INVESTIGATING THE INTENTION TO ADOPT FINANCIAL ROBO-ADVISORS IN MALAYSIA

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BY

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

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SEPTEMBER 2025

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 19159.

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DEDICATION

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PREFACE

The study investigates the emerging field of financial technology by focusing on the adoption of robo-advisors in the Malaysian market. It was motivated by the rapid evolution of financial technology in Malaysia's investment landscape and by the limited understanding of the factors of intention to adopt the robo-advisors in Malaysia among the youth. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) enriched with additional external independent variables of Financial Knowledge, this study aims to provide a more comprehensive analysis of factors that influence the intention to adopt these emerging services in the realm of automated financial services.

Beyond the theoretical foundation, this study also bridges theoretical perspectives with practical implications for researchers, financial institutions, and policymakers. It has been a transformative academic experience, fostering analytical and critical skills, and simultaneously indicating how financial theories can be applied to address real-world challenges. Especially in the era of AI development transformation, wealth management and financial planning are being reshaped for individuals, especially for young people. Therefore, this study serves as a valuable reference for future research, raises awareness of financial robo-advisors (FRA) services, and contributes to a broader academic exploration of FRA for the future of investment management.

ABSTRACT

Financial robo-advisors (FRA) have begun to attract attention in Malaysia's financial industry, offering users customised investment portfolios without human intervention and requiring only a minimal investment amount. However, their adoption in Malaysia has been slower compared to regional counterparts such as Singapore and Hong Kong. Therefore, this study examines the factors influencing the intention to adopt FRA in Malaysia, using the Unified Theory of Acceptance and Use of Technology (UTAUT) as the underlying research framework. The independent variables drawn from UTAUT are performance expectancy, effort expectancy, social influence, and facilitating conditions, with an additional factor of financial knowledge incorporated into the model. The study targeted individuals aged 18 to 30 across all regions of Malaysia. Data were collected via an online questionnaire and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS software. The results indicate that performance expectancy, effort expectancy, social influence, and financial knowledge significantly influence the intention to adopt FRA, whereas facilitating conditions have no significant effect. These findings provide valuable insights into the adoption intentions of young Malaysians and offer theoretical and practical implications for researchers, financial institutions, and policymakers seeking to promote the development of robo-advisors in Malaysia.

Keywords: UTAUT, financial knowledge, robo-advisors, PLS-SEM, technology adoption

Subject Area: HG 4621 Stockbrokers. Security dealers. Investment advisers.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AUM	Asset Under Management
AVE	Average Variance Extracted
BNM	Bank Negara Malaysia
CA	Cronbach's Alpha
COVID-19	Coronavirus Disease
CR	Composite Reliability
C-TAM-TPB	Combined TAM and TPB
DIM	Digital Investment Management
EE	Effort Expectancy
ELT	Extract, Load, Transform
FinTech	Financial Technology
FC	Facilitating Conditions
FK	Financial Knowledge
FRA	Financial Robo-Advisors
GFC	Global Financial Crisis
HTMT	Heterotrait-Monotrait Ratio of Correlation
ICMR	Institute for Capital Market Research
IDT	Innovation Diffusion Theory

INT	Intention to Adopt Financial Robo-Advisors
IT	Information Technology
KYC	Know Your Customer
LSTM	Long Short-Term Memory
MPT	Modern Portfolio Theory
NGO	Non-Governmental Organization
NLP	Natural Language Processing
PE	Performance Expectancy
PLS-SEM	Partial Least Squares Structural Equation Modelling
SC	Security Commission
SI	Social Influence
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
XAI	Explainable AI

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CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This chapter will provide an in-depth introduction to the research background of financial robo-advisors, focusing on their evolution, mechanism, and current development in Malaysia. The rapid advancement of financial robo-advisors has transformed traditional investment advisory services, making automated, algorithm-driven platforms increasingly popular among investors. Despite their potential, market adoption remains a key concern in Malaysia's financial landscape. Additionally, this chapter outlines the research problems, research objectives and questions, and the study's contributions, providing a comprehensive foundation for understanding the significance and relevance of the study.

1.1 Research Background

1.1.1 Background of Financial Robo-Advisors (FRA)

Definition of FRA

FRA is an AI-powered solution for automated portfolio management (Jung et al., 2018a). Robo-advisors typically operate with minimal human involvement, relying on standardized online questionnaires to assess clients' risk profiles (Coombs & Redman, 2018; Bruckes et al., 2019). This approach differs from traditional financial advisors, who evaluate risk through direct interpersonal communication (Ruhr et al., 2019). According to research by the U.S. Financial Industry Regulatory Authority (2016, as cited in Hou et al., 2025), robo-advisors perform seven core functions, as illustrated in Figure 1.1.

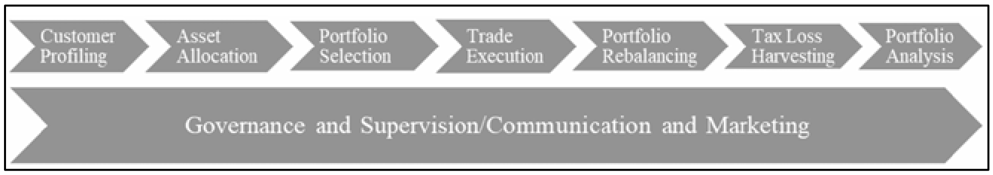

Figure 1.1. Investment value chain of robo-advisors. Adapted from Hou, J. R., Li, Y. H., & Kankham, S. (2025). The service attributes of robo-advisors: a choice-based conjoint analysis. *Information Technology & People*, *38*(1), 338-362.

Global Evolution of FRA

Robo-advisors began to emerge following the 2008 global financial crisis (Zogning & Turcotte, 2024). During this time, there was a general lack of trust in traditional financial institutions, and new, transparent, and reasonably priced investing platforms emerged. Pioneering platforms like Betterment and Wealthfront adopted Modern Portfolio Theory (MPT) to optimise investment portfolios by balancing risk and return (Markowitz, 1952, as cited in Abbas, 2024; Scholz & Tertilt, 2021).

Between 2011 and 2015, robo-advisors transitioned from being niche tools to becoming mainstream in the investment world, with major financial institutions like Vanguard and Charles Schwab embracing automated advisory services. Vanguard introduced its hybrid model, Personal Advisor Services, in 2015, blending robo-advisory technology with human financial advisors (Ho & Jun, 2022; Benavent, 2021). Around the same time, algorithms grew more sophisticated by integrating machine learning methods, such as linear regression and decision trees, to better assess investor risk tolerance and provide more personalized investment suggestions (Chudoba et al., 2013). Also in 2015, Charles Schwab launched Intelligent Portfolios, offering features like free automated portfolio rebalancing and tax-loss harvesting (Shanmuganathan, 2020).

Artificial intelligence (AI) started integrated into their robo-advisory services since 2016 (Belanche et al., 2019). Companies like Wealthsimple and SigFig applied AI techniques to enhance user experience and investment returns (Imerman & Fabozzi, 2020). Natural Language Processing (NLP) was introduced, enabling consumers to converse in conversational manner. NLP-based chatbots became common in instantly responding to customers enquires and providing financial guidance (Lopez-Martinez & Sierra, 2020). Robo-advisors advanced significantly with the integration of ensemble models and neural networks (Chung et al., 2023). The introduction of reinforcement learning enabled systems to adaptively manage portfolios in response to changing market conditions and investor preferences, utilizing tools such as Google's TensorFlow and scikit-learn (Galea & Capelo, 2018). At the same time, investment recommendations became increasingly tailored through algorithmic personalisation, allowing strategies to be customized based on each investor's specific goals, preferences, and financial background (Abbas, 2024).

Since 2019, deep learning advancements have significantly transformed robo-advisors, enabling them to provide timely, tailored investment recommendations (Tiberius et al., 2022). Companies like Moody's and NetOwl leveraged NLP-driven sentiment analysis to assess market sentiment from news and social media. This laid out the framework for robo-advisors to integrate Market Risk Premium (MRP) data into their models, enhancing investment decision-making (Hermansson, 2018; Siyongwana, 2022). The adoption of Long Short-Term Memory (LSTM) neural networks improved time series forecasting and allowed for more accurate market assessments (Sahoo et al., 2019). These robo-advisors were then improved to enhance customer experience and diversify businesses' services. These developments helped robo-advisors adapt to investor goals, market conditions, and risk tolerance, enhancing customer experience and service diversification (Abbas, 2024).

Transparency and trust are crucial for robo-advisors, and Explainable AI (XAI) framework adoption from 2022 to 2024 has helped address this issue. XAI provides logical rationales for investments, appealing to consumers concerned about "black box" AI models (Tchuente et al., 2024; Abbas, 2024). Apart from that, hybrid models combining human and AI are also becoming popular and are aimed at balancing the strengths and weaknesses of artificial and human intelligence (Gnewuch et al., 2024). One example is Vanguard upgraded their Personal Advisor Services, which uses GPT-based chatbots and reinforcement learning algorithms for client interaction, acted as an exemplary model for these trends (Benavent, 2021). Thus, investment in hybrid systems demonstrates the industry's recognition of human involvement in financial planning (Abbas, 2024).

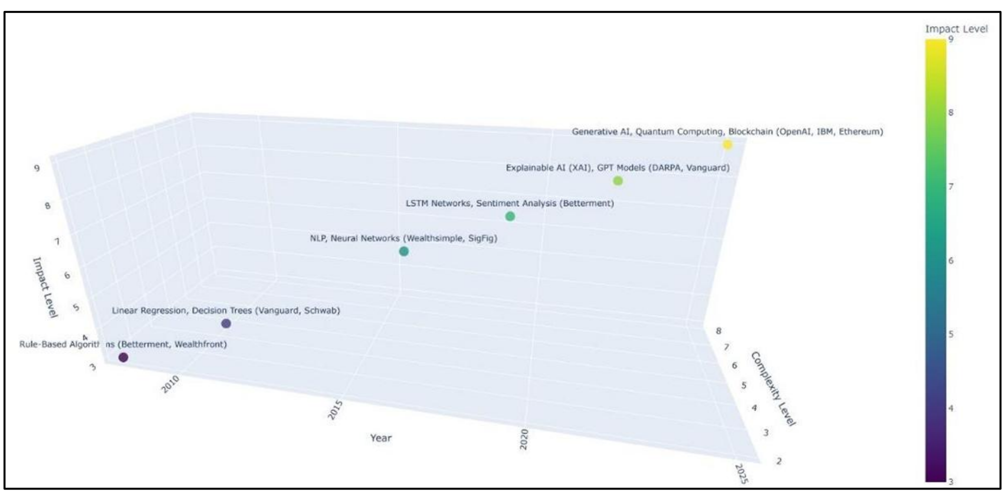

Figure 1.2. Timeline of robo-advisors excluding MPT. Adapted from Abbas, S. K. (2024). AI Meets Finance: The Rise of AI-Powered Robo-Advisors. *Journal of Electrical Systems*, *20*(11), 1011-1016.

Mechanism of FRA

FRA offer computerised and individualised financial planning and investment guidance through the integration of AI algorithms. Large volumes of marketplace information can be analysed by these algorithms, which can also be used to discover trading prospects as well as automate purchase and sale processes using predetermined approaches (Wang et al., 2024). The three main stages of FRA operation involve configuration, matching and customisation along with maintenance (Jung et al., 2017).

During the product configuration phase, a robo-advisor determines the individual's financial objectives and requirements and subsequently capitalises on identifying to figure out the client's risk and investment (So, 2021). Robo-advisors provide strategies for investing in a range of objectives, such as retirement, rainy-day fund establishment, large-expenditure savings, or creating revenue streams to pay bills. These enquiries are supplemented by both subjective and objective enquiries that assess the customer's risk tolerance and commitment (Abraham et al., 2019). Compared to in-person interviews, internet-based customer onboarding is more efficient along with fewer complicated (Kaya, 2017). Surveys online allow individuals to submit financial details, including revenue, investment objectives, willingness to take risks, along with time horizons. This data is crucial for customising suggestions for improvement (Bianchi & Briere, 2021). To ensure accurate analysis and modelling, such information must be effectively organised and structured using sophisticated data integration techniques like Extract, Load, Transform (ELT) (Soloshchuk, 2023). In this stage, the client-facing interface is essential since it helps individuals through processes for onboarding such as Know Your Customer (KYC) procedures and profiling, and it uses dynamic functions to increase involvement from users (Wipro, 2020).

The matching and customisation stage follows, during which advanced algorithms analyse the collected information to pair an individual's profile with appropriate financial portfolios. This matching process is often considered a "black box" because it typically relies on proprietary algorithms that are not publicly disclosed (Jung et al., 2017). Leveraging automated learning techniques, the system can process vast amounts of financial data, identify patterns, and forecast market movements (Hong et al., 2023). These algorithms use tools such as automated rebalancing approaches and tax-optimised approaches for customisation, as well as suggest investment plans that align with the user's financial goals and tolerance for risk (Vincent et al., 2015). Wealthfront uses FRA, for instance, to develop highly personalised financial planning remedies that dynamically modify investment portfolios in response to shifting market circumstances and information from users (Onabowale, 2025). Commonly, an offer signifies the conclusion of a matching stage.

The final stage, which is the maintenance phase, robo-advisor maintains the percentages of the different asset categories in the portfolio through automated restructuring, which guarantees that the overall portfolio's risk stays constant (Torno & Schildmann, 2020). FRA monitors the performance of the assets and adjusts the investment portfolio in response to any adjustment (So, 2021). Stated differently, risk profile development for robo-advising is an initial move towards ensuring the long-term sustainability of investment offerings and service since extensive risk evaluation not merely satisfies regulatory standards yet foster customer interaction and confidence, along with promotes financial accessibility (Kaya, 2017). Individual products that overperform or underperform, as well as responses to external factors, can result in changes to the portfolio structure by preserving a desired level of portfolio risk (Jung et al., 2019). Finally, robo-advisor takes part in reporting during the maintenance phase. Along with the always-available online access, the robo-advisory providers additionally offer their clients financial headlines, constantly informative material, and analysis capabilities at various points in time (Torno & Shildmann, 2020).

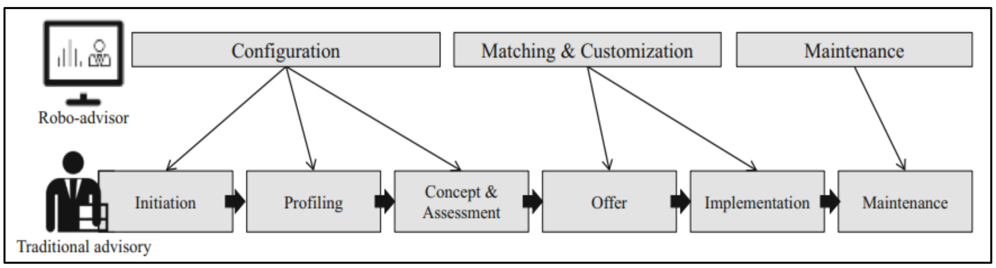

Figure 1.3. Process of robo advisor. Adapted from Jung et al. (2018a). Robo-Advisory: Digitalization and Automation of Financial Advisory. *Business & Information Systems Engineering*.

