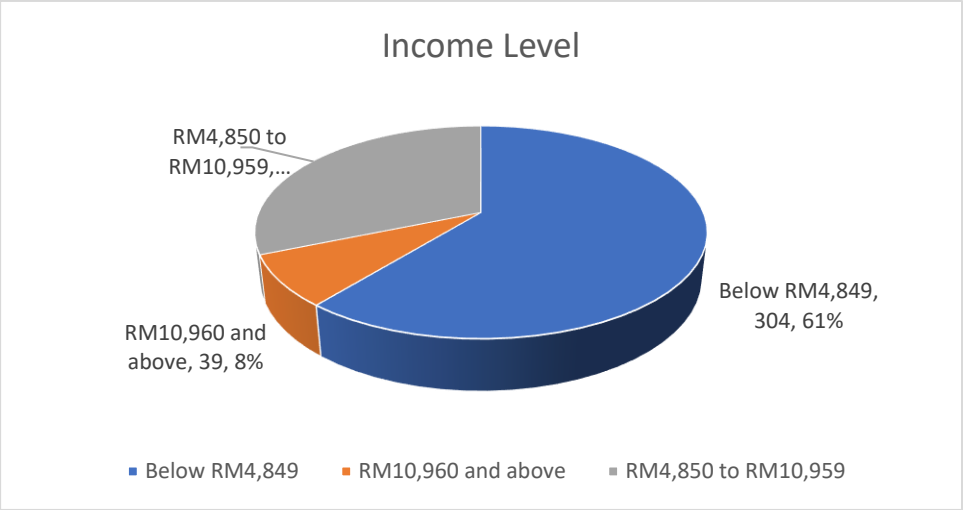

Figure 4.4. Statistics of Income Level. Developed by the authors.

4.3.4 Experience & Currently Using Financial Robo-Advisory (FRA)

Figure 4.5 illustrates whether the 499 respondents had experience in using Financial Robo-Advisory (FRA) and whether respondents are currently using FRA in this study. By observing the pie charts in figure 4.6, it is shown that the majority of respondents, a total of 370 individuals, reported no experience in using FRA, which contributed 74% of the chart's data. In contrast, 129 respondents reported "yes", which accounts for 26% from the chart. For the next question, the vast majority of respondents, accounting for 76% and totalling 377 people, claimed currently are not using FRA in this question. On the other hand, there are 122 respondents declared currently are using FRA, which contributed 24% of the of the total respondents in this study.

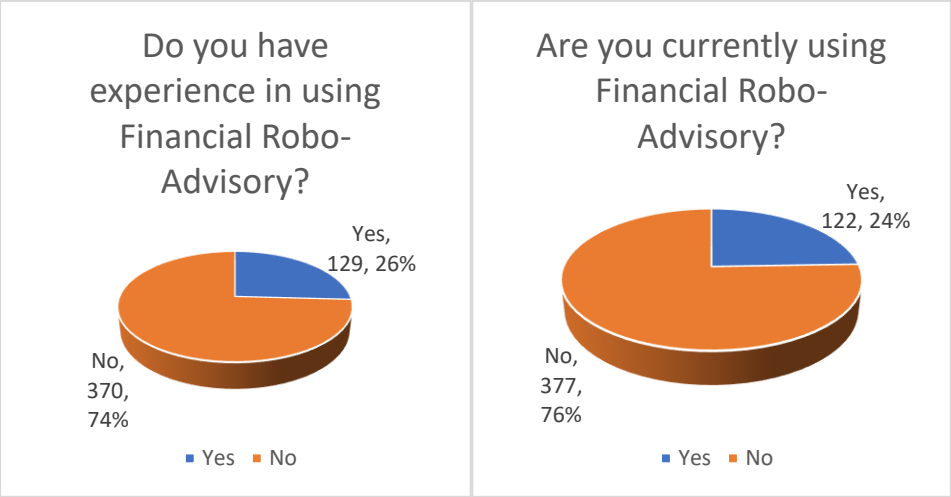

Figure 4.5. Statistics of Experience & Currently Using Financial Robo-Advisory (FRA). Developed by the authors.

4.3.5 Investment Experience with Investment Options

Figure 4.6 presents the investment experience of 499 respondents who participated in the survey by selecting the type of investments that respondents had been invested in. There are 11 types of selection in this survey which consists of 9 different investment options, two additional options indicating others and no experience. The results obtained in this question were more than 499 responses as this is a multiple question. According to the data received, the selections of no experience, stocks, mutual funds, property, and bonds received higher responses, whereas derivatives, cryptocurrencies, NFT, P2P lending, equity crowdfunding and others obtained lower responses.

Among all the investment options, derivatives, which include futures and options, received the lowest number of responses, with only 32 respondents selected. While the selection of no experience received the highest number of responses compared to others, a total of 216 respondents selected this option.

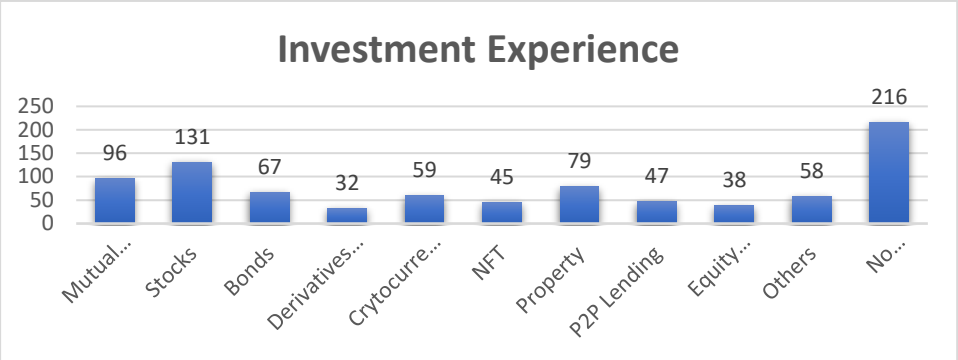

Figure 4.6. Statistics of Investment Experience with Different Investment Options. Developed by the authors.

4.3.6 Central Tendency (Mean)

This research determines the mean value of each item to identify which items have the most agreement from the respondents. The checking is crucial as it provides meaningful insight when designing the research implication. Table 4.3 shows the result of the mean value of each item.

Table 4.3

Central tendency (Mean)

	Items	Mean Value
BI1	I prefer using Financial Robo-Advisory rather than a traditional financial advisor for managing my investment activities.	3.158
BI2	I have positive opinions on Financial Robo-Advisory.	3.477

BI3	I intend to use Financial Robo-Advisory for my investment once I can access it.	3.353
BI4	I intend to use Financial Robo-Advisory to handle my entire investment portfolio.	3.228
BI5	I intend to use Financial Robo-Advisory to complement my investment activities.	3.337
BI6	I plan to use a Financial Robo-Advisory for my short-term investment (less than 1 year).	3.343
BI7	I plan to use a Financial Robo-Advisory for my long-term investment (more than 1 year).	3.345
BI8	I am interested in learning Financial Robo-Advisory platform for my investment.	**3.571***
DIS1	I think Financial Robo-Advisory are not helpful because they don't explain things in the way I understand.	2.946
DIS2	I think Financial Robo-Advisory are not reliable as compared to traditional financial advisors.	2.886
DIS3	I think Financial Robo-Advisory could not provide personal support because it lacks human interactions.	2.910
DIS4	Sometimes, I think that Financial Robo-Advisory is not designed for use by ordinary people.	**2.994***

DIS5	It is difficult to understand the automated algorithm of Financial Robo-Advisory.	2.878
DIS6	I think Financial Robo-Advisory makes it too easy for governments and companies to access my financial condition.	2.974
DIS7	I think Financial Robo-Advisory has the chance to fail in carrying out its function.	2.830
DIS8	I think Financial Robo-Advisory has safety risks that are not discovered until after people have used them.	2.818
INS1	I think I will be too dependent on Financial Robo-Advisory to make investment decisions.	2.976
INS2	I believe relying too much on Financial Robo-Advisory will distract people from learning financial knowledge.	3.044
INS3	I think Financial Robo-Advisory limits our social circle by reducing human interaction. (e.g., with financial advisors or friends)	3.022
INS4	I am not confident making investments with Financial Robo-Advisory that can only be reached online.	2,910
INS5	I worry that others may misuse my personal information I make available over the Financial Robo-Advisory.	2.924