1.1.3 Current Development of FRA in Malaysia

In Malaysia, the robo-advisor adoption has progressed more slowly compared to regional counterparts like Singapore and Hong Kong, as the technology only made its debut in the country in 2017 (KPMG, 2021). The Securities Commission's (SC) regulatory actions have contributed to the full disclosure of automated discretionary investment portfolio handling in Malaysia, which has aided in the development of robo-advisors within the country. The SC has introduced the Digital Investment Management (DIM) Framework, which is a component of the SC's internet-based agenda for the investment community and seeks to give investors a greater readily available cost-effective, and easy way to handle and build their financial position (Securities Commission Malaysia, 2017). This regulatory framework provides guidelines for the operation of robo-advisors, ensuring investor protection, transparency, and compliance with relevant laws and regulations. By providing a clear regulatory path, the SC has instilled confidence in investors and paved the way for the emergence of various robo-advisory platforms in the country.

In Malaysia, SC defines "robo-advisor" as Digital Investment Manager that involves key components of automated portfolio management including risk assessment, suitability evaluation, portfolio rebalancing and asset distribution (Securities Commission Malaysia, n.d.). A total of nine DIM companies, which provide a variety of approaches to investing catered to various investor requirements, have been licensed thanks to this framework (Ruslan et al., 2022). Under DIM, SC indicated that the digital investment manager should be able to perform few main fund management activities as illustrated in Figure 1.4. With the regulatory sandbox approach, the SC of Malaysia has taken the initiative to promote financial technology advancement, including FRA services (Okasha, 2025). By using this approach, robo-advisory services can function in a regulated setting and test their offerings on a small sample of market participants prior to receiving complete regulatory approval (Gan et al., 2021).

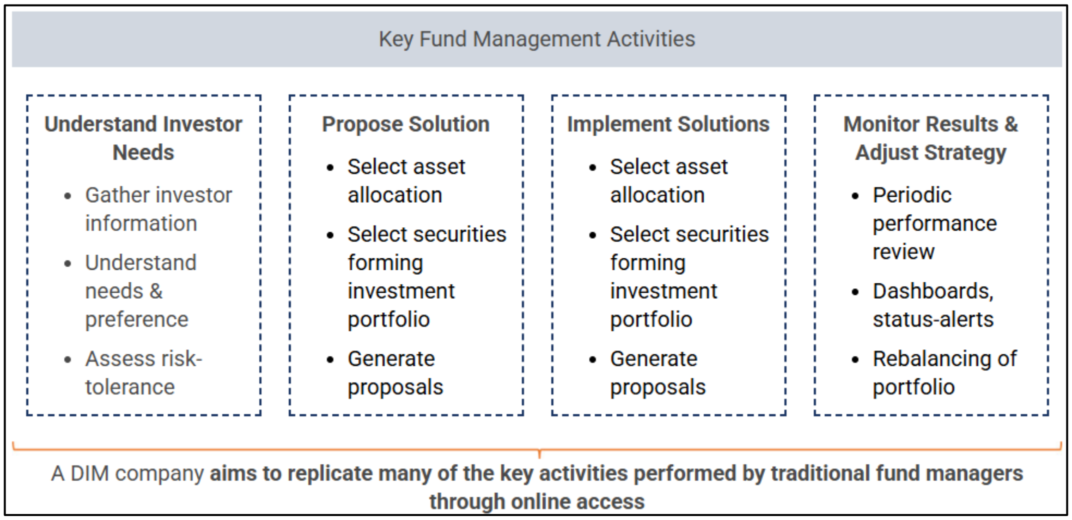

Figure 1.4. Key fund management activities of DIM company. Adapted from Securities Commission Malaysia. (n.d.). *Digital Initiatives.*

Recently occurring developments show that Malaysian investors are increasingly utilising FRA. Numerous local and foreign robo-advisory platforms have opened offices in Malaysia in recent years, offering the public computerised and algorithm-based financial advisory services and such systems usually offer an easy-to-use interface where individuals may react with queries about their financial objectives and level of risk tolerance (Ibrahim et al., 2023). According to Statista (2025), FRAs sector within Malaysia is predicted to continue to expand at a yearly rate of 4.25%, reaching US$2.50k of revenue per user by 2025 and US$2.95k by 2029 (Figure 1.5). Apart from that, collaboration between DIM companies and conventional financial institutions is also driving the growth of financial robo-advisory services in Malaysia. This can be seen from the partnership between GAX MD and Affin Bank to benefit the customers of Affin Avance to build wealth by utilising investment algorithms that will totally automate the rebalancing of their portfolio based on market conditions and diversify their investments across the worldwide market (Affin Bank Berhad, 2022). These recurring trends demonstrate Malaysia's rapidly developing willingness to embrace internet-based services for investing and increase the adoption rate of robo-advisors since the users are given assurance with the licensing and regulation of SC.

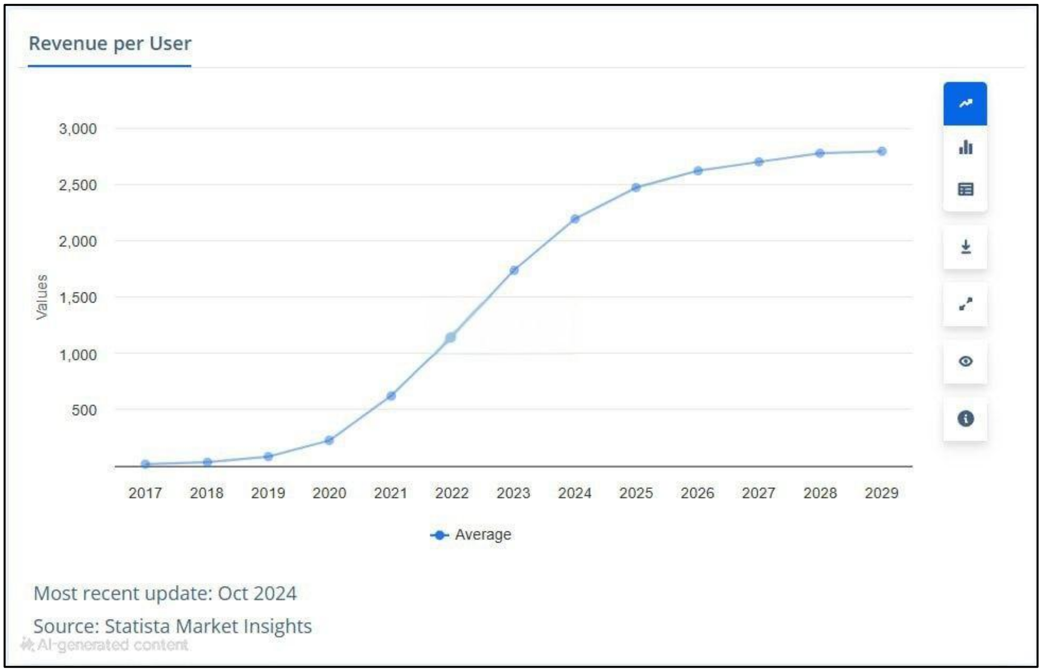

Figure 1.5. Revenue per user of robo-advisor. Adapted from Statista (2025). *Robo-Advisors- Worldwide.*

1.2 Research Problem

Bank Negara Malaysia (n.d.-a) highlights the growing market acceptance of financial service applications that utilise AI and machine learning, such as robo-advisory platforms in its Financial Sector Blueprint 2022–2026. The rapid advancement of digital finance presents significant opportunities to empower consumers through more personalised, needs-based financial solutions and innovative tools that facilitate informed decision-making. However, this technological shift also presents challenges, particularly for traditional financial agents who risk being displaced if they fail to upskill or adapt to providing high-value, client-specific, or cost-efficient advisory services. This underscores the urgency for robo-advisory intermediaries to remain competitive through digital transformation and elevated professional standards. The Financial Capability and Inclusion (FCI) Survey 2021–2022 revealed that 55% of Malaysian households experienced a decline in income during the COVID-19 pandemic, 15% struggled to meet basic needs, and 47% could not raise RM1,000 in emergency funds. These financial vulnerabilities have exacerbated long-term insecurity and the risk of falling into debt cycles (Bank Negara Malaysia, n.d-b). Robo-advisory platforms, which offer automated, algorithm-based financial guidance, have the potential to address these issues by making investing more accessible, especially for individuals with limited financial knowledge (Securities Commission Malaysia, 2022a).

In this context, it is critical to encourage participation from digitally inclined younger generations in the capital market. According to the Securities Commission Malaysia (2024a), identifying innovative, low-cost, and transparent investment solutions is essential for attracting youth investors, particularly through DIM platforms and online brokers. As noted by Bursa Malaysia (n.d.), Lim Chia Wei, Executive Director of Malacca Securities, highlighted that the younger, tech-savvy generation, who are empowered by access to financial education and online resources, is increasingly comfortable using advanced charting tools and exploring innovative trading methods such as robo-advisory and algorithmic trading, which align well with their digital-first mindset. Aligned with national efforts to build a robust digital economy, the Malaysian Digital Economy Blueprint outlines a multi-phase approach to digital transformation of Malaysia's economy. Between 2023 and 2025, Phase 2 of Malaysia's digital strategy emphasizes expanding digital inclusion, laying the groundwork for Phase 3 (2026–2030), which intended to strengthen Malaysia role as a key regional player in digital content and cybersecurity. Promoting digital financial services, including robo-advisors, is a key component of this national vision (MyGovernment, n.d.).

Despite the growing presence of DIM services, their adoption remains limited. Referring to Figure 1.6 and 1.7, although the assets under management (AUM) for the DIM industry grew 500-fold since 2018, reaching RM1.9 billion in December 2024, this still represents only 0.18% of the total fund management industry's RM1.07 trillion AUM (Securities Commission Malaysia, 2024a). Moreover, a study by ICMR (2021) found that youths comprise just 23% of DIM users, indicating a significant gap in adoption among the demographic most aligned with digital tools. This highlighted that DIM services have been underrated in Malaysia and shows it is still lagging behind traditional, wholesale fund, crypto, and others.

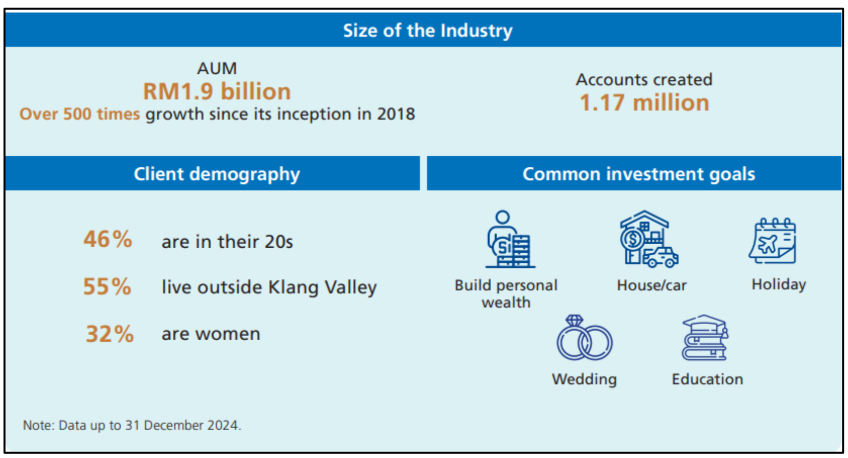

Figure 1.6. Size of the DIM industry. Adapted from Securities Commission Malaysia (2024a). *Annual Report 2024*

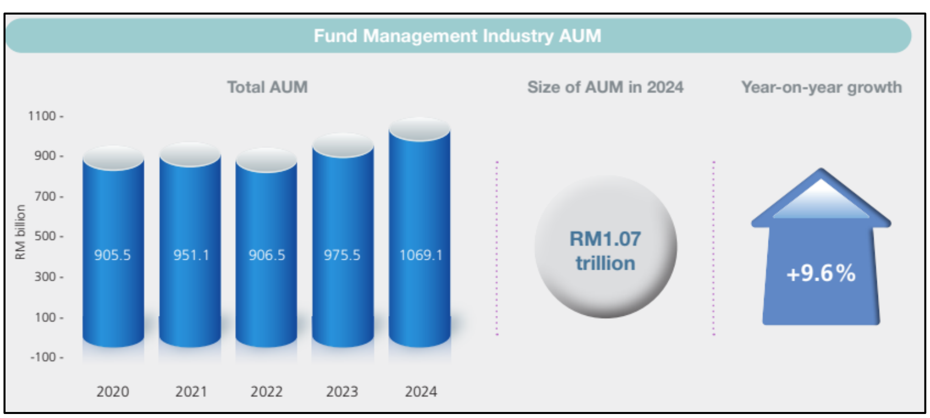

Figure 1.7. AUM of fund management industry. Adapted from Securities Commission Malaysia (2024a). *Annual Report 2024*

While previous studies have examined robo-advisor adoption using UTAUT, most have focused on the general population, with limited attention given to Malaysian youths. This group is uniquely positioned: they are digitally adept but often financially inexperienced (Nourallah, 2023), and their financial behaviours are shaped by peer networks and online communities (Bernice et al., 2024). Furthermore, past research has produced inconsistent findings regarding the influence of UTAUT constructs on adoption intention, indicating an unresolved gap in understanding.

Young people in Malaysia are increasingly influenced by digital platforms in shaping their financial behaviours and investment intentions. Unlike older generations, who often rely on traditional financial advisors or personal experience, youths today are more likely to base their decisions on peer opinions, online trends, and content shared across platforms such as TikTok, Instagram, and YouTube. This shift in behaviour has made social media a significant source of financial information and influence. Research by Daulay et al. (2025) confirms the role of these platforms in shaping stock market participation among young users. Further reinforcing this trend, the Securities Commission Malaysia (2022b) reported in its Youth Capital Market Survey that the internet, particularly social media, has become a primary source of financial information, overtaking traditional print media. For instance, youths engage in stock market investment after listening to Gamestop’s and TopGlove rise due to fear of missing out or herd mentality. This emerging dynamic necessitates greater attention to how these online environments shape youths’ decisions regarding innovative financial technologies like robo-advisors.