INS6	Whenever something gets automated, I need to check carefully that the Financial Robo-Advisory is not making mistakes.	2.948
INS7	I prefer that any transaction I do electronically be confirmed later with a written confirmation.	**3.110***
INS8	I do not feel safe providing payment card numbers to Financial Robo-Advisory when I transfer my investment funds.	2.956
INV1	I would recommend Financial Robo-Advisory services to others for managing their finances.	3.138
INV2	In general, I am among the first in my circle of friends to acquire Financial Robo-Advisory when it appears.	3.188
INV3	I can figure out Financial Robo-Advisory without help from others.	3.487
INV4	I intend to remain informed about the latest advancements in the field of Financial Robo-Advisory on my social media.	3.499
INV5	I enjoy exploring the potential benefits and features of Financial Robo-Advisory.	3.513
INV6	I believe that robo-advisory services can help me to achieve my financial goals.	3.451

INV7	I am open to receiving personalised investment recommendations using technology-driven algorithms.	3.443
INV8	I am always open to learning the newly launched Financial Robo-Advisory available to manage my investments.	**3.685***
OPT1	I think Financial Robo-Advisory can do better than me in managing my portfolio composition.	3.629
OPT2	I believe Financial Robo-Advisory gives me more options for my portfolio composition.	3.567
OPT3	I believe that Financial Robo-Advisory can let me change my portfolio composition faster than traditional financial advisors.	3.573
OPT4	I think Financial Robo-Advisory can give me more control over my investment portfolio.	3.563
OPT5	I think Financial Robo-Advisory helps me save time and effort in doing my investment research.	**3.874***
OPT6	I feel confident that Financial Robo-Advisory will act based on my investment preferences.	3.529
OPT7	I feel confident that Financial Robo-Advisory will provide me an accurate investment recommendations.	3.397
OPT8	I think Financial Robo-Advisory can react to external environmental factors (e.g., changes in	3.365

	microeconomic conditions, geopolitical issues, Etc.) faster than humans.	
PU1	I believe using a Financial Robo-Advisory enables me to make financial decisions more quickly.	3.647
PU2	I believe using a Financial Robo-Advisory would make it easier to do my financial planning and management.	3.533
PU3	I believe using a Financial Robo-Advisory would lead me to positive financial outcomes.	3.236
PU4	I believe using a Financial Robo-Advisory would enhance my financial planning skills.	3.437
PU5	I believe using a Financial Robo-Advisory can prevent me from investing with behavioural bias.	3.685
PU6	I believe using a Financial Robo-Advisory can reduce the risk exposure on my investment portfolio.	**3.689***
PU7	I think Financial Robo-Advisory can help me save costs when making investments.	3.665
PU8	I think Financial Robo-Advisory will be helpful in my lifelong financial planning and management.	3.367

Note. Developed by the authors.

Despite the fact that 43% of the respondents in this study have no prior investment experience, Table 4.3 reveals that they are eager to learn about

investment innovations, as evidenced by statements BI8 (I am interested in learning Financial Robo-Advisory platform for my investment) and statement INV8 (I am always open to learning the newly launched Financial Robo-Advisory available to manage my investments). This can be explained by their traits, as most were early adopters of technology and internet users. However, it is essential to note that when it comes to personal wealth, people are not yet prepared to accept robots to a high degree, as indicated by the lowest mean value of BI1 (I prefer using Financial Robo-Advisory rather than a traditional financial advisor for managing my investment activities.)

In addition, the results indicate that many respondents are unfamiliar with Financial Robo-Advisory (FRA) services, whereas most agree that FRA is not designed for use by ordinary people (DIS4). This explained that the respondents feel that the FRA services are more tailored to the investor or individual with specific financial knowledge since 74% have yet to experience using FRA services, and 43% have no investment experience.

Moreover, the respondents are more concerned about the transparency of their financial transactions, as evidenced by the highest mean value for statement INS7 (I prefer that any transaction I do electronically be confirmed later with a written confirmation.). This result reflects individuals' lack of confidence in the FRA services provider platform, especially in the payment sector.

On the other hand, the benefit of portfolio diversification and time-saving of FRA services appears to be the primary factors of people to using it, as respondents are more likely to agree with statement OPT5 (I think Financial Robo-Advisory helps me save time and effort in doing my investment research.) and statement PU6 (I believe using a Financial Robo-Advisory can reduce the risk exposure on my investment portfolio.).

4.4 Measurement Model Analysis

4.4.1 Outer Loadings and Cross Loadings

Outer loadings is a measurement of indicator reliability, commonly used to understand how well an indicator represents the underlying construct. Table 4.4 shows a comprehensive result of Outer loading and Cross-loading of preliminary study.

Table 4.4

Reliability Test and Discriminant Validity Test

	BI	DIS	INS	INV	OPT	PU
BI1	**0.814***	-0.148	-0.299	0.562	0.630	0.699
BI2	**0.823***	-0.161	-0.286	0.550	0.739	0.635
BI3	**0.871***	-0.210	-0.266	0.651	0.674	0.671
BI4	**0.782***	-0.183	-0.313	0.520	0.580	0.595
BI5	**0.842***	-0.028	-0.153	0.563	0.666	0.570
BI6	**0.850***	-0.085	-0.192	0.589	0.699	0.662
BI7	**0.842***	-0.100	-0.188	0.590	0.727	0.577
BI8	**0.838***	-0.090	-0.123	0.554	0.727	0.570
DIS1	-0.111	**0.815***	0.462	0.027	-0.205	-0.098
DIS2	-0.194	**0.822***	0.461	-0.137	-0.238	-0.147
DIS3	-0.083	**0.810***	0.540	-0.130	-0.211	-0.144
DIS4	-0.123	**0.809***	0.506	-0.101	-0.163	-0.166
DIS5	0.008	**0.829***	0.503	-0.013	-0.103	-0.082

DIS6	-0.096	**0.800***	0.547	-0.066	-0.208	-0.157
DIS7	-0.051	**0.802***	0.557	-0.098	-0.167	-0.070
DIS8	-0.072	**0.788***	0.554	-0.140	-0.191	-0.119
INS1	-0.182	0.402	**0.668***	-0.212	-0.270	-0.192
INS2	-0.205	0.367	**0.742***	-0.272	-0.281	-0.390
INS3	-0.207	0.431	**0.789***	-0.228	-0.266	-0.277
INS4	-0.296	0.496	**0.784***	-0.270	-0.286	-0.317
INS5	-0.159	0.481	**0.821***	-0.186	-0.319	-0.226
INS6	-0.166	0.474	**0.762***	-0.316	-0.240	-0.177
INS7	-0.177	0.630	**0.775***	-0.183	-0.263	-0.234
INS8	-0.221	0.544	**0.787***	-0.180	-0.311	-0.240
INV1	0.628	-0.045	-0.243	**0.801***	0.507	0.603
INV2	0.581	-0.028	-0.251	**0.837***	0.449	0.560
INV3	0.485	-0.152	-0.287	**0.803***	0.417	0.442
INV4	0.534	-0.073	-0.268	**0.842***	0.470	0.496
INV5	0.591	-0.132	-0.220	**0.849***	0.462	0.523
INV6	0.558	-0.141	-0.171	**0.848***	0.486	0.476
INV7	0.551	-0.029	-0.278	**0.832***	0.423	0.475
INV8	0.608	-0.179	-0.302	**0.817***	0.543	0.580
OPT1	0.647	-0.145	-0.258	0.515	**0.761***	0.498
OPT2	0.591	-0.263	-0.246	0.369	**0.767***	0.455
OPT3	0.594	-0.254	-0.312	0.445	**0.768***	0.503
OPT4	0.593	-0.212	-0.261	0.360	**0.773***	0.521
OPT5	0.518	-0.197	-0.283	0.359	**0.701***	0.469
OPT6	0.548	-0.181	-0.298	0.411	**0.744***	0.497
OPT7	0.687	-0.100	-0.258	0.483	**0.765***	0.571
OPT8	0.688	-0.189	-0.286	0.449	**0.723***	0.688
PU1	0.631	-0.108	-0.352	0.585	0.621	**0.810***
PU2	0.604	-0.184	-0.393	0.517	0.601	**0.796***
PU3	0.682	-0.068	-0.140	0.493	0.626	**0.692***
PU4	0.601	-0.177	-0.155	0.486	0.566	**0.828***
PU5	0.572	-0.135	-0.246	0.501	0.477	**0.834***
PU6	0.496	-0.203	-0.316	0.456	0.475	**0.778***

PU7	0.552	-0.232	-0.336	0.496	0.553	**0.805***
PU8	0.572	0.020	-0.272	0.452	0.525	**0.813***

Values with bold representing Outer loadings; without bold* representing Cross loadings

Note. Developed by the authors.

Table 4.4 shows that the value of the Outer loadings ranges from 0.668 to 0.871, meeting the 0.6 acceptable level proposed by Yana et al. (2015). As a result, no items will be removed from the model for estimation. At the same time, all the items are statistically significant in explaining the construct (Appendix 4.1). Apart from that, Table 4.4 also shows that all the Outer loadings values are greater than the Cross loadings value, indicating that the discriminant validity is established.