Performance expectancy, the perceived practicality, effectiveness, and time-efficiency of technology, is a crucial factor influencing technology adoption among youth

(Vinerean et al., 2022). Despite the rising importance of FRA in capital markets, these services remain underrated and underutilised by the digitally inclined youth demographic. A critical challenge lies in understanding how young users perceive the ability of FRAs to deliver superior financial outcomes such as higher returns, faster goal achievement, and improved decision-making. Without addressing these perceptions, financial institutions risk limited youth engagement in FRA platforms, hindering broader participation in the capital market. This study aims to investigate the role of performance expectancy in shaping Malaysian youths' intention to adopt FRA, addressing a significant gap in promoting financial technology adoption among this key segment.

Another factor central to technology adoption intention among youths is the perceived ease of use. For first-time users, especially those unfamiliar with financial systems, systems that are intuitive and user-friendly can significantly increase the likelihood of adoption. According to the Securities Commission Malaysia (2022b), making financial information more accessible and comprehensible is critical to encouraging participation in the capital market. In Malaysia's youth demographic, varying levels of exposure to financial knowledge could affect how easily these individuals understand and navigate digital investment tools. As a result, simplicity in platform design, transparent information presentation, and minimal barriers to entry are essential to drive adoption. However, the situation may be different from more experienced or tech-savvy young investors. For this group, features that offer greater customisation and advanced functionality may signal professionalism and enhance trust in the platform's capabilities. These preferences align with the growing sophistication of Malaysia's digital economy, particularly in national initiatives such as the Malaysian Digital Economy Blueprint and Horizon 3 of the country's AI strategy (MASTIC, 2023). These initiatives aim to position Malaysia as a regional leader in digital content, innovation, and cybersecurity, which further underscores the importance of aligning robo-advisory platforms with the evolving expectations of young digital natives. Misalignment with user needs could hinder adoption despite digital economy growth initiatives.

In addition to usability, broader infrastructural and systemic issues can hinder adoption intention. Although many Malaysian youths are digitally literate, they still face challenges such as unstable internet connectivity, outdated technology, and limited institutional support for navigating complex financial platforms (Bank Negara Malaysia, 2024). These barriers can prevent even those with financial knowledge from transitioning from intention to actual usage. The lack of integration across digital financial services, coupled with insufficient technical support, exacerbates these limitations and creates a disconnect between awareness and action. Previous studies offer mixed findings regarding the role of these structural conditions. While some researchers highlight their critical influence on adoption intention (Roh et al., 2023), others argue that their relevance diminishes over time as users become more accustomed to the system (Venkatesh et al., 2003). Nevertheless, practical barriers remain significant, especially for first-time investors who may be deterred by the absence of supportive infrastructure or secure environments. These constraints must be addressed if digital financial inclusion among Malaysian youths is to be meaningfully advanced.

Compounding the issue is the widespread lack of financial literacy. Despite being highly connected, many Malaysian youths have limited understanding of investment risks, financial planning, and the actual costs associated with digital investment tools. The Securities Commission Malaysia (2022b) reported that young people tend to focus their spending on immediate needs, such as food, bills, and debt repayment, leaving little for savings or investments. Consequently, many rely more heavily on familiar products like unit trusts, often introduced through agents or financial planners. Without targeted financial education and awareness initiatives, these youths may struggle to engage with more complex tools like robo-advisors, even when the platforms are low cost and transparent in their offerings. However, the lack of confidence and misconceptions about investment risks continue to discourage adoption among those with lower financial literacy.

In summary, despite the growing availability of robo-advisory services in Malaysia, youth adoption intention remains low. Given their digital affinity yet limited financial exposure, it is crucial to explore how the independent variables shape their intention to adopt FRA. This study addresses a critical gap in the literature by focusing specifically on Malaysian youths and aims to provide insights that can support policy, industry development, and youth financial empowerment during Malaysia's digital and AI-driven transformation.

1.3 Research Objectives

1.3.1 General Objectives

To examine the relationship between various determinants and intention to adopt FRA in Malaysia.

1.3.2 Specific Objectives

RO1: To examine the relationship between performance expectancy (PE) and intention to adopt FRA in Malaysia.

RO2: To examine the relationship between effort expectancy (EE) and intention to adopt FRA in Malaysia.

RO3: To examine the relationship between social influence (SI) and intention to adopt FRA in Malaysia.

RO4: To examine the relationship between facilitating conditions (FC) and intention to adopt FRA in Malaysia.

RO5: To examine the relationship between financial knowledge (FK) and intention to adopt FRA in Malaysia.

1.4 Research Questions

RQ1: Is there any significant relationship between performance expectancy (PE) and intention to adopt FRA in Malaysia?

RQ2: Is there any significant relationship between effort expectancy (EE) and intention to adopt FRA in Malaysia?

RQ3: Is there any significant relationship between social influence (SI) and intention to adopt FRA in Malaysia?

RQ4: Is there any significant relationship between facilitating conditions (FC) and intention to adopt FRA in Malaysia?

RQ5: Is there any significant relationship between financial knowledge (FK) and intention to adopt FRA in Malaysia?

1.5 Significance of Study

1.5.1 Researchers

This research fills the gap by studying the robo-advisors adoption intention through UTAUT and additional variable of financial knowledge, focusing on Malaysian youths who aged from 18 to 30 in Malaysia. Besides, there is a lack of existing literature to explore FRA adoption intention from region demographics. Therefore, this research enriches the literature of FRA adoption intention by utilising quota sampling to facilitate balanced representation among Malaysian youths from distinct regions. By investigating key factors such as financial knowledge, performance expectancy, and facilitating conditions to examine the intersection of intention to adopt FRA and Malaysian youths, this study can serve as a valuable reference for researchers and inspire further studies to support future research development on robo-advisors in Malaysia.

1.5.2 Financial Institutions

The findings offer meaningful implications and practical guidance for financial institutions. Isaia and Oggero (2022) highlight that the relationship between sociodemographic factors and the intention to use robo-advisors remains inconclusive. Understanding the intention to adopt FRA among Malaysian youths can help financial institutions refine the design and marketing of FRA to better align with consumers' needs and preferences. By adapting to evolving consumer expectations and new technological advancements, financial institutions can remain competitive, better discover new market opportunities, and match their offerings with market trends. Moreover, these insights enable them to enhance brand recognition, attract new customers, and effectively cater to the Malaysian youth.

1.5.3 Policy Makers

This study provides insights for policy makers looking to boost the intention of Malaysian youth investors to adopt robo-advisor services. By pinpointing crucial factors such as financial knowledge (FK), performance expectancy (PE), facilitating conditions (FC), social influence (SI) as well as effort expectancy (EE) that affect the intention to adopt robo-advisor, the findings provide a useful basis for creating more effective policy strategies. As stated by Securities Commission Malaysia (2022a), even though digital investment tools such as robo-advisors are more accessible, the intention to adopt among Malaysian youths still relatively low, indicating an apparent need for focused intervention. This study can also be used as a guide or recommendation in the creation of financial literacy initiatives or regulatory frameworks that facilitate digital financial solutions.

1.6 Chapter Summary

This chapter presented an in-depth discussion surrounding FRA, particularly in Malaysia. It also highlighted significant evolution and timeline of development of robo-advisors up to present day. Moreover, it also examined the research problem that motivate us to conduct this study as well as clearly state the research objectives and questions. The study’s significance lies in its potential to guide researchers, financial institutions and policy makers in enhancing robo-advisory services to better meet the needs of Malaysian youths, ultimately fostering greater financial inclusion and literacy.

CHAPTER 2: REVIEW OF LITERATURE

2.0 Introduction

In Chapter 2, the Unified Theory of Acceptance and Use of Technology (UTAUT) will be explored as the significant foundation of this study. It will be discussed and explained comprehensively in this chapter with its definition, key function, as well as its principles. Besides, the role of the dependent variable and each of the five independent variables will be clarified and explained. This will also follow by a series of hypotheses to test for these relationships. In addition, conceptual frameworks will be developed and established to illustrate and shape out what is the relationship between these five factors and intention to provide a clearer view and understanding for this study.

2.1 Underlying Theory

2.1.1 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT was suggested by Venkatesh et al. (2003) which incorporated determinants from eight fundamental models in technology acceptance research areas, which are Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Combined TAM and TPB (C-TAM-TPB), Innovation Diffusion Theory (IDT), Motivational Theory, Model of PC Utilization, Social Cognitive Theory. UTAUT model is a well-recognized framework for assessing people's intentions to embrace and utilize technology (Bajunaied et al., 2023). This model assumed that usage intention influences behaviors and introduced four main aspects to explore the behavioral intention of user to use a technology which are performance expectancy, effort expectancy, social influence and facilitating conditions. It could capture approximately 70 percent of the variability in the behavioral intention of user towards utilization of a technology and around 50% of the variability in the technology use (Venkatesh et al., 2003).

In this theory, effort expectancy, performance expectancy and social influence are deemed to impact behavioral intention to utilize a technology, whereas facilitating conditions and behavioral intention explain technology use (Venkatesh et al., 2012). Venkatesh et al. (2003) defined performance expectancy as the extent to which the user perceived using the application would enhance their performance. She also proposed that PE could be a main factor to determine intention in most circumstances; Effort expectancy is defined as the perception of utilizing a particular technology involved minimal or no effort; Social influence implies that how user depends on the opinions of others when deciding to use a technology; Facilitating conditions refer to the belief of a user that a technical, operational infrastructure is readily available to support the technology use (Venkatesh et al., 2003).

Previous empirical studies have researched adoption intention of robo-advisory using UTAUT in different context. Nazmi et al. (2024) found out that to encourage adoption of robo-advisor among the individuals who are generally conservative and are not literate in digital finance, it should focus on the transparency of the robo-advisory process and digital financial education. The study of Gan et al. (2021) suggested that consumers, who are more financial literate and rely on robo-advisors, are more likely to adopt financial robo-advisor during COVID-19 crisis. The constructs of UTAUT have proven to impact usage intention of robo-advisor in private pension investments (Eren, 2023).

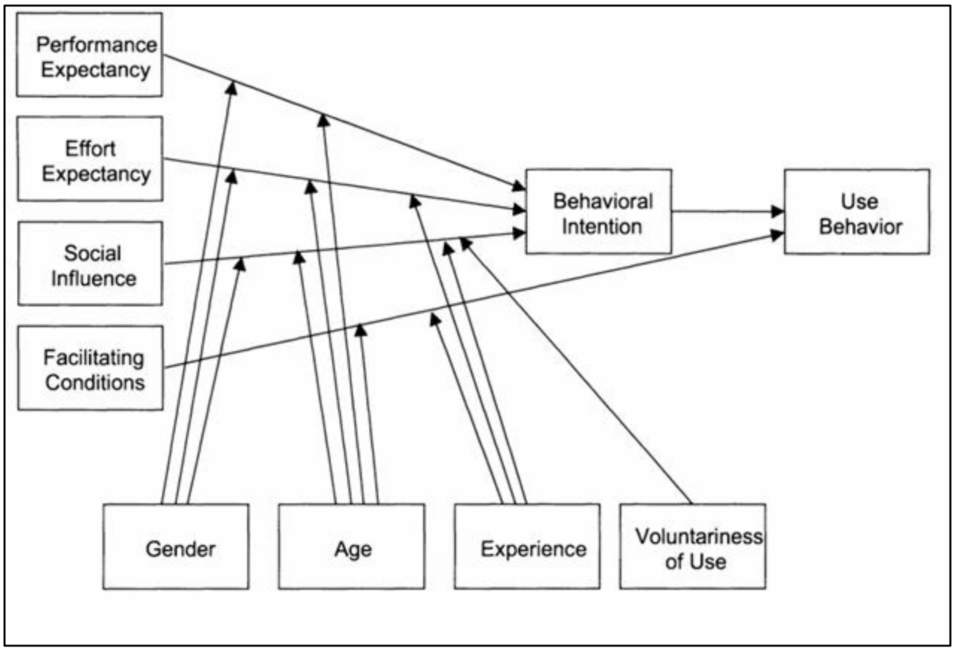

Figure 2.1. Research model of UTAUT. Adapted from Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

2.2 Literature Review on Dependent Variable

2.2.1 Intention to Adopt Financial Robo-Advisors (INT)

The concept of behavioral intention plays a very significant role in getting a deeper understanding of the adoption of not only financial robo advisory but the technology, especially AI. According to Peng and Yan (2022), it is widely recognized as the key predictor and indicator for technology adoption. Intention toward adoption can be described as an individual's readiness to engage with or use something, driven by their motivational behavior ("What is adoption intention", 2017, as cited in Chong et al., 2019). For further explanation, it is defined as the level of an individual's readiness, motivation, or plan to engage in some specific behaviour. In this study, intention to adopt FRA is used as a dependent variable to understand how the young Malaysians is willing to adopt FRA. It will be investigated in a range of factors which include performance expectancy, effort expectancy, social influence, facilitating conditions and financial knowledge.

According to Gobler (2024), traditional financial services especially advisory services heavily rely on human judgment and human interaction. This might have a high possibility of error due to human limitations. Therefore, FRA might be one of the choices for the investor to investigate. According to Sabir et al. (2023), early-stage consumer scepticism is a common psychological feeling when facing these kinds of disruptive technologies. People will worry and be concerned about the uncertainty of AI services. However, similar to the previous technological innovations, this trend will be diminished as users become more familiar, more understood, and clearer with the system (Gan et al., 2021). For example, Touch and Go, RFID, E-sim, My Digital, E-lessen, and Online Banking Services. This pattern has been observed in the evolution of the digital services in Malaysia.

According to Beirne et al. (2021), the COVID-19 pandemic has sparked human awareness of technology. It plays a vital role, in this accelerating digitalization era across all industries. During the lockdown period, service sectors were facing challenges due to the social distancing measures and even caused some in-person services were temporarily unavailable (Zainun et al., 2022). These situations forced consumers to use digital platforms, especially in the financial industry (Idris, 2020). It marked a turning point in encouraging people to gradually accept, understand, and explore technological innovations and own their benefits. According to Accenture (2020), these changes have not only increased the frequency of digital transformation but also altered consumers' perceptions of the risk and safety regarding online services.

However, INT does not operate solely. It is shaped by a combination of factors. In this study, the independent variables are based on the UTAUT theory model. INT is not a static measure, but it will evolve with the development of technology nowadays. Initial concerns will transform when users gain hands-on experience with them. This evolution is an important milestone for FinTech companies since they are trying to address the specific needs and concerns of different kinds of populations.

In conclusion, INT is an essential indicator in getting to know the willingness of young Malaysians to adopt the FRA. This will directly reflect on the performance expectancy, effort expectancy, social influence, facilitating conditions and financial knowledge. Understanding these details is essential for those Fintech companies.

2.3 Literature Review on Independent Variables

2.3.1 Performance Expectancy (PE)

PE is one of the fundamental elements of UTAUT model, which assets that PE refers to how much technology can enhance the experience of individuals in carrying out specific tasks (Venkatesh et al., 2012). PE emphasizes the practicality, effectiveness, and time-efficiency potential of technologies for those using it (Vinerean et al., 2022). Simply put it another way, it evaluates how much individuals think that utilizing the technology will strengthen their performance by rendering their work simpler or more effective (Martinez & McAndrews, 2022). The PE towards robo-advisor in this study indicates how much investors are convinced that utilizing a robo-advisor will enhance their financial performance and lead to greater yields (Eren, 2023). The broad acceptance and utilization of digital financial services such as FRA depend on optimizing consumer experiences to satisfy expectations of performance (Savitha, 2022). PE is especially important when considering Malaysian youths, who are becoming more adapted with technology and receptive to digital financial services. This generation is expected to view FRA as a valuable resource for effective investment, in line with their inclination towards digital accessibility and effectiveness (Kiran Kumar & Monisha, 2024).

Several studies have shown that PE and INT are positively correlated. The studies of Eren (2023) which focus on examining the factors that drive the intention to utilize robo-advisor for private pension investment indicated that PE greatly affects individuals' choices regarding the adoption of robo-advisor services in their financial planning. Similarly, research focusing on the early stages of the COVID-19 pandemic among Malaysians found a strong link between PE and individuals' willingness to adopt FRA (Gan et al., 2021). This result aligns with the evidence reported by Roh et al. (2023), who confirmed that PE positively influences people's perceptions of robo-advisors, which in turn shapes their intention to use such services.

In short, these current findings have demonstrated consistent findings on how important PE is in fostering the intention of utilizing the robo-advisor services. All of these studies have shown that PE is significantly associated with the intention to adopt robo-advisor services. Therefore, the following hypothesis is developed to examine the relationship between PE and intention to adopt FRA among Malaysian youths:

H_0: There is no significant relationship between performance expectancy (PE) and the intention to adopt financial robo-advisors (INT).

H_1: There is a significant relationship between performance expectancy (PE) and the intention to adopt financial robo-advisors (INT).

2.3.2 Effort Expectancy (EE)

EE refers to the degree of ease associated with using a system (Rizkalla et al., 2024). In simple terms, it refers to the level that an individual perceives that specific system is required for minimal effort to use. EE plays an important role in user experience since the digital revolution has integrated into most of the industry and sectors nowadays. The ease of use becomes increasingly important, especially for the potential user or a new user, since people are more likely to develop a more favourable attitude to use when they believe that the using a particular system will be effortless (Yi et al., 2023). According to Securities Commission Malaysia (2022b), the Youth Capital Market Survey shows and states that ensuring that information is easily accessible and easy to understand is critical for a beginner to want to start participating in the capital market. Therefore, this study will use the UTAUT to provide insight into the perceived ease of use to find out and provide individuals' subjective assessment of the simplicity and user-friendliness of the FRA. Besides, EE elements include not only the smoothness of the system but also interface design, user navigation, system responsiveness, and the overall learning curve associated with new technology (Ashraful, 2024).

With the rapid Fourth Industrial Revolution, Malaysia is undergoing a rapid expansion of digital literacy, especially among the younger generations. As digital skills are being widely adopted, people have a higher baseline expectation toward the usability of the new technology to meet their needs efficiently and effectively (Yi et al., 2023). This trend has highlighted the growing importance of designing intuitive, user-friendly systems that improve productivity, convenience, and adaptability to meet user demands (Nguyen et al., 2023). Therefore, when developing the FRA, developers need to consider the youth's digital skills. The ease of using the system to manage their finance and execute transactions and personalized insights becomes a critical factor in their decision-making process.

Ensuring the system has a minimal cognitive load is critical. For example, having a clear menu, straightforward navigation, and helpful and supportive customer service can improve the user experience (Gan et al., 2021). Nain and Rajan (2024) suggest that the likelihood of adopting FRA platforms increases when their interfaces and functionalities closely align with users' everyday digital habits and needs. However, some of the users may still rely on using traditional banking systems instead of digital platforms in Malaysia (Chong et al., 2019). A platform that offers a smooth and easy-to-understand experience can reduce barriers to adoption and positively influence behavioural intention (Windasari et al., 2022). Therefore, this study will examine whether youth exhibit distinct demands in FRA, particularly in terms of efficiency and convenience. Moreover, the reliability and responsiveness of the system are also one of the key elements of EE (Bashir et al., 2025). User will always expect that when they are using FRA, the system will respond and process their input accurately and quickly. In the finance world, any minor delays or errors can have significant consequences ranging from missed investment opportunities to a financial crisis. In the competitive financial market nowadays, any indication that a system might be unreliable will deter potential users from adopting it, especially in FinTech (Wan Abdullah & Hisamudin, 2024).

However, some may argue that the effect of EE on intention to adopt robo-advisors is not universally positive. Some research that shows this relationship may not always be consistent. For experienced and tech-savvy investors, more functions and customised products convey a sense of sophistication, professionalism, and reliability in a system, which may increase their intention to adopt it, particularly in today's rapidly evolving technological landscape (Brière & Thomadakis, 2024). According to Eren (2023), research shows that for tech-savvy users, a high EE might not be a strong or key element to deter them from adopting FRA. They are more focused on the advanced features, functions, and accessibility instead of the complexity of the systems. Besides, according to Khoo et al. (2024), research shows that there is no significant relationship between EE and intention to adopt robo-advisory services in Malaysia.

Therefore, this study aims to investigate the role of EE in the adoption intention of robo-advisors among the youth generation. It determines whether the relationship between INT and EE is significant across the youth. This will help in clarifying the dependent effects of EE and provide a more comprehensive and deeper understanding of how EE influences intention to adopt FRA.

H0: There is no significant relationship between effort expectancy (EE) and intention to adopt financial robo-advisors (INT).
H1: There is a significant relationship between effort expectancy (EE) and intention to adopt financial robo-advisors (INT).

2.3.3 Social Influence (SI)

SI refers to an individual's perception of how others, especially those significant to them, view the importance of adopting a new system. It is a critical factor in shaping behaviours, feelings, and decisions, particularly in the context of technology adoption (Haverila et al., 2023). This study contextualizes SI as the influence exerted through social media platforms, especially among young adults, who are highly receptive to digital interactions. Festinger's Social Comparison Theory supports this framing of SI. According to this theory, individuals look to others for cues to reduce decision-making anxiety and gain social validation (Singh & Kumar, 2024). For young users unfamiliar with robo-advisors, social media becomes a key medium through which these cues are received, especially when firsthand experience is lacking (Nguyen et al., 2023). Therefore, the opinions and endorsements visible on platforms like Instagram, TikTok, and YouTube act as digital "reference groups" for young Malaysians.

With the growing reliance on online communication, SI, particularly via social media, is expected to be a key determinant of the intention to adopt FRA. Social media facilitates both voluntary and involuntary exposure to the viewpoint of friends, family, influencers, or even strangers (Nguyen et al., 2023). As technology becomes more integrated into everyday life, individuals may adopt digital tools not just for personal utility but to sustain social connectivity and peer alignment (Roh et al., 2023). For example, if robo-advisors are perceived positively within their social media circles, youths may be more inclined to try them, both out of interest and a desire for social inclusion. Further supporting this, studies have found that trust in social others and perceived popularity of technology influence adoption. Individuals are more inclined to use robo-advisors when they perceive that trusted peers or online influencers endorse them (Wang & Ma, 2023; Bernice et al., 2024). This is especially true for young people, whose digital behaviours are often influenced by feedback and trends observed on social platforms.

This relationship is further reinforced by Yeh et al. (2022), whose research demonstrates a positive correlation between SI and the intention towards robo-advisors' adoption. Besides, people are impacted by the experiences and viewpoints of people in their social circle in addition to the technology itself

(Ahmad et al., 2021). From a sociological standpoint, Eren (2023) suggests that individuals are more inclined to decide to use the relevant technology if they get referrals or feel that others who are significant to them ought to. Supporting this, SI has additionally been shown to result in a positive and substantial impact on INT. One possible reason for this is that individuals would see utilizing robo-advisors favourably if important people, like relatives and close acquaintances, utilize or suggest them (Nguyen et al., 2023). Mathew et al. (2024) also carried out an empirical study to investigate the variables influencing investors' intention in using robo-advisors and concluded that social presence has a significant role in determining this intention.

Securities Commission Malaysia (2022b) reported that young individuals are increasingly relying on social media as a primary source of financial information. This demographic is particularly vulnerable to media-driven influences, often shaped by the fear of missing out and herd behavior, which is a phenomenon that has intensified in contemporary financial markets with the proliferation of social media platforms and online investment communities (Jajoo & Baag, 2025). Research suggests that the likelihood of investing in a particular asset increases with the volume of information available about it on social media. When investment-related content is easily accessible, frequently updated, and delivered in real time through social media, individuals are more inclined to leverage such information to make informed investment decisions (Abu-Taleb & Nilsson, 2021). Social media encompasses interactive digital platforms that enable users to access, create, upload, and share content, ideas, and interests across diverse online channels (Rais et al., 2023). In line with this perspective, Gruzd et al. (2024) conceptualized SI to include exposure to online influencers as well as financial content disseminated by both formal and informal organizations through websites and digital platforms.

While direct research on the influence of social media on robo-advisor adoption remains limited, several studies have examined its role in broader FinTech adoption. For example, Solarz and Swacha-Lech (2021) found that individuals who rely on social media opinions are more inclined to use FinTech solutions when making financial decisions, viewing these platforms as vital sources of information. Similarly, Safitri et al. (2021) identified a significant positive relationship between SI and the intention to adopt FinTech, as peer-shared content can effectively persuade users. Building on these insights, this research seeks to address the research gap by examining how social media influences the intention of Malaysian youth to adopt FRA.

However, perspectives on SI differ. Cardoso et al. (2024) argue that the direct impact of digital influencers on FinTech adoption is limited, as users often prioritize brand reliability and user experience over influencer endorsements. Likewise, Wang and Ma (2023), Mahmutovic (2024), and Singh and Kumar (2024) found that SI was not a significant predictor of robo-advisor adoption intention in their respective studies.

By incorporating UTAUT's established relationships into the robo-advisory context, SI is expected to play a key role in driving the adoption intention of FRA. Thus, this study postulated that:

H_0: There is no significant relationship between social influence (SI) and intention to adopt financial robo-advisors (INT).
H_1: There is a significant relationship between social influence (SI) and intention to adopt financial robo-advisors (INT).

2.3.4 Facilitating Conditions (FC)

FC that embraces circumstances like assistance from technology experts, user-friendliness, and instructional materials, states that individuals are far more inclined to embrace technology advancement when they perceive sufficient support and have the amenities that they require to effectively utilize them readily (Bernice et al., 2024). In regard to FRA, FC is known as a user's access to facilities, resources and advantage that can either help or impede their ability to effectively utilize the technology (Ansari & Bansal, 2024). FC also represents the conviction that users can access guidance as needed or that they are equipped with the knowledge and resources needed to utilize FRA (Eren, 2023).

The presence of FC is thought to be a significant factor in the intention towards the utilization of FRA services as people's expectation regarding technology are shaped in part by their uncertainties regarding confidentiality, safety, and dependability (Dwivedi et al., 2016). It also noted that people may be reluctant to embrace web-based technology if they receive insufficient support, delayed assistance, insufficient details, or lack of facilities. Uncertain regulation regarding privacy and system specification could also deter individuals from employing internet-based services (Chawla & Joshi, 2020). Bajunaied et al. (2023) also discovered that people's confidence in utilization of FRA was significantly improved by having access to technical assistance.

Research has identified that FC has a positive impact on the intention to adopt FRA. According to Roh et al. (2023), the individuals undoubtedly utilize the advantageous features offered by robo-advisors, which include transparent information dissemination, portfolios restructuring by timescale and circumstance and affordable charges, for the reason investing guidance given by traditional financial planners is complicated and challenging to comprehend. Additionally, it suggests that the organizational and technical infrastructure is adaptable and effortless to use, which results in a favourable evaluation that could increase adoption intention among users (Yeh et al., 2022). Moreover, research shows that the intention to adopt technological innovations like FRA is directly correlated with FC (Bernice et al., 2024). The willingness to embrace FRA by consumers may thus be enhanced by guaranteeing strong FC including sufficient resources and technical guidance.

Despite its potential, several studies have shown that FC does not significantly influence the intention to adopt FRA. Gan et al. (2021) observed that FC had little predictive power regarding FRA usage. This lack of impact may stem from negative user experiences, such as technical errors, server issues, or delayed support from customer service centers (Kusuma & Kusumawati, 2023). Similarly, Nourallah (2023) found FC to be insignificant in shaping adoption intentions, suggesting that users often possess the necessary skills and knowledge to use FRA platforms independently, without relying on external technical support (Sebastian et al., 2022). Furthermore, Mahmutovic (2024) emphasized that within the UTAUT framework, PE and EE are the primary drivers of adoption, while FC play a minimal role.

The aforementioned research has shown conflicting results about how FC affects robo-advisor adoption intentions. As a result, the following hypothesis is developed to examine the relationship between FC and FRA adoption intention among Malaysian youths:

H_0: There is no significant relationship between facilitating conditions (FC) and intention to adopt financial robo-advisors (INT).
H_1: There is a significant relationship between facilitating conditions (FC) and intention to adopt financial robo-advisors (INT).

2.3.5 Financial Knowledge (FK)

According to Lusardi and Mitchell (2014), FK is known as an individual's perceived and self-assessed financial understanding. Stavrova (2014) also defined FK as "financial education", "financial literacy", "economic literacy", which refers to the essential requirement for people to possess the information, abilities, and behaviors to make informed decisions regarding banking, lending, and investing, as well as to manage their daily lives and make wise and accurate decisions. An individual gained more knowledge and discovered the phenomena of the illusion of knowledge when they were exposed to new information from various sources (Barber & Odean, 2001; Konana & Balasubramanian, 2005, as cited in Gan et al., 2021). Alternatively, a person's perceived belief about the precision, scope and depth of their knowledge could surpass their actual levels of knowledge. Nonetheless, it was discovered that perceived FK significantly influenced investment behaviors more than objective knowledge (Henager & Cude, 2016, as cited in Gan et al., 2021). Financial literacy is an essential construct in this research as it significantly impacts individuals' ability to assess risks, comprehend financial products, and make well-informed financial choices (Megha & Gupta, 2025). The 2022 survey conducted by the Securities Commission Malaysia revealed that 62% of young people in Malaysia exhibited low financial literacy levels, incorporating financial knowledge is particularly crucial to understanding how gaps in literacy affect intentions to adopt (Securities Commission Malaysia, 2022b).