4.4.2 Average Variance Extracted (AVE), Cronbach's Alpha, Composite Reliability (CR)

Average Variance Extracted (AVE) is a measure of convergent validity, which is usually applied to examine how well the items measure the same construct and relate to one another. Cronbach's Alpha is one of the measures of internal consistency used to determine how well the items are intercorrelated and produce consistent results. Composite reliability (CR) is another measurement of internal consistency used to ensure the reliability of the items in measuring the construct. Table 4.5 illustrates a comprehensive AVE, Cronbach's Alpha, and CR result.

Table 4.5

Reliability Test

Construct	Average Variance Extracted (AVE)	Cronbach's Alpha	Composite Reliability (CR)
Behavioural Intention	0.694	0.937	0.948
Discomfort	0.655	0.932	0.938
Insecurity	0.588	0.900	0.919
Innovativeness	0.687	0.935	0.946
Optimism	0.563	0.889	0.912
Perceived Usefulness	0.633	0.917	0.932

Note. Developed by the authors.

Table 4.5 demonstrates that all variables have good convergent validity, as the Average Variance Extracted (AVE) values range from 0.563 to 0.694 and surpass the 0.5 threshold. Specifically, Behavioural intention (0.694) has the highest convergent validity, indicating that the items for this construct are highly interrelated, followed by innovativeness (0.687), discomfort (0.655), perceived usefulness (0.633), insecurity (0.588), and optimism (0.563).

Besides, Table 4.5 shows the variables are considered as in high internal consistency, with Cronbach's Alpha values vary from 0.889 to 0.937. Specifically, the items of behavioural intention (0.937) are the most reliable at measuring the same underlying construct, followed by innovativeness (0.935), discomfort (0.932), perceived usefulness (0.917), insecurity (0.900), and optimism (0.889).

Moreover, Table 4.5 shows that the composite reliability value ranges from 0.912 to 0.948, demonstrating a strong internal consistency is achieved. Generally, the items used to measure behavioural intention (0.948) have the highest consistency reflecting the underlying construct, followed by innovativeness (0.946), discomfort (0.938), perceived usefulness (0.932), insecurity (0.919), and optimism (0.912). Since all the values fall between the threshold of 0.7 to 0.95, all the items are reliable for estimation.

4.4.3 Heterotrait-Monotrait Ratio of Correlation (HTMT)

The Heterotrait-monotrait ratio of correlation is the latest discriminant validity measurement proposed by Henseler et al. in 2015. Table 4.6 shows a comprehensive result of the preliminary study's HTMT.

Table 4.6

Discriminant Validity Test

	BI	DIS	INS	INV	OPT	PU
BI						
DIS	0.136					

INS	0.285	0.685			
INV	0.730	0.131	0.329		
OPT	0.887	0.256	0.409	0.616	
PU	0.798	0.186	0.373	0.672	0.767

Note. Developed by the authors.

Table 4.6 indicates that discriminant validity is established where all values are less than the 0.9 threshold. In other words, the results indicate that each variable is distinct and measured using a different concept. Specifically, the correlation between discomfort and innovativeness is 0.131, which suggests the weakest relationship possible. Simultaneously, the correlation between behavioural intention and optimism is 0.887, indicating that they have the strongest relationship.

4.5 Structural Model Analysis

4.5.1 Collinearity (Variance Inflation Factors)

The collinearity issue in this research is measured by using Variance Inflation Factors (VIF). Table 4.7 illustrates no severe multicollinearity issue among the independent variables in the model since all the VIF values range between 1 and 3.

Table 4.7

Collinearity Test

Construct	Variance Inflation Factors (VIF)
DIS > BI	1.676
INS > BI	1.853
INV > BI	1.779
OPT > BI	2.191
PU > BI	2.389

Note. Developed by the authors.

4.5.2 Path Coefficient

Table 4.8 provides an overview of the structural model. The table above shows the summary of the structural model. The significant level of this research study is 5% or 0.05. The rule of rejection is whenever the p-value is larger than 0.05, the hypothesis will be rejected, showing that the relationship between the variables is insignificant.

Table 4.8

Bootstrapping Test

Hypothesis	Paths	Path Coefficient	T-Statistic	P-value	Result

H1	DIS -> BI	- 0.003	0.074	0.941	Not Supported
H2	INS -> BI	- 0.079	2.412	0.016	Supported
H3	INV -> BI	0.261	8.232	0.000	Supported
H4	OPT -> BI	0.532	15.881	0.000	Supported
H5	PU -> BI	0.237	6.944	0.000	Supported

Note. Developed by the authors.

According to the table 4.8, the p-value of Insecurity, Innovativeness, and Perceived Usefulness are less than 0.05, which indicates the hypothesis is significant. Besides, Discomfort shows a value that is larger than significant level 0.05, which will be rejected by the hypothesis, indicating the absence of significant relationship between Discomfort and the intention to use Financial Robo-Advisory (FRA).

Based on the studies of Flavián et al. (2021), Oehler et al. (2021), and Salim et al. (2022), they concluded that optimism will bring significance and positive effect towards the intention to use the Fintech product or services. Acheampong et al. (2017) also mentioned that individuals with high optimism characteristics have a predetermined favourable perspective of new technology before being exposed to it. Peter et al. (2010) also concluded that high optimism people will trust FRA to benefit their life. The finding of this result is said can be explained by these journals, which the optimism has had an impact on the intention to use the FRA in Klang Valley, Malaysia.

Besides, according to the studies established by Cruz-Cárdenas et al. (2021), Salim et al. (2022), and Alharbi & Sohaib (2021), innovativeness also acts as a variable that positively impacts on the intention to use the FRA. As per Lu et al. (2005) word, they described that highly innovative people are constantly on the lookout for fresh ideas as well as fresh and new technology like FRA. Setiawan et al. (2021) also further explained that individuals with high technology awareness tend to behave as pioneers to try the new Fintech product as well as FRA. Therefore, the results of this study are being supported.

The outcome of discomfort is not significant towards the intention to use FRA. The result was not consistent with the past journals. Yet, the research carried out by Flavián et al. (2021) has shown that the discomfort has not affected the intention to use the FRA negatively. In fact, it influences the intention to use the FRA positively.

Furthermore, the research of Flavián et al. (2021), Shirahada et al. (2019), Alharbi & Sohaib (2021), and Salim et al. (2022) on insecurity towards intention to use FRA or Fintech related technology are showing a significant negative relationship. As per Akhtar & Khawaja (2018) explanation, individuals who face the advanced technology will normally encounter problems in using and they would like to avoid using the FRA as they have no confidence to use it (Shirahada et al., 2019).

Based on the research developed by Flavián et al. (2021), Chung et al. (2023), and Seiler & Fanenbruck (2021), their results indicates that the perceived usefulness has a positive effect on the intention to use the FRA or Fintech related services. This is because the potential user normally will expect the FRA is simple to use as well as helpful to their financial management. The positive view on the expected benefits from FRA tends to raise the intention to use.

4.6 Conclusion

In summary, Chapter 4 provides an overview of the descriptive information, measurement model analysis and structural model analysis generated by Smart PLS software.

During the pilot study, the outcomes of the assessments indicate the reliability of the items, as they consistently meet the criteria. As a result, all the items will be retained and proceed to actual data collection.

During the preliminary study, among the 499 respondents, 54% were male, and 46% were female, with a significant proportion holding a bachelor's degree and reported income below RM4,849. Out of hundred per cent, 26% of respondents have experience using Financial Robo-advisory (FRA), and 24% continued using it. Most importantly, 43% of respondents had no prior investment experience. For those who did invest, stock investment was more favourable for them, while financial derivatives were less preferable.

During measurement model analysis of the preliminary study, the indicator reliability, convergent validity, internal consistency reliability, and discriminant validity were established since the result of Outer Loadings, Average Variance Extracted (AVE), Cronbach Alpha, Composite Reliability (CR), Cross Loadings, and Heterotrait-Monotrait Ratio of Correlation (HTMT) have met the criteria.

During structural model analysis, Variance Inflation Factors (VIF) range between 1 and 3, indicating no serious collinearity issue. Upon studying the path coefficients, optimism, innovativeness, and perceived usefulness are positively related to behavioural intention, and optimism tends to have the largest effect. On the other hand, discomfort and insecurity are negatively related. All the variables are statistically significant at 0.05 significant level except discomfort. This outcome will be discussed in detail in Chapter 5.

Chapter 5: Discussion, Conclusion, and Implication

5.0 Introduction

The determinants of intention to use Financial Robo-Advisory (FRA) is studied in this research through the variables discomfort, insecurity, innovativeness, optimism, and perceived usefulness. Chapter 4 has provided a clear view on the data analysis done in this research, including the reliability, validity and significance of the research. In this chapter, the key findings, which is the significance of the variables in the whole research study will be further elaborated, explained and concluded in this chapter. The chapter then followed by the implication for the research, limitation of study and recommendation of study. The chapter ends with a conclusion for the whole research study.

5.1 Summary of Statistical Analysis

Based on the outcome in the data analysis process, the summary of significance results is shown as below:

Table 5.1

Summary of Result

Hypothesis Testing	**Result (Significance at P-Value ≤0.05)**	**Consistency with Expected Results**
H1: There is a relationship between discomfort and intention to use FRA in Malaysia.	0.941	Inconsistent
H1: There is a relationship between insecurity and intention to use FRA in Malaysia.	0.016	Consistent
H1: There is a relationship between innovativeness and intention to use FRA in Malaysia.	0.000	Consistent
H1: There is a relationship between optimism and intention to use FRA in Malaysia.	0.000	Consistent
H1: There is a relationship between perceived usefulness and intention to use FRA in Malaysia.	0.000	Consistent

Note. Developed by the authors.

5.1.1 Discomfort - Behavioural Intention

According to table 5.1, there is a negative and insignificant relationship between discomfort and behavioural intention to use Financial Robo-Advisory (FRA). The result implies that the feeling of discomfort towards the new technology does not significantly affect the intention of the 18-29 years old Malaysian individuals to use a financial robo-advisory. The result has been surprising as most studies found a significant negative effect on the relationship between discomfort and intention of use FRA or Fintech service, including Shirahada et al. (2019) on self-service products, Salim et al. (2022) on blockchain technology and Alharbi & Sohaib (2021) on cryptocurrency.

As discomfort was defined as the feeling of lack of control and ability in dealing with the new technology as stated in chapter 2, the result can be explained as 76% respondent of this study have no experience in using any FRA services and more than half of them have no investing experience. The variable requires respondents to have certain experience or level of knowledge to be aware of the discomfort level towards FRA. As a huge portion of respondents have no experience in using FRA or even investing an equity, the respondent does not physically feel the discomfort when using a brand-new robot-based technology to manage their hard-earned savings. This might lead them into a misconception that personal discomfort does not affect their intention to try out the new technology.

Moreover, the study conducted by Flavián et al. (2021) explained their positive correlation between discomfort and the intention to use FRA because the Artificial Intelligence (AI) systems in FRA could solve the discomfort of respondents towards technology. However, this research directly studies the discomfort feeling of individuals toward the FRA service but not technology discomfort. Hence, the result of negative correlation

found between discomfort and intention to use FRA is logically tallied with all of the studies mentioned above.

5.1.2 Insecurity – Behavioural Intention

Based on the result in table 5.1, there is a significant relationship between insecurity towards the behavioural intention to use Financial Robo-Advisory (FRA) (P-value 0.016< significance level 0.05). The significant negative relationship between the variables indicates that the feelings of insecurity towards FRA will significantly affect the intention of 18-29 years old individuals in using the investment tool in Malaysia. According to Flavián et al. (2021), when the clients have security concerns of the FRA services, their intention to use them will significantly decrease, which is tallied with the results shown in table 5.1.

As there is limited research on insecurity towards intention to use FRA, some research on the similar area regarding new financial technologies has also shown similar results regarding insecurity towards intention to use the product or services. For example, research on online public self-service technologies by Shirahada et al. (2019), research on cryptocurrency by Alharbi & Sohaib (2021) and research on blockchain technology by Salim et al. (2022). As the FRA involves personal assets and information to make investments, the safety of FRA platforms is undeniably the most concerning issue for investors. Moreover, negative consequences of the FRA, including lack of two-way interpersonal communication and overly relying on technology might also bring feelings of insecurity to the customers (Flavián et al, 2021).

5.1.3 Innovativeness – Behavioural Intention

The result in table 5.1 shows that there is a significant positive relationship between innovativeness towards the behavioural intention to use Financial Robo-Advisory (FRA) (P-value 0.000< significance level 0.05). This shows that the innovativeness of the individuals aged 18-29 on the view of technology performance will significantly influence the intention to use FRA in Malaysia. Most research with technology acceptance model shows significant relationship between innovativeness with intention to use, including research on technology-based products and services by Oehler et al. (2021), research on blockchain technology by Salim et al. (2022), and research on cryptocurrency by Alharbi & Sohaib (2021).

Although Flavián et al. (2021) stated that FRA might not be creative enough to attract innovative individuals from North America as they are still based on traditional investment products, the result of this study shows that the Malaysian market has different thoughts on FRA. The lack of popularity of FRA in the Malaysian market as introduced in Chapter 1 brings the unfamiliarity to the Malaysian investors, which innovative individuals might be attracted and have more intention to use the FRA service.

5.1.4 Optimism – Behavioural Intention

Table 5.1 shows the result of significant relationship between optimism towards the behavioural to use Financial Robo-Advisory (FRA) (P-value

0.000< significance level 0.05). This indicates the feeling of having greater control, flexibility and efficiency towards the new technology will significantly influence the intention to use FRA. Similar results can be found in research on FRA by Flavián et al (2021), robo-only investing by Oehler et al. (2021), and blockchain technology by Salim et al. (2022).

According to Flavián et al. (2021), customers with higher technology optimistic believe that FRA will perform their investments better to increase their quality of life, especially after the Covid-19 pandemic, where AI-based technology has been better established into all kinds of sectors. Having a younger age group as the respondents of this study, their acceptance and implementation of technology will be greater than other age groups. When the respondents were asked on their thoughts of FRA helping them save time and effort in investment research, the question was rated 3.874 out of 5. This shows the high optimism of Malaysia's young generation towards technology and trust towards new technologies.

5.1.5 Perceived Usefulness - Behavioural Intention

Perceived usefulness is an additional variable from the Technology Acceptance Model (TAM) added into this study. According to the results in table 5.1, perceived usefulness has a significant positive relationship towards the behavioural to use Financial Robo-Advisory (FRA) (P-value 0.000 < significance level 0.05. This indicates that the better the investors think that the FRA could increase their investment performance, the higher their intention to use a FRA in Malaysia. The result is tallied to the limited studies of FRA including by Flavián et al. (2021), Chung et al. (2023) and Seiler & Fanenbruck (2021).

The study by Seiler & Fanenbruck (2021) stated that perceived usefulness as one of the main drivers and most decisive factors to increase the individual's intention to use FRA. In contrast, the study from Belanche et al. (2019) found an insignificant relationship between perceived usefulness and behavioural intention to use FRA. However, they explained that respondents may need more understanding of the FRA as they found out that perceived usefulness significantly affects the customer's attitude towards FRA in the early stage of adoption (Belanche et al., 2019). In this research, detailed explanation of FRA was provided to respondents to fully understand the rationale behind FRA before the survey, hence bringing the result of significant relationship between perceived usefulness to behavioural intention to use FRA.

5.2 Research Implications

Results in this study have implications for academia, the policy makers and stakeholders which includes investors and financial robo-advisory firms as stated in chapter 1.6.

5.2.1 Academia

Research studies relating to Financial Robo-Advisory (FRA) have been exclusively limited especially in the Malaysian region. As this FRA research

used a combination of Technology Acceptance Model (TAM) and Technology Readiness Index (TRI), this study can give future research a reference of the significant factors, mainly during the introduction stage of FRA in Malaysia. With 4 out of 5 variables showing significant results with high consistency compared with the previous reference research, this study provides a reliable foundation for future researchers to extend the research from different angles of FRA in Malaysia based on this research study.

As the discomfort variable shows insignificant relationship in our study, it remains as an ambiguity result and a research gap for future research to clarify and make further studies. Also, further studies in academia could take investors' personality and other personal factors into account to study the intention to use FRA. The personal factors include risk attitudes towards investments, characteristics, need of social interactions, religious and ethnic culture. All these factors might be highly related in affecting the intention to use FRA.

5.2.2 Regulators & Government

Regulators that were meant to set rules and regulation for the firms providing Financial Robo-Advisory (FRA) services should have a clearer picture on the investors' concern towards FRA through this study. As insecurity is a significant factor for the intention to use FRA, regulators could improve their regulations on security issues of FRA, especially on licensing, insured deposit, and personal data. Also, to enhance the perceived usefulness of FRA, regulators should also advise FRA providers in making improvements on user experience as FRA providers could provide different facilities for different groups. For example, the Muslims must make investments based on companies with shariah compliance.