Previous research indicates that people who possess greater financial knowledge tend to embrace cutting-edge financial solutions, such as robo-advisors, particularly in light of increasing market complexity and advancements in technology within the financial industry (Anwar, 2025). When creating a passive investment portfolio using robo-advisors, the investor ought to identify their risk tolerance, investment objectives, time horizon, and preferred investment amount and intervals. These fundamental investment requirements necessitate a basic understanding of financial principles, which can be crucial to the success of an investment (Eichler & Schwab, 2024).

Gan et al. (2021) found that during the COVID-19 crisis, higher financial knowledge was associated with stronger intentions to adopt FRA. This finding was further supported by Yi et al. (2023), who demonstrated that individuals' willingness to adopt robo-advisors as a wealth management tool was significantly influenced by their financial literacy. Qadoos and AbouGrad (2025) found that people who are more financially adequate and skilled are more inclined to adopt robo-advisors and take advantage of all related features.

Conversely, Piehlmaier (2022) stated that individuals with higher objective investment knowledge are less intended to adopt robo-advisors. Similarly, a study of U.S. investors by Brenner and Meyll (2020) found that users of robo-advisory platforms tend to have lower levels of objective financial literacy. Additionally, Todd and Seay (2020) identified that younger individuals with low to mid-range incomes, lower objective investment knowledge, and non-retirement investment accounts are more incline to utilize robo-advisors. This aligns with the findings of Fan and Chatterjee (2020) whereby investors with a solid understanding of finance and investing typically manage their investments themselves or collaborate with a human advisor, therefore they are unable to delegate their portfolio management decisions to robo-advisors.

These conflicting findings highlight the necessity of examining whether a significant or insignificant relationship exists between FK and FRA adoption intention among Malaysian youths. Hence, this study proposes the following hypotheses:

H_0: There is no significant relationship between financial knowledge (FK) and intention to adopt financial robo-advisors (INT).

H_1: There is a significant relationship between financial knowledge (FK) and intention to adopt financial robo-advisors (INT).

2.4 Conceptual Framework

The conceptual framework is developed in light of the research conducted by Nazmi et al. (2024) and Gan et al. (2021). An external independent variable, which is financial knowledge is added to the framework because it is crucial to examine its role whether it facilitates or hinders the intention to adopt FRA, specifically among Malaysian youths. Since youths are considered financially vulnerable as they face challenges like student loans and rising living costs. Furthermore, BNM reported low financial literacy among Malaysian youths. Given these circumstances, this study investigates whether financial knowledge equips young individuals with the confidence and capability to engage with innovative financial technologies such as FRA, or whether its absence acts as a barrier to adoption. Apart from that, the construct of social influence is focused on the influence from online communities and people on social media rather than traditional family, friends, and peers.

Besides, actual behavior is not measured in this study because this study aims to investigate Malaysian youths' readiness and openness towards robo-advisors. Moreover, the dependent variable of this study is the intention to adopt FRA. This study focuses on individuals who have used and not used FRA before, allowing the study to capture a broader spectrum of adoption intention. This approach is consistent with previous studies by Nazmi et al. (2024), Gan et al. (2021), Eren (2024), Cho (2019) and Bajunaied et al. (2023). It is also supported by prior studies since the UTAUT framework is explicitly designed to explain users' behavioral intention to use technology (Chong et al., 2019; Gan et al., 2021; Nazmi et al., 2024; Roh et al., 2023; Zhafira et al., 2025). Hence, there are five determinants are being studied to investigate how they impact the intention to adopt FRA among Malaysian youths.

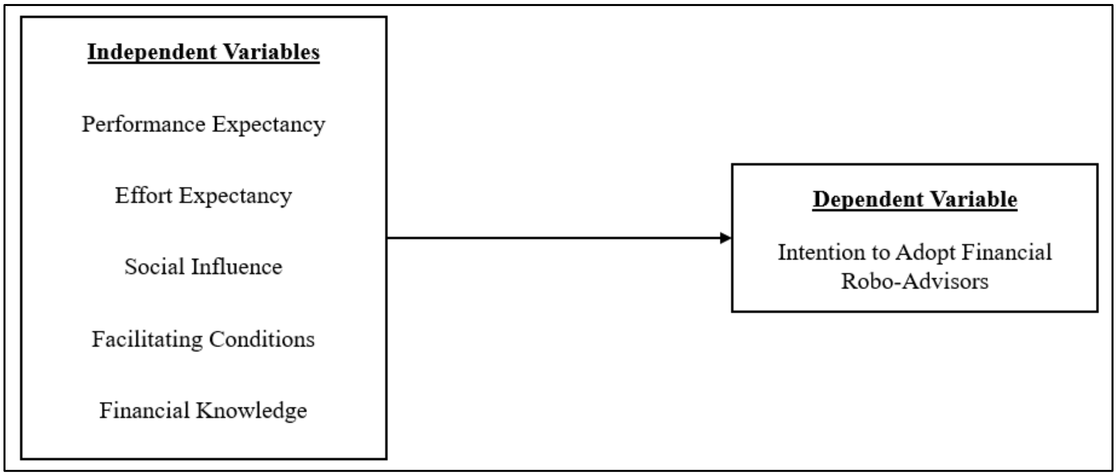

Figure 2.2. The proposed conceptual framework. Developed by the authors.

2.5 Chapter Summary

This chapter examines earlier study on relevant theories and variables. It examines the relationship between each independent variable and the intention to adopt the FRA in Malaysia. Additionally, the conceptual framework, along with the hypotheses that illustrate the relationships between the dependent and independent variables, has been formulated and presented. The next chapter will focus on the research methodology.

CHAPTER 3: METHODOLOGY

3.0 Introduction

Chapter 3 covers with research design, data collection method, sampling techniques, research instruments, measurement scales and data analysis techniques which were applied in this research. It aims to provide a clear, well-developed plan to collect and analyse the collected data to identify the relationship between various stated determinants as well as the intention to adopt FRA in Malaysia.

3.1 Research Design

Research design pertains to the structure for conducting a study (Marczyk et al., 2005). This study employs a quantitative research design to test hypotheses and analyse the relationship between these determinants by collecting numerical data through a survey form. A quantitative design is chosen as it provides an objective way and is critical in measuring attitudes and intentions.

3.2 Data Collection Method

This study will gather primary data using an online survey questionnaire tailored to address the study's objectives. An online survey method has been chosen for its convenience and cost-effectiveness, especially in reaching respondents distributed across different parts of Malaysia, such as the Northern, Southern, Central, and Eastern regions, as well as East Malaysia. The survey will be conducted using Google Forms, a user-friendly and free tool that enables easy distribution and streamlined data collection for analysis. It will be disseminated through popular digital channels like social media and email, which are commonly used by young Malaysians.

The questionnaire will serve as the primary data collection tool — a standard approach in quantitative studies. It will predominantly feature closed-ended questions to support numerical analysis and enhance respondent ease. By focusing on structured response options, the survey will minimise variability in answers, making data coding and statistical analysis more efficient.

3.3 Sampling Design

3.3.1 Sampling Technique

This study employs a non-probability sampling technique, specifically quota sampling, to obtain 384 responses from Malaysian youths aged 18 to 30. Quota sampling is used to ensure proportional representation of respondents across different regions of Malaysia, helping to reflect regional diversity within the sample. This approach also helps to reduce user-status bias by targeting participants according to predefined demographic quotas.

The questionnaire will be distributed through various online platforms, including Facebook, Instagram, email, and WhatsApp, to reach the target respondents across each region effectively. This method is considered practical and realistic given the time and resource constraints of the study. Additionally, the relatively large and geographically diverse sample size contributes to reducing bias and capturing a broader range of perspectives. As a result, the collected data is expected to be more comprehensive and representative, thereby enhancing the reliability of the analysis. The population of Malaysian youths aged 15 to 30 is referenced in Appendix 3.1, while the distribution of questionnaires across regions is detailed in Table 3.1.

Table 3.1:

Total number of youth population and quota percentage for each region

Region	**Total Number of Youth Population (‘000)**	**Quota**
North Region	1944.3	20.6%
South Region	1511.3	16.0%
Central Region	2636.8	27.9%
East Region	1398.8	14.8%
East Malaysia	1959.3	20.7%

Note. Developed by the authors.

3.3.2 Targeted Respondents

The Malaysian Ministry of Youth and Sports defines youth as individuals aged between 15 and 30 (Institute for Youth Research Malaysia, 2024). However, according to SC’s regulations, the minimum age to open an account on a robo-advisor platform is 18. Therefore, this study will target respondents aged between 18 and 30, with a total of 384 responses planned for collection.

Youth investors now represent the largest generational cohort in Malaysia and are expected to have a significant influence on consumer and market trends over the next decade, according to the Institute for Capital Market Research Malaysia (ICMR) (2021). Supporting this, the Securities Commission Malaysia (2024a) reports that nearly 46% of clients on DIM platforms are in their twenties. Bank

Negara Malaysia (n.d.-c) further highlights that Malaysian youths are becoming increasingly digitally savvy and actively participating in financial education programmes supported by nationwide initiatives. This rise in digital literacy suggests they are well-prepared to adopt advanced digital financial services, including robo-advisory and algorithmic trading. Robo-advisory, in particular, provides automated, algorithm-driven financial advice that simplifies investing and makes it more accessible, especially for youths with limited financial knowledge (Securities Commission Malaysia, 2024b).

The targeted respondents will include both current users and non-users of FRA within the Malaysian youth demographic (aged 18 to 30). Including non-users allows this research to explore their perceptions, awareness, and intentions regarding FRA adoption, rather than focusing solely on existing users. Gunasinghe and Nanayakkara (2021) emphasise that considering both users' and non-users' intentions is important for obtaining a comprehensive understanding within the UTAUT framework. This inclusive approach enables the collection of diverse perspectives on adoption intention factors and facilitates comparative analysis among youth, providing a more holistic understanding of their intentions.

3.3.3 Sampling Location

The sampling locations cover the North Region (Kedah, Perlis, Penang, Perak), South Region (Malacca, Johor), Central Region (Selangor, Kuala Lumpur, Negeri Sembilan), East Region (Kelantan, Terengganu, Pahang), and East Malaysia (Sabah, Sarawak). These regional groupings follow the "Youth Capital Market Survey" by the Securities Commission Malaysia (2022b). No restrictions were placed on respondents from any specific region. The online survey distribution strategy deliberately targets both urban and rural areas across all regions to capture diverse perspectives on FRA. This approach aims to ensure comprehensive nationwide representation while reducing potential bias and enhancing geographical diversity.

3.3.4 Sampling Size

Selecting an appropriate sample size is critical to ensure the reliability and validity of research outcomes (Dawkins, n.d.). Generally, larger samples enhance representativeness and statistical precision, while smaller samples may lead to Type II errors (false negatives) due to lower statistical power (Andrade, 2020). The sample size for this study was determined using Krejcie and Morgan table, which offers standardised guidance for selecting sample sizes based on the total population.

As of recent estimates, Malaysia's total population, including both citizens and non-citizens, stands at approximately 34.1 million (Department of Statistics Malaysia, n.d.). According to the Institute for Youth Research Malaysia (IYRES) (2024), the youth population aged between 15 and 30 years is estimated to be 9.5 million. Given this large population, Cochran's formula was applied to determine an adequate sample size. For populations exceeding 131,262, a sample size of 384 respondents is generally sufficient to achieve a 95% confidence level and a 5% margin of error (Krejcie & Morgan, 1970). Therefore, this study adopts a minimum sample size of 384 to ensure statistically reliable and generalisable results for Malaysia's youth population.

To ensure regional representation, this study employs a quota sampling method, allocating respondents proportionally based on the population distribution across Malaysia's major regions. As presented in Table 3.1, the North Region (1.94 million) contributes 20.6% of the total sample, the Central Region (2.64

million) contributes 27.9%, the South Region (1.51 million) contributes 16.0%, the East Region (1.40 million) contributes 14.8%, and East Malaysia (1.96 million) contributes 20.7%. This quota-based approach enhances the representativeness of the sample and supports more accurate, region-specific insights within the study.

3.4 Research Instruments

Research instruments are basic equipment for gathering information relevant to the research study via a variety of initiatives. Several instruments can be used in a research study (Birmingham & Wilkinson, 2003). This study will use questionnaire as the research instrument to collect data for further analysis.

3.4.1 Questionnaire Design

Large amounts of data can be gathered from a wide range of respondents using questionnaires. It is inexpensive to administer, requires minimal training to develop, and can be readily and rapidly analysed after completion. A well-designed questionnaire can facilitate the transfer of accurate and valuable data or information from the respondents to the researchers. This entails asking questions in a straightforward and understandable way so that participants can understand them, formulate answers, and successfully communicate them to the researchers (Birmingham & Wilkinson, 2003).

In this study, the questionnaire entails 34 closed-ended questions in total, which can be categorised into Sections A and B. The first section comprises the screening question and demographic information of the respondents, including gender, academic qualifications, region and experience in investing. The next section, which includes dependent and independent variables, is adapted from Venkatesh et al. (2003), Gan et al. (2021), Eren (2022), and Nazmi et al. (2024). This questionnaire will use 5-point Likert scale to examine the respondent's opinion on each scale item. Scale 1 indicates that respondent strongly disagrees with the statement, and 5 indicates that respondent strongly agrees with the statement.

To effectively assess the variables influencing the intention to adopt FRA, a detailed set of measurement items has been outlined in Appendix 3.2. These items are adapted from well-established studies and aim to capture key dimensions of performance expectancy, effort expectancy, social influence, facilitating conditions, financial knowledge, along with the dependent variable. Each variable is measured through carefully crafted questions that reflect important factors highlighted in previous research.

3.4.2 Pilot Test

The pilot test is conducted before finalizing the research questionnaire to assess the feasibility and effectiveness of the methods planned for the major study. Without this step, researchers risk launching a large-scale study without sufficient understanding of the proposed methods. Importantly, the pilot test helps prevent costly and time-consuming errors that could jeopardise the entire study (Lowe, 2019). To sum up, a pilot test allows researchers to evaluate the adequacy of their planned procedures and increase the likelihood of a successful major study (Polit & Beck, 2017). Several analyses, such as outer loadings, cross loadings, Cronbach's Alpha, composite reliability and average variance extracted, will be conducted to determine the reliability of the proposed questionnaire. In this study, the pilot test will involve collecting responses from 30 individuals who meet the questionnaire criteria. Subsequently, the questionnaire will be revised and adjusted based on the responses gathered, in preparation for the full-scale study.