Moreover, being a government-backed agency, the regulators could assist the Malaysian Government on the education of financial literacy to the

Malaysian society. This study has shown the low financial literacy and knowledge of young individuals in Malaysia, as even though the study was done in the most innovative region in Malaysia, more than 40% of respondents have not tried any investments. To improve Malaysia's economy and end the stagnant situation in the Malaysian stock market over the past decade, the Malaysian government has to take immediate action in educating the next generation on their finances. With a standardised education and publicity regarding investments and FRA services, it could reduce the discomfort of individuals towards investments and increase investors' innovativeness.

5.2.3 Stakeholders (Financial Institutions and Investors)

Financial institutions refer to the firms that have introduced the Financial Robo-Advisory (FRA) service and those that are interested in expanding their business into FRA, including several local investment banks and financial intermediaries. As the low penetration rate of FRA continues in Malaysia, FRA firms could refer to this study to increase the acceptance of Malaysia individuals, specifically aged 18-29 on the FRA service. As perceived usefulness and optimism is one of the significant factors affecting the intention to use FRA, firms could improve their services and promote their service through the perspective of efficiency and effectiveness of FRA in managing their investments to gain exposure and trust from the potential customers.

According to the results from the questionnaire, 216 out of 499 or 43.28% of respondents have never invested through any investment tools on equities. This has shown the low financial literacy situation of teenagers aged 18-29 in Malaysia, and FRA might be the best suited investment tool for them to invest as it does not require deep investment knowledge. Through this study,

beginners that are new to investment could identify the advantages and limitations of FRA. Although this study promotes the usage of FRA, investors should still make a detailed study of the provider of FRA services on their trustworthiness to avoid being involved in any financial scams that are infamous in Malaysia.

On the other hand, experienced investors could also benefit from this research by studying the insights of FRA and can better position FRA as their replacement or additional investment tool. Experienced investors might have better understanding of their investment expectation, and they could actively communicate with the FRA providers in providing feedback to improve their investment robot and also user experience. This could help the development of FRA, expanding the equity market which indirectly brings benefits to themselves and the financial market. As FRA might be an effective alternative of investment tools to reduce the behavioural bias of investors in making investment decisions and cost less than traditional human advisors, this study could help and stimulate more studies related to FRA in Malaysia for interested individuals to refer, increasing their trust and understanding towards FRA.

5.3 Limitations of Study

Using SmartPLS as the data analysis tool for this study, 4 out of 5 independent variables are significant and in-line with expectation during the research study. Feedbacks from respondents towards the questionnaire were collected verbally and most respondents thought that they have never heard about Financial Robo-Advisory (FRA), especially those without any investing experience. Undeniably, surveying respondents with investment might be more appropriate and have more accurate results for this study. However, this study aims to get the real data from

the 18-29 age group as the FRA service aims them as their main customers as introduced in chapter 3.3.2. Hence, most validity in this study has a close-to-invalid numbers. The 18–29-year-old age group is also a limitation to the study as a portion of respondents does not really have their own income and have limited savings. This might affect their investment experience and limit their intention to use financial robo-advisory.

Moreover, the geographical location of the study carried out has become one of the limitations of this study. Being the most developed region in Malaysia, Klang Valley has been selected as the sampling location of this study due to its robust infrastructure and having more early adopters of technology. However, the controversial part is that individuals in the Klang Valley might not fully represent all the individuals in Malaysia in terms of different income level, employment rate, innovativeness, and cultural thinking and education. However, due to the lack of popularity of FRA in other regions, this study has to be done in Klang Valley to maintain its significance.

On the other hand, there is a limitation of the form of this research. The data captured in this study is up to mid-year of 2023 and could not capture the future changes of the intention to use FRA in Malaysia. Also, using a questionnaire to collect data limits the respondent's freedom in expressing their views in the FRA and ignoring personality factors that affect the intention to use FRA. Research gaps still exist as can be seen in the significance results explanations in the variable.

5.4 Recommendations

For future research studying the Financial Robo-Advisory (FRA) in Malaysia, there are still various research gaps to be filled to have a clearer look of FRA in the Malaysia market. Firstly, future research could expand the research geological location to other areas in Malaysia, including Penang, Ipoh and Johor when FRA

has been more introduced and well-known in the country. Researchers could study and compare the difference of intention to use FRA in different states due to the huge cultural difference between states in Malaysia.

On the other hand, the sampling frame could be changed to study the intention to use FRA in different age groups. The elder age group might have advantage in investment experience, but lack of innovativeness in trying new technology for their investments; younger age groups might have advantage in the courage of trying new technology but usually prefer trading by themselves for the excitement of price fluctuation. Hence, different age groups might prioritise on different factors affecting their intention to use FRA. It is advised to modify the research study based on specific targeted participants in future studies.

Lastly, longitudinal studies on intention to use FRA could be carried out in the future and the research could be brought out through interviews to provide precise reasons for the intentions. As if FRA has been popularized in the future, studies regarding the user experience might be significant to the academia, regulators and FRA providers as this study could only help them understand the initial stages during the introduction and adoption of FRA in the region. Studies on user experience and feedback could provide a channel between investors and the FRA providers to have better recognition towards the unsatisfactory factors of FRA to create a better investment and FRA environment.

5.5 Conclusion

This research study seeks to determine the intention to use Financial Robo-advisory (FRA) in Malaysia due to the low penetration rate of FRA in the region. Four out of five determinants are found to be significant, including insecurity, innovativeness, optimism, and perceived usefulness, while discomfort was found to be insignificant but yet negatively correlated to the intention to use FRA. This might be caused by

the lack of understanding and physical experience in using financial robo-advisory by the respondents. This study also finds out the low financial literacy of young Malaysians, as almost half of the respondents do not have any experience in investments.

Although this research provides a clearer view and better understanding towards FRA in Malaysia, this effort might be minor in changing the region's financial literacy and investment knowledge. Without proper education on managing personal finance and an appropriate sense of money for teenagers, Malaysia's future economic development might be worrying. Therefore, to create a healthy investment environment and appropriate investment tools like the FRA requires effort not only from the providers of financial tools, but also the government, parents, educational institutions, and even experienced investors.

In conclusion, discomfort is insignificant in affecting the intention to use FRA within the 18-29 years old age group in Malaysia, while other independent variables remain significant. Limitation of this study is justified in this chapter and recommendations for future research are explained in detail to benefit academia, policy makers, and stakeholders of FRA in Malaysia.

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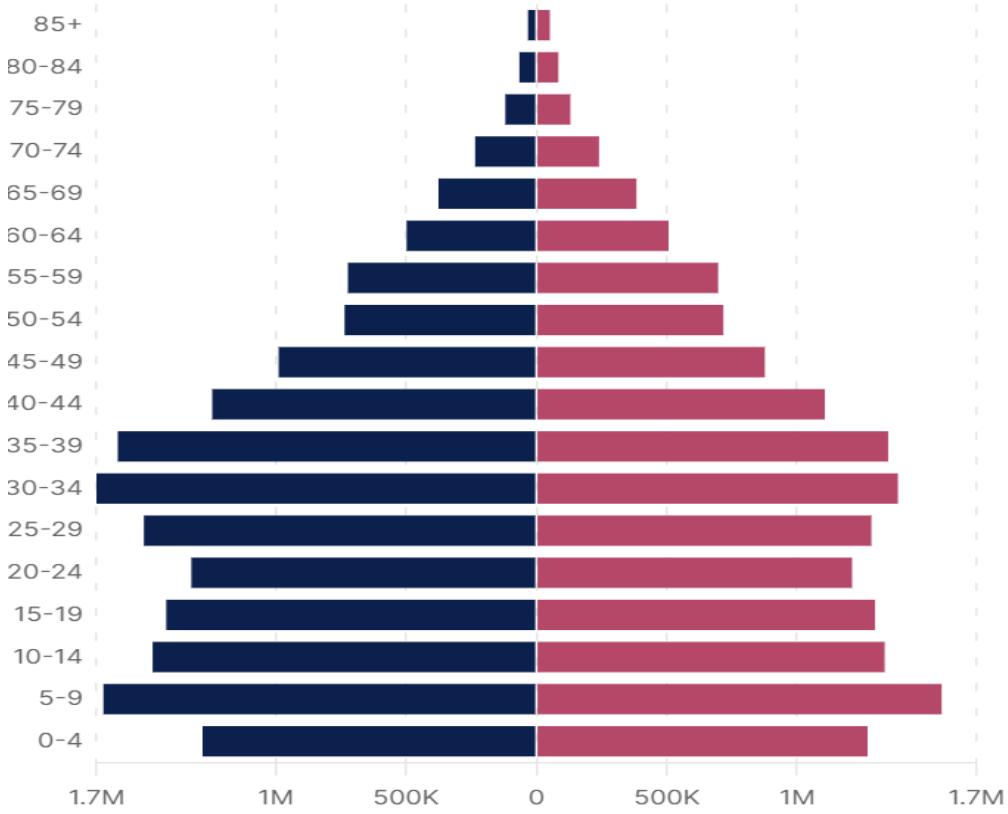
APPENDICES

Appendix 3.1: Age Structural Malaysia, 2020



Source: Department of Statistics Malaysia (DOSM) website

Appendix 3.2: Permission to Conduct Survey

UNIVERSITI TUNKU ABDUL RAHMAN *DU012(A)*
Wholly owned by UTAR Education Foundation *(200201010564(578227-M))*
Faculty of Business and Finance
Jalan Universiti, Bandar Barat, 31900 Kampar, Perak
Phone: 05-468-8888
https://fbf.utar.edu.my/

10th April 2023

To Whom It May Concern

Dear Sir/Madam,

Permission to Conduct Survey

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

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

The student are as follows:

Name of Student	**Student ID**
Chan Siew Chen	19ABB03345
Lim Jia Yi	19ABB02510
Liew Xin Wei	19ABB02458
Man Siong Kit	19ABB02418

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

Thank you.

Yours sincerely,

.....

Dr Lee Chee Loong
Head of Department
Faculty of Business and Finance
Email: lcloong@utar.edu.my

Appendix 3.3: Survey questionnaire

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Universiti Tunku Abdul Rahman

Faculty of Business and Finance

Bachelor of Finance (HONS)

Topic: Determinants of the Intention to Use Financial Robo-Advisory in Malaysia

Section A: Introduction

Dear Participants,

We are bachelor's degree students of Universiti Tunku Abdul Rahman (UTAR) doing our final-year project related to the subject mentioned above. Our group consist of 4 members who are Chan Siew Chen, Lim Jia Yi, Liew Xin Wei and Man Siong Kit. The purpose of this survey is to know more about the determinants that affect the intention to use financial robo-advisory in Malaysia.

Financial robo-advisory is a digital wealth management platform that provides automated investment advice and portfolio management services to investors. Investors can commence by registering for an account on a robo-advisory platform. Investors will then be required to respond to a series of questions regarding their investment goals, risk tolerance, investment horizon, and other personal information. Using the provided information, the robo-advisor will proceed to evaluate and generate a portfolio allocation recommendation for each investor. The portfolio allocation may be diversified through a combination of assets, such as Exchange-Traded Funds (ETFs), bonds, and equities. Periodically, the robo-advisors will monitor the portfolio to ensure that it adheres to investor's specified asset allocation once investors have funded their account. According to Statista

(2023a), the financial robo-advisory market has experienced significant growth in the last five years in terms of the assets under management and revenue. Financial robo-advisory technology has created a new opportunity for investors by providing them with an innovative way to manage their investments. The purpose of this study is to identify the factors that influence Malaysians in their decision to adopt financial robo-advisory.

We would like to invite you to participate in this research study by completing this questionnaire. The entire questionnaire will take approximately 10 - 15 minutes to complete. We would appreciate if you could answer all the questions.
This questionnaire consists of SEVEN (7) sections:
Section A: Basic Demographic
Section B: Behavioural Intention
Section C: Optimism
Section D: Innovativeness
Section E: Discomfort
Section F: Insecurity
Section G: Perceived Usefulness

There will be no risk involved in your participation in this survey. Your identity and responses will be kept private and confidential. All information obtained from the survey is solely for academic research purposes.
Your voluntary participation will greatly contribute to the success of this study. We deeply appreciate your assistance and kind response to this survey. If you have any questions regarding this study, please drop us an email at mansiongkit2000@gmail.com. Thank you for your contribution and participation in this study.

Section B: 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

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 mansiongkit2000@gmail.com.

Acknowledgment 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.

Section C: Screening question

1. Are you currently staying in Klang Valley?
    - Yes
    - No

Section D: Basic demographic information

1. Gender
    - Male
    - Female

2. Age:

3. Education level
    - SPM / O-level
    - STPM / UEC / A-level
    - Diploma / Certificate
    - Bachelor's Degree
    - Master's Degree
    - PHD
    - Professional Paper:

4. Income level
    - Below RM4,849
    - RM4,850-RM10,959
    - RM10,960 and above

5. Do you have experience in using financial robo-advisory?
    - Yes
    - No

6. Are you currently using financial robo-advisory?
    - Yes
    - No

7. Do you have any investment experience in the options below?
    - Mutual Funds

- Stocks
- Bonds
- Derivatives (Futures / Options)
- Cryptocurrencies
- NFT
- Property
- P2P Lending
- Equity Crowdfunding
- Others

Section E: Dependent variable (Behavioural intention)

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Items	Description	1	2	3	4	5
BI1	I prefer using financial robo-advisory rather than a traditional financial advisor for managing my investment activities.					
BI2	I have positive opinions on financial robo-advisory.					
BI3	I intend to use financial robo-advisory for my investment once I can access it.					
BI4	I intend to use financial robo-advisory to handle my entire investment portfolio.					
BI5	I intend to use financial robo-advisory to complement my investment activities.					
BI6	I plan to use a financial robo-advisory for my short-term investment (less than 1 year).					
BI7	I plan to use a financial robo-advisory for my long-term investment (more than 1 year).					

BI8	I am interested in learning financial robo-advisory platform for my investment.					

Section F: Independent variable (Optimism)

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Items	Description	1	2	3	4	5
OPT1	I think financial robo-advisory can do better than me in managing my portfolio composition.					
OPT2	I believe financial robo-advisory gives me more options for my portfolio composition.					
OPT3	I believe that financial robo-advisory can let me change my portfolio composition faster than traditional financial advisors.					
OPT4	I think financial robo-advisory can give me more control over my investment portfolio.					
OPT5	I think financial robo-advisory helps me save time and effort in doing my investment research.					
OPT6	I feel confident that financial robo-advisory will act based on my investment preferences.					
OPT7	I feel confident that financial robo-advisory will provide me an accurate investment recommendations.					

OPT8	I think financial robo-advisory can react to external environmental factors (e.g., changes in microeconomic conditions, geopolitical issues, Etc.) faster than humans.					

Section G: Independent variable (Innovativeness)

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Items	Description	1	2	3	4	5
INV1	I would recommend financial robo-advisory services to others for managing their finances.					
INV2	In general, I am among the first in my circle of friends to acquire financial robo-advisory when it appears.					
INV3	I can figure out financial robo-advisory without help from others.					
INV4	I intend to remain informed about the latest advancements in the field of financial robo-advisory on my social media.					
INV5	I enjoy exploring the potential benefits and features of financial robo-advisory.					
INV6	I believe that robo-advisory services can help me to achieve my financial goals.					
INV7	I am open to receiving personalised investment recommendations using technology-driven algorithms.					
INV8	I am always open to learning the newly launched financial robo-advisory available to manage my investments.					

Section H: Independent variable (Discomfort)

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Items	Description	1	2	3	4	5
DIS1	I think financial robo-advisory are not helpful because they don't explain things in the way I understand.					
DIS2	I think financial robo-advisory are not reliable as compared to traditional financial advisors.					
DIS3	I think financial robo-advisory could not provide personal support because it lacks human interactions.					
DIS4	Sometimes, I think that financial robo-advisory is not designed for use by ordinary people.					
DIS5	It is difficult to understand the automated algorithm of financial robo-advisory.					
DIS6	I think financial robo-advisory makes it too easy for governments and companies to access my financial condition.					
DIS7	I think financial robo-advisory has the chance to fail in carrying out its function.					
DIS8	I think financial robo-advisory has safety risks that are not discovered until after people have used them.					

Section I: Independent variable (Insecurity)

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Items	Description	1	2	3	4	5
INS1	I think I will be too dependent on financial robo-advisory to make investment decisions.					
INS2	I believe relying too much on financial robo-advisory will distract people from learning financial knowledge.					
INS3	I think financial robo-advisory limits our social circle by reducing human interaction. (e.g., with financial advisors or friends)					
INS4	I am not confident making investments with financial robo-advisory that can only be reached online.					
INS5	I worry that others may misuse my personal information I make available over the financial robo-advisory.					
INS6	Whenever something gets automated, I need to check carefully that the financial robo-advisory is not making mistakes.					
INS7	I prefer that any transaction I do electronically be confirmed later with a written confirmation.					
INS8	I do not feel safe providing payment card numbers to financial robo-advisory when I transfer my investment funds.					