3.5 Measurement Scales

Measurement is crucial to the research field because reliable measurements of constructs are needed so as to ensure the statistical findings pertaining to those constructs is precise (Helwig, 2020). According to Omisile (2014), measurement is broadly defined as the assignment of numbers to events or items based on rules and assigning the numbers results in a distinct type of scales. There are four commonly accepted measurement scales, as suggested by Omisile (2014): nominal, ordinal, interval, and ratio. Only nominal and ordinal scales will be used for data classification in this investigation.

3.5.1 Nominal Scale

Nominal data involve collection of information on a variable that may be divided into two or more mutually exclusive and collectively exhaustive categories (Blumberg et al., 2014). It is frequently employed in surveys where data is gathered from significant demographic subgroups (Dalati, 2018). This study's demographic questions, including gender, age, region, yes or no questions, are examined using a nominal scale. The scale is used to label variables without any quantitative value. The numbers assigned to these categories are arbitrary and only serve as labels (Omisile, 2014). In other words, the numbers assigned do not convey any quantitative meaning (Helwig, 2020). For instance, gender is designated as either 0 for female or 1 for male. Both represent different categories in this instance.

3.5.2 Ordinal Scale

The scale involves order or ranking, but the intervals between ranks are not necessarily equal. It is used to determine which items are greater or lesser relative to others (Omisile, 2014). Hence, the numbers assigned convey only the order of events or items. For variables measured on an ordinal scale, calculating the mean and standard deviation does not possess any validity. It should be focused on the quantiles of the distribution (Helwig, 2020). In this study, academic qualifications, dependent and independent variables are measured using an ordinal scale. Specifically, a Likert scale is employed to provide an ordered category by gauging respondents' opinions based on their level of agreement. The attributes are arranged in ascending order from 1 to 5.

3.6 Data Processing

Once data collection is completed, the raw responses must be converted into meaningful insights through a process known as data processing. This step ensures the accuracy, completeness, and reliability of the data for analysis. It involves activities such as checking, editing, coding, and transcribing. Questionnaires will be distributed to collect responses from the target population. The collected data were subsequently entered into SmartPLS 4.0 for further analysis.

3.6.1 Data Checking

Data checking involves screening out irrelevant or unusable data after collecting survey responses to ensure its validity. The objective is to guarantee that the target respondents complete the entire questionnaire accurately. Therefore, researchers should exclude questionnaires that contain incomplete or inaccurate responses. Additionally, surveys that are filled out by the incorrect demographic ought to be removed. This step is essential to obtaining reliable and precise research findings from the target population, as errors from respondents could compromise the accuracy of the analysis.

3.6.2 Data Editing

Before analysis can begin, the raw data must first be edited. This process entails reviewing and correcting any errors or omissions in the responses provided by respondents to enhance accuracy and consistency. Data editing ensures that the data is precise and aligns with the research objectives. It is a crucial step in guaranteeing that survey responses are reliable and accurately represent the views of the target population. Besides, data editing simplifies the coding and classification of data, making it easier for further analysis.

3.6.3 Data Coding

The process of assigning numbers or symbols to survey results to organise them into a few numbers of categories is known as data coding. This process simplifies data entry into SmartPLS 4.0, ensuring efficient analysis. Its primary purpose is to assist researchers in interpreting and classifying the responses effectively. The questionnaire used in this study consists of 2 sections, labelled A and B. For example, in Section A, male respondents are assigned a code of 1, while female respondents are coded as 2. For Section B, the five-point Likert scale is used to assess the respondents' degree of agreement with the statements in the questionnaire, with each response option assigned a code ranging from 1 to 5. [Strongly disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Strongly agree = 5].

3.6.4 Data Transcription

Finally, the last stage of data processing is data transcription. It involves converting the data collected from the questionnaires into a machine-readable format. In this study, the collected data is first transformed into Excel format, allowing it to be directly imported into SmartPLS 4.0 for analysis.

3.7 Proposed Data Analysis Techniques

This study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 4.0 software. One of the main benefits of PLS-SEM is its capability to estimate complex models involving multiple constructs, indicators, and structural paths without requiring the data to meet strict distributional assumptions. More importantly, PLS-SEM is a causal-predictive approach to SEM, designed to prioritise prediction while offering causal insights. It is particularly suitable for studies with complex models and relatively small sample sizes. The algorithm applies separate ordinary least squares regressions to estimate relationships within both the measurement and structural models (Hair et al., 2019). The measurement model assesses the relationships between constructs and their indicators, while the structural model examines the relationships among the constructs themselves.

3.7.1 Descriptive Analysis

Descriptive analysis gives thorough foundation in comprehending data through efficient information organisation, summarisation, and presentation. It is frequently employed as an initial analysis strategy to better comprehend the information prior to using more intricate statistical techniques. It helps researchers to simplify complex data sets and assists in decision making process. It examines the data sets through a variety of measurement tools, including central tendency measures (mean, median, mode), variability indicators (variance, standard deviation), and then present the data in a graphical means such as histogram and scatter plot (Alabi & Bukola, 2023). In this study, the data collected from Section A, which is basic demographic information, will be used to conclude the attributes of respondents. Moreover, the data from section B is taken and evaluated through the opinions of different respondents from Malaysian youth category.

3.7.2 Measurement Model Analysis

Measurement model is a crucial part of SEM which focuses on the connection between implicit variable and the respective indicators (Bhale & Bedi, 2024). The measurement model's observed indicators consist of both formative and reflective indicators. Reflective indicators are used in this study in an attempt to explain observed variances or covariances. They are thought to be typical of classical test theory and factor analysis models. Conversely, formative indicators are not intended to take observed variables into consideration (Jarvis et al., 2003).

Outer Loadings

Outer loadings refer to the single coefficient of regression that exists between the latent parameter and the indicator variables. It evaluates the degree to which the latent variables and the measured variables are related to each other. When an indicator has a high outer loading (usually ≥ 0.70), it means that it accurately reflects its construct, guaranteeing reliability (Hair et al., 2019). Poor reliability of indications may be indicated by loadings less than 0.70, and indicators with loadings less than 0.40 are frequently eliminated to enhance the accuracy of the model (Henseler et al., 2015). According to Subhaktiyya (2024), the outer loading of an indicator should exceed 0.708 given that value squared (0.7082) yields 0.50, which shows that the underlying construct outlines minimum 50% of the indicator's variance and demonstrates indicator reliability. Hair et al. (2019) also claimed that 0.70 is typically regarded as being sufficiently close to 0.708 to be deemed acceptable.

Average Variance Extracted (AVE)

Average Variance Extracted (AVE) refers to a measurement that represents how much variance is captured by a construct compared to how much variance is caused by the error in measurement (Santos & Cirillo, 2021). Cheung et al. (2023) claimed that the latent construct must account for at least 50% of the indicator variance, with the AVE not falling below 0.5 to exhibit a satisfactory degree of validity for convergence. According to Guenther et al. (2025), the AVE must reach a minimum value of 0.50, which indicates that a construct accounts for no less than half of the variance of its items. AVEs greater than 0.50 always result in PLS-SEM, so studies ought to be mindful that an AVE is ineffectual when there are only two indicators for a construct.

Cronbach's Alpha (CA)

Cronbach Alpha (CA) has emerged as a number between 0 and 1 that indicates how internally consistent the measure or scale is (Tavakol & Dennick, 2011). The more closely CA value approaches 1, the more internally consistent it appears to be on the scale (Saidi & Siew, 2019). A CA value exceeding 0.70 typically indicates stronger internal consistency, suggesting that the items are closely connected and assessing the same item. Tavakol and Dennick (2011) state that CA value beyond 0.90 denotes beneficial internal consistency. A low alpha value may be the result of heterogeneous constructs, an insufficient number of questions, or inadequate measure interrelatedness. A high CA could indicate that certain concerns are ineffective because they examine the same concern under an alternate title. The suggested greatest alpha value is 0.90. Despite its widespread use, CA makes the assumption that all indicators are equally reliable, but this might not constantly hold true in SEM (Hair et al., 2019). Accordingly, complementary reliability measures like Composite Reliability (CR) are frequently taken into account (Peterson & Kim, 2013).

Composite Reliability (CR)

Composite reliability (CR) is one of the primary measurements in PLS-SEM which used to analyse a construct's internal consistency and reliability (Hair et al., 2014). As Ylinen and Gullkvist (2014) emphasize, convergent validity is capable of being assessed by looking at CR, where CR denotes construct consistency. Each construct's CR is computed in relation to the cut-off measurement of 0.6 (Pervan et al., 2017). Higher reliability levels are indicated by higher CR values. According to Henseler et al. (2015), strong construct is indicated by a higher CR, which guarantees the dependability of the model's latent variables. CR values between 0.60 and 0.70 are deemed "acceptable" while values between 0.70 and 0.90 fall into the "satisfactory to good" range.

Values greater than 0.90 which show that the measurements are ineffective and thus diminish the construct's reliability (Hair et al., 2021b).

Heterotrait-Monotrait Ratio of Correlation (HTMT)

The Heterotrait-Monotrait Ratio of Correlation (HTMT) is a key metric used to evaluate validity of discriminant in variance-based SEM. HTMT calculates geometric mean of the average correlations among indicators within the same construct and compares it to the mean correlations between different constructs (Voorhees et al., 2016). As noted by Hair et al. (2019), a lower HTMT value supports discriminant validity by indicating that constructs are distinct, whereas a higher value suggests a lack of distinction among constructs. There are two primary approaches to evaluating discriminant validity using HTMT: one involves testing the hypothesis that HTMT equals 1 through inferential statistics (Franke & Sarstedt, 2018), and the other involves comparing HTMT values against recommended thresholds of 0.85 or 0.90 (Henseler et al., 2015). For discriminant validity to be confirmed, HTMT values should fall below these thresholds, and the null hypothesis that HTMT equals 1 should be rejected (Rasoolimanesh, 2022). Values approaching 1 indicate the absence of discriminant validity (Hamid et al., 2017). To determine whether HTMT significantly deviates from 1.0, researchers use bootstrap confidence intervals (Henseler et al., 2015). Depending on the context of the study, a stricter threshold such as 0.85 or 0.90 may be more appropriate (Franke & Sarstedt, 2018). A 95% confidence interval for HTMT can be constructed to assess whether the upper bound is below 1, 0.90, or 0.85 (Hair et al., 2021b). HTMT has demonstrated superior precision and sensitivity rates (97% to 99%) compared to the Fornell-Larcker criterion (20.82%) and cross-loadings method (0.00%).

Cross-Loading

Cross-loadings examine discriminant validity by finding out if an indicator takes more on its designated construct compared to other constructs. Cross-loadings are used by studies to enhance validity of constructs and find possible models' misspecifications (Henseler et al., 2015). According to Hair et al. (2019), to ensure appropriate construct distinction, every parameter ought to have the greatest loading on its construct. Cross-loading of the indicator can be used to assess the discriminant validity. Discriminant validity is verified when an indicator's outer loading on its assigned construct is greater compared to its cross-loadings across other constructs, signifying that every item indicates the targeted construct precisely rather than overlaps with one another (Hamid et al., 2017).

3.7.3 Structural Model Analysis

Structural model analysis, referred to as the inner model in PLS-SEM, illustrates the relationships between the conceptualised variables, including both independent and dependent variables outlined in the research framework (Memon et al., 2021). SmartPLS 4.0 supports a non-parametric bootstrapping technique to generate these estimates. Through bootstrapping, statistical outputs such as path coefficients and R-squared values, along with their significance levels, will be obtained (Ringle et al., 2024).

Collinearity (Variance Inflation Factor)

Collinearity occurs when two or more predictor variables in a statistical model exhibit a linear correlation, which can be either positive or negative. This relationship can hinder the accurate estimation of results. The occurrence of collinearity can make parameter estimation more complex by raising the variance of regression coefficients, leading to parameter estimates becoming unstable, standard errors being inflated, and inference statistics being biased (Dormann et al., 2013). This could therefore result in the model's key variables being mistakenly identified. To make sure the outcome is impartial, Hair et al. (2021a) advise identifying collinearity prior to calculating the path coefficient. Collinearity is evaluated by employing the variance inflation factor (VIF), which provides insight into the degree of collinearity between variables. The VIF is evaluated against a threshold level, and collinearity issues may emerge if the VIF value becomes too high. A VIF of 1 indicates no correlation, whereas values greater than 1 indicate moderate correlation. When the VIF falls between 5 and 10, it signals potential multicollinearity issues. If the VIF exceeds 10, severe multicollinearity is present, which can result in inaccurate regression coefficient estimates. Therefore, if a predictor's VIF approaches or surpasses 5, multicollinearity could be a concern and should be addressed accordingly (Akinwande et al., 2015).

Path Coefficient

Path coefficient analysis examines the significance of relationships between dependent and independent variables in research. This method facilitates the assessment of these connections' strength and supports hypothesis testing of causal connections (Purwanto & Sudargini, 2021). According to Khan et al. (2022), a statistically significant path coefficient indicates the presence of a causal relationship between the dependent and independent variables. The relevance of the path coefficient is typically evaluated on a scale ranging from

-1 to +1. Any value beyond this range could signal a significant issue. Values closer to -1 signify a strong negative relationship between independent and dependent variables, while values near +1 indicate a strong positive relationship. Moreover, a path coefficient near zero indicates no relationship between the variables (Hair et al., 2021a).

P-Value

This study assesses the statistical significance of the determinants using a predefined significance level (α) of 5%, which allows for a 5% margin of error in the findings. The null hypothesis posits that there is no difference between the variables, indicating they are alike. The evaluation of relationship significance is based on p-value thresholds. A statistically significant relationship between the variables is indicated when the p-value is below 0.05, which rejects the null hypothesis. Conversely, if the p-value is greater than 0.05, the null hypothesis is not rejected, implying that the relationship between the variables is statistically insignificant. According to Fisher (1958), the significance level (α) of 5% is considered as the conventional standard and serves as a practical benchmark for assessing statistical significance. Moreover, this significance level also ensures that comparability with the past study of FRA and thereby enhances the robustness and replicability of the results.

3.8 Chapter Summary

In short, the methodology used in the study has been highlighted in this chapter, including the research design, sampling strategy, research tools, along with data analysis. It details the strategies and approaches used to conduct the study, along with the steps taken to ascertain the accuracy and dependability of the findings. The methodology is a crucial component, as it facilitates the transformation of raw data into insightful information, enabling researchers to perform analysis as well as make conclusions regarding to the target population.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

Chapter 4 analyses and explains results of the survey questionnaire responses. After collecting and screening the raw data, this chapter delves into a descriptive analysis of the demographics of the respondents, and also explores deeper into measurement model analysis, such as Cronbach's Alpha, discriminant validity, and r-squared using SmartPLS software.

4.1 Data Collection & Data Screening

Using Google form surveys that were disseminated online, 401 responses in all were obtained for this study. According to the questionnaire's age screening question, 17 replies in total were eliminated from the survey since they were not included in the sample. Consequently, 384 replies were employed for data analysis in order to produce precise results.