Section J: Independent variable (Perceived usefulness)

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Items	Description	1	2	3	4	5
PU1	I believe using a financial robo-advisory enables me to make financial decisions more quickly.					
PU2	I believe using a financial robo-advisory would make it easier to do my financial planning and management.					
PU3	I believe using a financial robo-advisory would lead me to positive financial outcomes.					
PU4	I believe using a financial robo-advisory would enhance my financial planning skills.					
PU5	I believe using a financial robo-advisory can prevent me from investing with behavioural bias.					
PU6	I believe using a financial robo-advisory can reduce the risk exposure on my investment portfolio.					
PU7	I think financial robo-advisory can help me save costs when making investments.					
PU8	I think financial robo-advisory will be helpful in my lifelong financial planning and management.					

Appendix 4.1: Bootstrapping test of Outer loadings

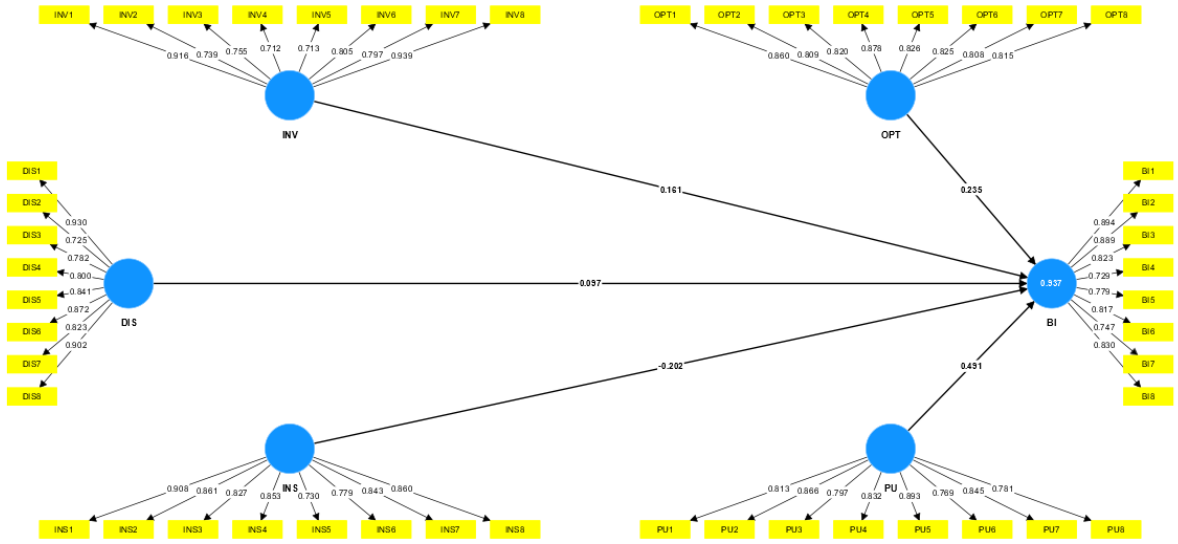
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI1 <- BI	0.814	0.814	0.015	54.535	0.000
BI2 <- BI	0.823	0.823	0.015	55.974	0.000
BI3 <- BI	0.871	0.870	0.012	75.277	0.000
BI4 <- BI	0.782	0.782	0.020	39.792	0.000
BI5 <- BI	0.842	0.842	0.013	63.836	0.000
BI6 <- BI	0.850	0.849	0.014	62.485	0.000
BI7 <- BI	0.842	0.842	0.015	57.245	0.000
BI8 <- BI	0.838	0.838	0.015	55.687	0.000
DIS1 <- DIS	0.815	0.783	0.115	7.099	0.000
DIS2 <- DIS	0.822	0.806	0.137	5.991	0.000
DIS3 <- DIS	0.810	0.772	0.120	6.743	0.000
DIS4 <- DIS	0.809	0.769	0.128	6.339	0.000
DIS5 <- DIS	0.829	0.777	0.165	5.022	0.000

DIS6 <- DIS	**0.800**	**0.756**	**0.139**	**5.757**	**0.000**
DIS7 <- DIS	**0.802**	**0.751**	**0.162**	**4.936**	**0.000**
DIS8 <- DIS	**0.788**	**0.740**	**0.155**	**5.079**	**0.000**
INS1 <- INS	**0.668**	**0.666**	**0.033**	**20.032**	**0.000**
INS2 <- INS	**0.742**	**0.739**	**0.030**	**24.786**	**0.000**
INS3 <- INS	**0.789**	**0.788**	**0.022**	**36.666**	**0.000**
INS4 <- INS	**0.784**	**0.786**	**0.021**	**37.199**	**0.000**
INS5 <- INS	**0.821**	**0.818**	**0.020**	**41.691**	**0.000**
INS6 <- INS	**0.762**	**0.758**	**0.025**	**30.042**	**0.000**
INS7 <- INS	**0.775**	**0.773**	**0.029**	**27.070**	**0.000**
INS8 <- INS	**0.787**	**0.785**	**0.027**	**29.457**	**0.000**
INV1 <- INV	**0.801**	**0.801**	**0.019**	**42.600**	**0.000**
INV2 <- INV	**0.837**	**0.837**	**0.012**	**67.424**	**0.000**
INV3 <- INV	**0.803**	**0.803**	**0.017**	**45.947**	**0.000**
INV4 <- INV	**0.842**	**0.842**	**0.016**	**52.771**	**0.000**

INV5 <- INV	**0.849**	**0.849**	**0.016**	**52.893**	**0.000**
INV6 <- INV	**0.848**	**0.848**	**0.014**	**61.404**	**0.000**
INV7 <- INV	**0.832**	**0.832**	**0.015**	**55.398**	**0.000**
INV8 <- INV	**0.817**	**0.817**	**0.019**	**44.121**	**0.000**
OPT1 <- OPT	**0.761**	**0.761**	**0.022**	**35.119**	**0.000**
OPT2 <- OPT	**0.767**	**0.767**	**0.021**	**36.242**	**0.000**
OPT3 <- OPT	**0.768**	**0.768**	**0.020**	**37.765**	**0.000**
OPT4 <- OPT	**0.773**	**0.772**	**0.023**	**32.974**	**0.000**
OPT5 <- OPT	**0.701**	**0.700**	**0.029**	**23.907**	**0.000**
OPT6 <- OPT	**0.744**	**0.743**	**0.026**	**28.963**	**0.000**
OPT7 <- OPT	**0.765**	**0.765**	**0.022**	**34.885**	**0.000**
OPT8 <- OPT	**0.723**	**0.723**	**0.025**	**29.194**	**0.000**
PU1 <- PU	**0.810**	**0.810**	**0.021**	**39.385**	**0.000**
PU2 <- PU	**0.796**	**0.796**	**0.018**	**45.373**	**0.000**
PU3 <- PU	**0.692**	**0.692**	**0.022**	**31.855**	**0.000**

PU4 <- PU	**0.828**	**0.828**	**0.014**	**58.916**	**0.000**
PU5 <- PU	**0.834**	**0.834**	**0.014**	**60.457**	**0.000**
PU6 <- PU	**0.778**	**0.777**	**0.021**	**37.766**	**0.000**
PU7 <- PU	**0.805**	**0.805**	**0.017**	**47.230**	**0.000**
PU8 <- PU	**0.813**	**0.813**	**0.016**	**51.416**	**0.000**