4.2 Descriptive Analysis

In this section, the gathered information from the survey participants is summarised and presented in an orderly comprehensible way. This section focused primarily on the respondents' demographic data, which was gathered in Section A of the survey.

4.2.1 Gender

The gender distribution of the 384 survey participants, expressed as a percentage, is shown in Figure 4.1. The study included 126 male respondents (32.81%) and 258 female respondents (67.19%) in total. With 132 respondents (34.38%) overall, there were more female respondents than male respondents.

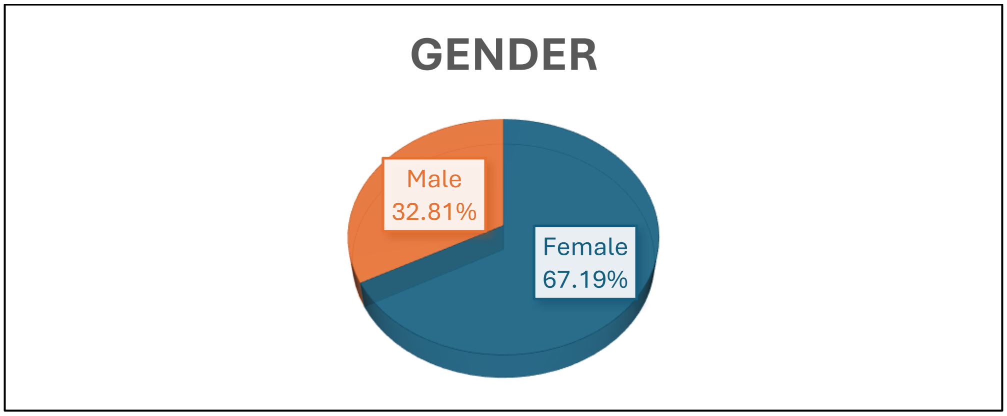

Figure 4.1. Statistics of gender. Developed by the authors.

4.2.2 Region

Quota sampling was employed in this study to guarantee equitable representation from every Malaysian area. In the final sample, the Central region accounts for 27.86%, the North for 20.57%, the South for 15.89%, the East for 14.84%, and East Malaysia for 20.83%. The sampling requirements were effectively fulfilled since the proportion of responders from each region matches the desired quotas.

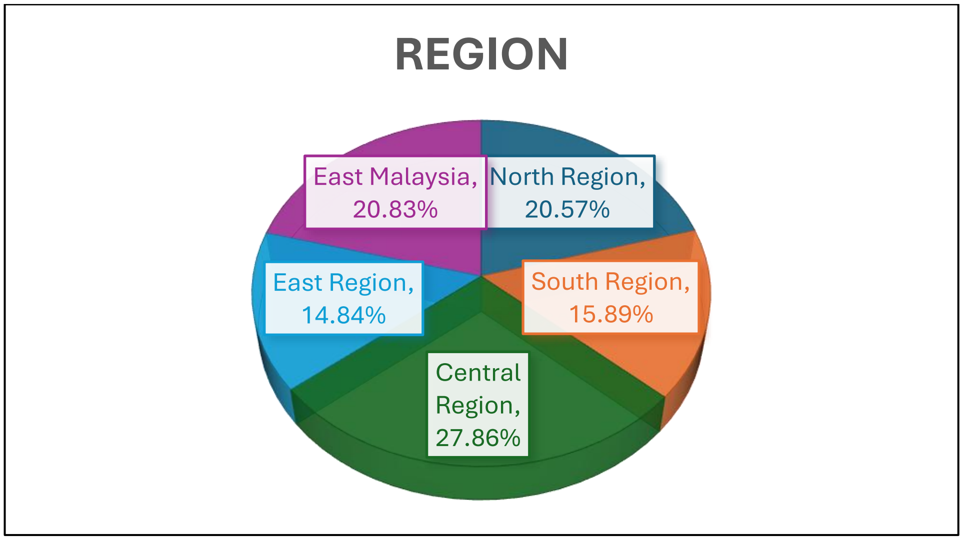

Figure 4.2. Statistics of region. Developed by the authors.

4.2.3 Highest Academic Qualifications

Figure 4.3 presents the highest academic qualifications of 384 respondents who participated in the survey, expressed in percentages. This survey comprises seven categories. The findings show that most respondents, amounting to 301 people or 78.39%, have obtained a bachelor's degree. This is followed by 38 respondents (9.90%) with a master's degree and 28 respondents (7.29%) who have completed STPM, UEC, A-level, Diploma, or Certificate qualifications. Additionally, 12 respondents (3.13%) hold SPM or O-level qualifications, while 4 respondents (1.04%) possess a Professional Certificate. Only 1 respondent (0.26%) reported having none of the listed qualifications, and no respondents indicated holding a PhD.

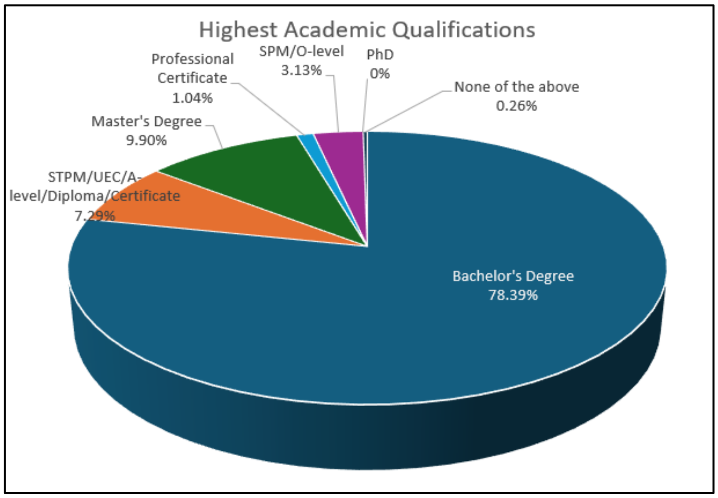

Figure 4.3. Statistics of highest academic qualifications. Developed by the authors.

4.2.4 Investment Experience with Investment Options

Figure 4.4 illustrates the investment experience of 384 participants, showing the different investment types, they have previously engaged in. The survey offered nine investment choices, including an option for those without any investment experience. Since multiple selections were permitted, the overall response count is greater than the participant count.

Based on the responses, stocks and bonds were the most common investment choice, selected by 183 respondents, followed by mutual funds (96 respondents) and cryptocurrencies (92 respondents). Additionally, 94 respondents indicated having no investment experience, making it one of the most frequently selected categories. Other less common investment options include NFTs (29 respondents), derivatives and real estate property (21 respondents each), P2P lending (17 respondents), and equity crowdfunding (16 respondents). These findings suggest that while traditional investments like stocks and mutual funds remain popular, a significant portion of respondents are either new to investing or have yet to explore newer asset classes.

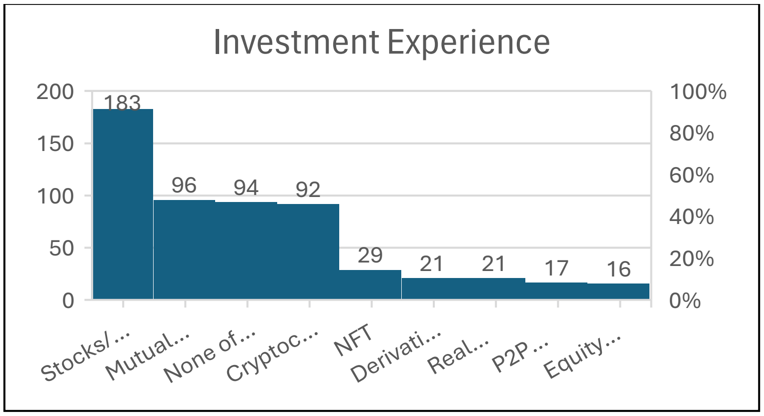

Figure 4.4. Statistics of investment experience across various investment options. Developed by the authors.

4.2.5 Experience & Currently Using Financial Robo-Advisor (FRA)

Figure 4.5 shows whether 384 respondents in this survey are currently using FRA and whether they have prior experience using FRA. As can be seen from the pie charts in Figure 4.5, the majority of respondents, 258 people, reported having no prior experience using FRA, accounting for 67.19% of the data in the chart. On the other hand, 32.81% of respondents, or 126 people, answered 'yes' according to the chart. A large proportion of respondents (80.73%, or 310 persons) to the following question stated that they do not use FRA currently. By contrast, 74 respondents reported using FRA at the moment, accounting for 19.27% of all respondents in this survey.

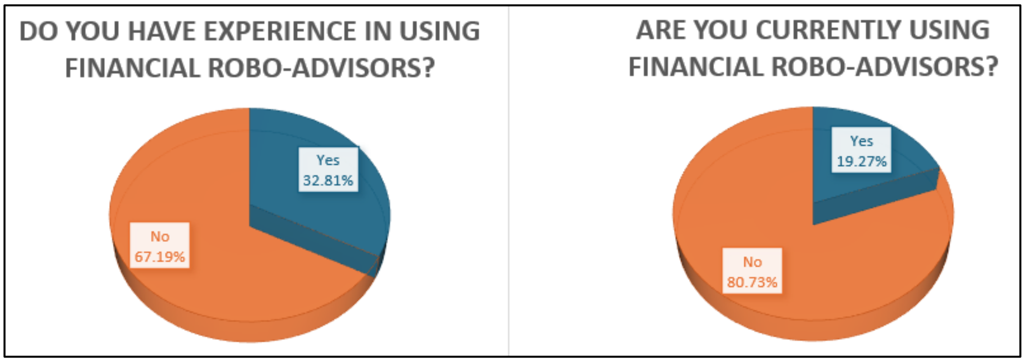

Figure 4.5. Statistics of respondents' experience and whether currently using financial robo-advisors (FRA). Developed by the authors.

4.2.6 Central Tendency (Mean)

To find out which items have the highest level of agreement among respondents, this study determines the mean value of each item. When developing the research implications, checking is essential because it offers valuable insight. Appendix 4.1 displays each item's mean value.

FRA services were seen favourably by the respondents, as indicated by the mean scores of the questionnaire items, particularly when it came to PE and EE. The majority of respondents have the resources (such as smartphones or internet access) needed to use FRA services, as seen by FC1's highest mean value of 4.737. PE1 (4.435) showed the strongest agreement among the performance expectancy items, indicating that respondents believe robo-advisors can help them make financial decisions. Furthermore, EE4 (4.362) and EE3 (4.336) demonstrated that people are optimistic that the FRA will be easy to use and that they can become proficient with the platform, indicating that the effort expectancy dimension was also well-supported.

Moreover, the respondents' opinions were shaped by the SI factor, especially when viewed through the perspective of social media impact. According to items like SI2 (4.169) and SI4 (4.292), online voices or platforms inspire respondents, and they believe that users of FRA are reputable and intelligent. This implies that social media, influencers, and online groups could greatly impact how younger, tech-savvy users feel about using FRA. These platforms' impact could increase awareness and normalise the usage of robo-advisors in investing.

On the other hand, responses were more moderate for the intention to use FRA. INT1 (3.935) and INT6 (3.987) scored lower, suggesting some hesitancy, particularly for substituting robo-advisors for human advisors, whereas items like INT4 (4.263) and INT5 (4.286) demonstrate encouraging levels of intention to use FRA for investment management. This supports earlier results showing many respondents are open to innovation and tech-savvy, but they are still hesitant to trust automated platforms completely with their personal wealth decisions. Additionally, the relatively moderate self-perceived level of financial literacy suggested by FK items like FK4 (3.984) may explain their cautious approach to independently adopting FRA. Despite this, the favourable responses to most constructs imply that with more exposure and education, acceptance and usage of robo-advisory services may increase.

4.3 Measurement Model Analysis

4.3.1 Outer Loadings and Cross Loadings

Outer loadings results reflect the correlation between each of the indicators and its associated latent construct. High loadings suggest that an item is a good representation of the underlying construct. In PLS-SEM, an outer loading value which more than 0.70 will be recommended and acceptable (Hair et al., 2019).

Referring to Appendix 4.2, all constructs demonstrated strong indicator loadings, surpassing the suggested limit of 0.70, which implies strong reliability. For PE, loadings ranged from 0.732 to 0.798, while EE ranged from 0.706 to 0.744. SI indicators loaded between 0.701 and 0.759 and FC between 0.711 and 0.752. FK showed the highest consistency, with loadings from 0.778 to 0.826. Lastly, the intention to adopt FRA ranged from 0.722 to 0.885. These results confirm that all indicators are reliable and acceptable for measuring the intention to adopt FRA services.

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

Table 4.3:

Cronbach's Alpha, Composite Reliability, Average Variance Extracted

Constructs	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
PE	0.776	0.783	0.597
EE	0.776	0.779	0.527
SI	0.714	0.716	0.538
FC	0.708	0.710	0.532
FK	0.818	0.819	0.647
INT	0.887	0.891	0.643

Note. Developed by the authors.

Table 4.3 displays that all variables exhibit CA values exceeding 0.70 and suggesting that each construct's internal consistency reliability is deemed acceptable. The variable of INT shows the highest value at 0.887, followed closely by FK with a value of 0.818, both fall within the good reliability range of 0.80 to 0.90. PE and EE show same value of 0.776, demonstrating reliable internal consistency. While SI and FC presents slightly smaller values of 0.714 and 0.708, correspondingly, they still adhere to the minimum reliability threshold. The results displays that all constructs are assessed with an acceptable level of consistency, reinforcing the reliability of the entire measurement model.

Besides, Table 4.3 illustrates that CR of all constructs exceeds the minimum threshold of 0.70, signifying strong internal consistency. Generally, the items measuring the INT demonstrate the strongest internal consistency with a reliability coefficient of 0.891, followed by FK with a coefficient of 0.819. Alternative constructs (PE, EE, SI, FC) have values ranging 0.710 to 0.783, which fall within acceptable thresholds and hence affirming reliable measurement throughout the model.

AVE demostrates all variable surpassed the threshold of 0.50 with values between 0.527 and 0.647. FK has the highest AVE at 0.647, with INT closely following at 0.643, demonstrating strong convergence. Other variables include PE, EE, SI and FC also meet the threshold, indicating good convergent validity is supported throughout the model.

4.3.3 Heterotrait-Monotrait Ratio of Correlations (HTMT)

Table 4.4:

Heterotrait-Monotrait Ratio of Correlations (HTMT)

	PE	EE	SI	FC	FK	INT
PE						
EE	0.702					
SI	0.608	0.644				
FC	0.801	0.668	0.803			
FK	0.521	0.566	0.592	0.686		
INT	0.724	0.636	0.656	0.721	0.648	

Note. Developed by the authors.