Appendix 4.2: Graphical output of Pilot Study



Appendix 4.3: Outer loadings Result of Pilot Study

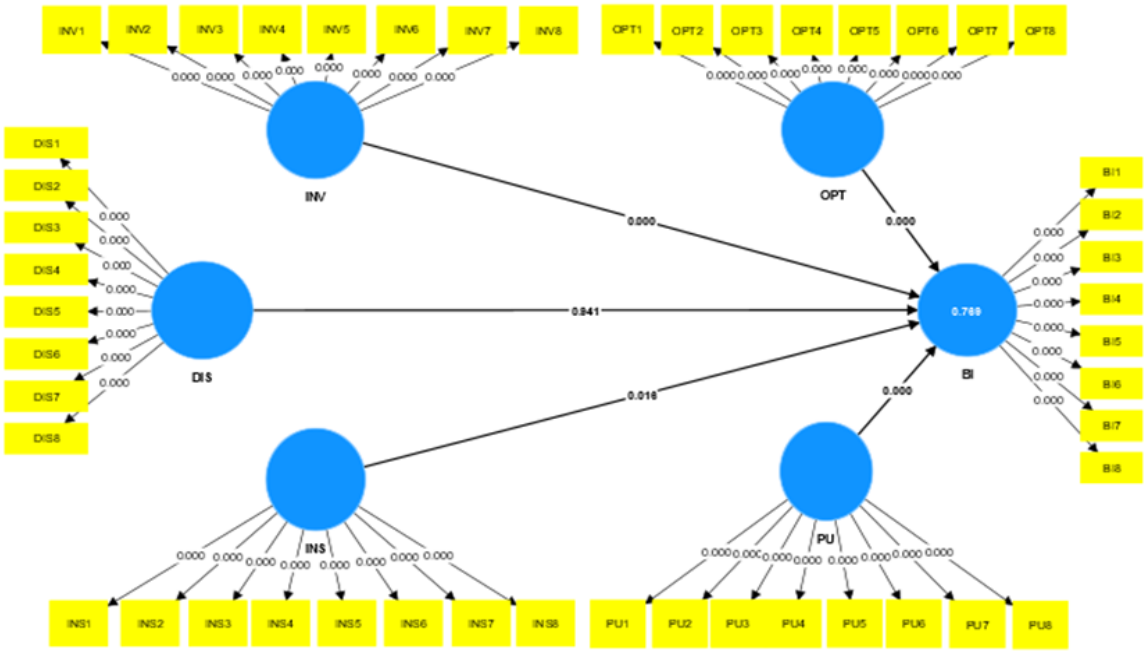
	BI	DIS	INS	INV	OPT	PU
BI1	0.894					
BI2	0.889					
BI3	0.823					
BI4	0.729					
BI5	0.779					
BI6	0.817					
BI7	0.747					
BI8	0.830					
DIS1		0.930				
DIS2		0.725				
DIS3		0.782				
DIS4		0.800				
DIS5		0.841				
DIS6		0.872				
DIS7		0.823				
DIS8		0.902				
INS1			0.908			
INS2			0.861			
INS3			0.827			
INS4			0.853			
INS5			0.730			
INS6			0.779			
INS7			0.843			
INS8			0.860			
INV1				0.916		
INV2				0.739		
INV3				0.755		
INV4				0.712		
INV5				0.713		
INV6				0.805		

INV7				0.797		
INV8				0.939		
OPT1					0.860	
OPT2					0.809	
OPT3					0.820	
OPT4					0.878	
OPT5					0.826	
OPT6					0.825	
OPT7					0.808	
OPT8					0.815	
PU1						0.813
PU2						0.866
PU3						0.797
PU4						0.832
PU5						0.893
PU6						0.769
PU7						0.845
PU8						0.781

Appendix 4.4: Construct Reliability and Validity Test of Pilot Study

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.927	0.931	0.940	0.665
DIS	0.938	0.950	0.949	0.700
INS	0.937	0.942	0.948	0.696
INV	0.918	0.928	0.934	0.642
OPT	0.936	0.937	0.947	0.690
PU	0.933	0.936	0.945	0.681

Appendix 4.5: Graphical Output of Actual Study



Appendix 4.6: Outer Loadings Result of Actual Study

	BI	DIS	INS	INV	OPT	PU
BI1	0.814					
BI2	0.823					
BI3	0.871					
BI4	0.782					
BI5	0.842					
BI6	0.850					
BI7	0.842					
BI8	0.838					
DIS1		0.815				
DIS2		0.822				
DIS3		0.810				
DIS4		0.809				
DIS5		0.829				
DIS6		0.800				
DIS7		0.802				
DIS8		0.788				
INS1			0.668			
INS2			0.742			
INS3			0.789			
INS4			0.784			
INS5			0.821			
INS6			0.762			
INS7			0.775			
INS8			0.787			
INV1				0.801		
INV2				0.837		
INV3				0.803		
INV4				0.842		
INV5				0.849		
INV6				0.848		

INV7				0.832		
INV8				0.817		
OPT1					0.761	
OPT2					0.767	
OPT3					0.768	
OPT4					0.773	
OPT5					0.701	
OPT6					0.744	
OPT7					0.765	
OPT8					0.723	
PU1						0.810
PU2						0.796
PU3						0.692
PU4						0.828
PU5						0.834
PU6						0.778
PU7						0.805
PU8						0.813

Appendix 4.7: Construct Reliability and Validity Test of Actual Study

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.937	0.938	0.948	0.694
DIS	0.932	0.984	0.938	0.655
INS	0.900	0.916	0.919	0.588
INV	0.935	0.937	0.946	0.687
OPT	0.889	0.892	0.912	0.563
PU	0.917	0.918	0.932	0.633

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

	BI	DIS	INS	INV	OPT	PU
BI						
DIS	0.136					
INS	0.285	0.685				
INV	0.730	0.131	0.329			
OPT	0.887	0.256	0.409	0.616		
PU	0.798	0.186	0.373	0.672	0.767	

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

	BI	DIS	INS	INV	OPT	PU
BI1	0.814	-0.148	-0.299	0.562	0.630	0.699
BI2	0.823	-0.161	-0.286	0.550	0.739	0.635
BI3	0.871	-0.210	-0.266	0.651	0.674	0.671
BI4	0.782	-0.183	-0.313	0.520	0.580	0.595
BI5	0.842	-0.028	-0.153	0.563	0.666	0.570
BI6	0.850	-0.085	-0.192	0.589	0.699	0.662
BI7	0.842	-0.100	-0.188	0.590	0.727	0.577
BI8	0.838	-0.090	-0.123	0.554	0.727	0.570
DIS1	-0.111	0.815	0.462	0.027	-0.205	-0.098
DIS2	-0.194	0.822	0.461	-0.137	-0.238	-0.147
DIS3	-0.083	0.810	0.540	-0.130	-0.211	-0.144
DIS4	-0.123	0.809	0.506	-0.101	-0.163	-0.166
DIS5	0.008	0.829	0.503	-0.013	-0.103	-0.082
DIS6	-0.096	0.800	0.547	-0.066	-0.208	-0.157
DIS7	-0.051	0.802	0.557	-0.098	-0.167	-0.070
DIS8	-0.072	0.788	0.554	-0.140	-0.191	-0.119
INS1	-0.182	0.402	0.668	-0.212	-0.270	-0.192
INS2	-0.205	0.367	0.742	-0.272	-0.281	-0.390
INS3	-0.207	0.431	0.789	-0.228	-0.266	-0.277
INS4	-0.296	0.496	0.784	-0.270	-0.286	-0.317
INS5	-0.159	0.481	0.821	-0.186	-0.319	-0.226
INS6	-0.166	0.474	0.762	-0.316	-0.240	-0.177
INS7	-0.177	0.630	0.775	-0.183	-0.263	-0.234
INS8	-0.221	0.544	0.787	-0.180	-0.311	-0.240
INV1	0.628	-0.045	-0.243	0.801	0.507	0.603
INV2	0.581	-0.028	-0.251	0.837	0.449	0.560
INV3	0.485	-0.152	-0.287	0.803	0.417	0.442
INV4	0.534	-0.073	-0.268	0.842	0.470	0.496
INV5	0.591	-0.132	-0.220	0.849	0.462	0.523

INV6	0.558	-0.141	-0.171	0.848	0.486	0.476
INV7	0.551	-0.029	-0.278	0.832	0.423	0.475
INV8	0.608	-0.179	-0.302	0.817	0.543	0.580
OPT1	0.647	-0.145	-0.258	0.515	0.761	0.498
OPT2	0.591	-0.263	-0.246	0.369	0.767	0.455
OPT3	0.594	-0.254	-0.312	0.445	0.768	0.503
OPT4	0.593	-0.212	-0.261	0.360	0.773	0.521
OPT5	0.518	-0.197	-0.283	0.359	0.701	0.469
OPT6	0.548	-0.181	-0.298	0.411	0.744	0.497
OPT7	0.687	-0.100	-0.258	0.483	0.765	0.571
OPT8	0.688	-0.189	-0.286	0.449	0.723	0.688
PU1	0.631	-0.108	-0.352	0.585	0.621	0.810
PU2	0.604	-0.184	-0.393	0.517	0.601	0.796
PU3	0.682	-0.068	-0.140	0.493	0.626	0.692
PU4	0.601	-0.177	-0.155	0.486	0.566	0.828
PU5	0.572	-0.135	-0.246	0.501	0.477	0.834
PU6	0.496	-0.203	-0.316	0.456	0.475	0.778
PU7	0.552	-0.232	-0.336	0.496	0.553	0.805
PU8	0.572	0.020	-0.272	0.452	0.525	0.813

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

Constructs	VIF
DIS -> BI	1.676
INS -> BI	1.853
INV -> BI	1.779
OPT -> BI	2.191
PU -> BI	2.389

Appendix 4.11: Bootstrapping Test of Path Coefficient of Actual Study

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
DIS -> BI	0.003	-0.004	0.042	0.074	0.941
INS -> BI	0.079	0.079	0.033	2.412	0.016
INV -> BI	0.261	0.263	0.032	8.232	0.000
OPT -> BI	0.532	0.530	0.033	15.881	0.000
PU -> BI	0.237	0.235	0.034	6.944	0.000