The HTMT is used to compare the correlations between constructs to those within the same construct and the ratio of the mean correlations between various constructs (Voorhees et al., 2016). In reference to Franke and Sarstedt (2018) and Henseler et al. (2015), the value of HTMT is recommended to be less than 0.85. If the HTMT value exceeds these thresholds, it suggests a lack of discriminant validity.

Based on the results above, all HTMT values are less than 0.85, which lies between 0.521 and 0.803. The highest ratios are between FC-PE (0.801) and FC-SI (0.803), suggesting that respondents perceive these pairs as related but still distinct concepts. The lowest ratios are between FK-PE (0.521) and FK-SI (0.592), indicating that FK differs significantly from PE and SI. Overall, the HTMT analysis confirms that all independent variables and INT are distinct constructs, supporting the robustness of the structural model for further analysis.

4.4 Structural Model Analysis

4.4.1 Collinearity (Variance Inflation Factor)

Table 4.5:

Collinearity

Constructs	Variance Inflation Factor (VIF)
PE -> INT	1.809
EE -> INT	1.681
SI ->INT	1.654
FC -> INT	2.067
FK -> INT	1.515

Note. Developed by the authors.

The collinearity concern in this analysis was assessed using VIF. According to Table 4.5, all VIF values for the independent variables—PE (1.809), EE (1.681), SI (1.654), FC (2.067), as well as FK (1.515)—are significantly lower than the 5 thresholds. This implies the model's multicollinearity does not exist. Akinwande et al. (2015) note that the values of VIF between 5 to 10 may indicate possible multicollinearity, whereas values exceeding 10 signal a serious concern. Given that all the VIF values in this model are well below the accepted thresholds, this indicates the absence of problematic multicollinearity among the predictors. Consequently, every independent variable contributes in a unique and significant way to the explanation of the intention to adopt FRA, thereby enhancing the stability and reliability of the model's estimates. Consequently, the model can be considered both statistically valid and robust.

4.4.2 Path Coefficient

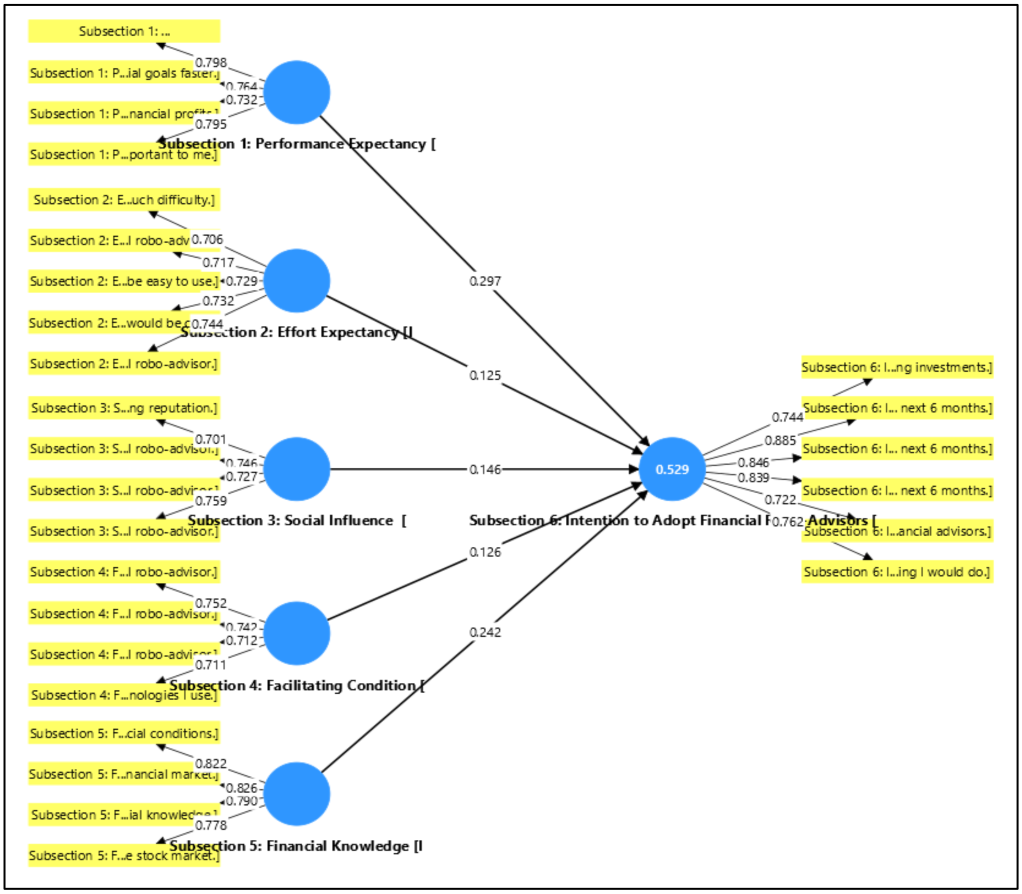

Figure 4.6. Bootstrapping Test. Developed by the authors.

Table 4.6:

Path Coefficient (Bootstrapping Test)

Constructs	Sample Mean	Standard Deviation	T-statistics	P-value	Result
H1: PE -> INT	0.293	0.068	4.338	0.000	Supported
H2: EE-> INT	0.125	0.056	2.214	0.027	Supported
H3: SI -> INT	0.148	0.072	2.022	0.043	Supported

H4: FC -> INT	0.129	0.074	1.710	0.087	Unsupported
H5: FK -> INT	0.242	0.066	3.645	0.000	Supported

Note. Developed by the authors.

Table 4.6 presents the results of the structural model derived from the SmartPLS bootstrapping analysis. In this research, a 5% significance level ($p < 0.05$) is applied for hypothesis testing. A relationship is considered significant, and the corresponding hypothesis is supported when the p-value is less than 0.05. Conversely, the hypothesis is rejected if the p-value exceeds 0.05, indicating that the relationship between the constructs is not statistically significant.

Based on Table 4.6, the relationship between PE and the INT is significant, showing a p-value of 0.000. It indicates that people are intended to adopt FRA when they perceive that it will enhance their financial decision-making and investment outcomes. This finding is consistent with the research carried out by Gan et al. (2021) and Roh et al. (2023), which highlight individuals who hold strong beliefs about performance are more inclined to utilise FRA. In relation to this research, it signifies that users in Malaysia are more likely to utilise FRA if they regard the technology as a valuable means to improve their financial results.

Furthermore, the result indicates that EE significantly influences the INT, demonstrated by p-value of 0.027. This result suggests that individuals exhibit stronger inclination to utilise robo-advisory services when they view the system as user-friendly and comprehensible. As highlighted by Nain and Rajan (2024), individuals are more inclined to use robo-advisory platforms when the design and function seamlessly integrate into their everyday routine. Windasari et al. (2022) also assert that a clear and user-friendly interface can lessen resistance and enhance user's readiness to embrace robo-advisors. Consequently, the findings of this study are supported since users' intention to utilise FRA is significantly influenced by EE.

The SI demonstrates a significant correlation with the INT, indicated by a p-value of 0.043. This result indicates that individuals' intention to use FRA is shaped by influences from their social networks, particularly through social media. As highlighted by Solarz and Swacha-Lech (2021), social media is viewed as a credible and accessible source of information, especially among digitally active users. The growing role of digital word-of-mouth allows social media to serve as a platform for sharing user experiences, product reviews, and financial advice. When individuals observe positive experiences or endorsements from others in their online networks, they become more likely to adopt financial technologies (Safitri et al., 2021). As a result, the findings of this study align with earlier research, reinforcing the idea that SI is a pivotal factor in shaping the FRA adoption intention.

Nevertheless, the findings in Table 4.6 show that FC has a p-value of 0.087, indicating an insignificant relationship with the INT. As Kusuma and Kusumawati (2023) highlight, adverse user experiences such as technical malfunctions or inadequate support can diminish reliance on existing assistance. Similarly, Nourallah (2023) and Sebastian et al. (2022) found that users possessing adequate digital skills frequently navigate platforms on their own, rendering external support less impactful. Consistent with this, Mahmutovic (2024) reported that factors such as resource availability, technical assistance, and system compatibility have minimal or statistically irrelevant effects on users' intention to adopt FRA. Roh et al. (2023) discovered that perceived FC has a minimal impact on users' intention to embrace FRA. Therefore, the results of this study align with much of the existing literature, indicating that FC plays only a minor role in influencing the intention to adopt FRA.

FK has a strong correlation with the INT, as demonstrated by a p-value of 0.000. Prior studies, including Yi et al. (2023) and Qadoos and AbouGrad (2025), have also highlighted a significant correlation between FK and INT. Todd and Seay (2020) reported that individuals who perceive themselves as having higher financial knowledge, regardless of their actual investment expertise, tend to engage with robo-advisors. In the same vein, Fan and Chatterjee (2020) observed that perceived FK influences INT. The results of this research are aligned with these findings.

4.4.3 Adjusted R-Square

The adjusted coefficient of determination (Adjusted R^2) for the dependent variable, intention to adopt FRA, is 0.523. This indicates that after adjusting for the number of predictors, approximately 52.3% of the variance in intention is explained by the model's independent variables. According to Hair et al. (2021a), this represents a moderate level of explanatory power, suggesting that the model provides a reasonably good fit in predicting the dependent variable.

4.5 Chapter Summary

This chapter presents the data analysis conducted using SmartPLS 4.0, encompassing both descriptive analysis and measurement model evaluation. The descriptive analysis outlines the demographic characteristics and response patterns of the participants, providing a clear profile of the sample. The measurement model evaluation examines the validity and reliability of the constructs through various measures. Overall, the findings confirm that the measurement model meets the required statistical thresholds, demonstrating the suitability of the indicators in representing the latent constructs.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

This chapter's analysis is based on the survey responses presented in the preceding chapter. It begins with a discussion of the key findings, then examines their implications as a foundation for future research. The chapter ends by outlining suggestions for more research and taking into account the shortcomings this work has revealed.

5.1 Summary of Statistical Analysis

According to the outcomes displayed in Chapter 4, the summary of significance of results is as shown in Appendix 5.1.

5.2 Discussion of Major Findings

5.2.1 Performance Expectancy (PE)

Referring to Appendix 5.1, there is a significant and positive relationship between PE and INT in Malaysia, with a p-value of 0.000. This suggests that Malaysian youths aged 18–30 are more inclined to adopt FRAs if they perceive robo-advisors as capable of enhancing their investment outcomes, such as generating higher returns or improving financial management. Notably, 67.19% of respondents reported having no prior experience using any FRA (Figure 4.5), indicating that their intention to adopt is largely driven by positive expectations rather than firsthand experience. Furthermore, since respondents generally perceived themselves as financially literate, they may have a stronger capacity to assess the potential benefits of FRAs. As many are already familiar with investment processes, they may be more receptive to innovative solutions that offer diverse risk–return portfolios to support their decision-making. Overall, the findings reinforce that perceived performance benefits can be a powerful motivator, even without prior direct engagement with technology.

The significance of PE aligns with the proposed hypothesis and is in line with earlier research that suggested PE is crucial in technology adoption (Gan et al., 2021; Roh et al., 2023; Nazmi et al., 2024). Since human intervention is not engaged in the automated robo-advisory process, consumers might possess a greater performance expectation towards robo-advisors instead of conventional human financial advisors during COVID-19 pandemic (Gan et al., 2021). Moreover, experienced value clear disclosure of profit data, reorganizing their portfolios based on timing and circumstances, as well as minimizing fees, which are provided by robo-advisors (Roh et al., 2023). The study of Nazmi et al. (2024) found that B40 group is more sensitive to the potential benefits of technology in improving their financial situation. Besides, they also prefer the features of low fees and automation of the FRA. In summary, the significance of PE in this study highlights the importance of designing robo-advisory platforms that meet user expectations. Developers should focus on features that clearly communicate the potential for improved financial outcome, in order to enhance the motivational power of PE among Malaysian youths.

5.2.2 Effort Expectancy (EE)

According to Appendix 5.1, EE shows a significant and positive relationship with INT, supported by a p-value of 0.027. This indicates that Malaysian youths are more inclined to embrace FRA when they perceive the platform as straightforward, easy to navigate, and requiring minimal effort. Most respondents have a high level of education, and about 75% have prior investment experience. They expect financial tools like FRAs to function as seamlessly as the everyday financing apps they use. Given their existing exposure to investment processes, they are more likely to adopt FRA if the platform complements their current practices without adding unnecessary complexity. Moreover, FRAs can be valued as financing tools that assist them in simplifying decision-making, automated routine processes, and present financial information in a clear and accessible format. This alignment with their expectations enhances their willingness to adopt FRA. EE helps overcome this barrier, as youths may be discouraged by the FRA platforms that require extensive learning or technical knowledge.

This finding contrasts with the results of Gan et al. (2021) and Eren (2023), who reported that EE did not significantly influence adoption intention. Discrepancies may stem from differences in cultural and economic contexts. Besides, the former study was carried out throughout the COVID-19 outbreak, while the latter focused on users in Turkey. Nevertheless, the present finding aligns with previous findings outlined by Yi et al. (2023), Nguyen et al. (2023), and Nain and Rajan (2024), which identified EE as a key factor in adoption intention. Users are more inclined to interact with robo-advisors when they find them effortless to use. As noted by Nguyen et al. (2023), the ability to access robo-advisory services offers convenience, eliminating the need for in-person consultations with financial advisors. Additionally, when users expect minimal effort in using the platform, it helps lower psychological and cognitive barriers, making them feel more confident and comfortable with the technology. This is especially important in fintech, where complex or unfamiliar systems can deter potential users (Roh et al., 2023). Therefore, ease of use plays a vital role in both bringing in new users and keeping hold of current ones. This highlights the importance for robo-advisory platforms to focus on user experience design, such as minimising technical jargon and offering responsive support, to enhance accessibility and encourage broader adoption.

5.2.3 Social Influence (SI)

With respect to Appendix 5.1, SI has a positive and significant relationship with the INT, as reflected by a p-value of 0.043. This suggests that the stronger perceived influence or encouragement from social media or people from social networks they value, the stronger the intention of Malaysian youths to adopt FRA. This is consistent with Solarz and Swacha-Lech (2021) and Safitri et al. (2021). The opinions shared through platforms such as Facebook, Twitter, or blogs significantly shape user perception, acting as informal recommendations or peer influence (Solarz & Swacha-Lech, 2021). The collective opinions and shared experiences available on social media help reduce uncertainty and increase perceived trust (Safitri et al., 2021). This aligns with Nguyen et al. (2023), who observed that users were more receptive to robo-advisors if others (such as trusted peers or online figures) also used or recommended them.

In the context of Malaysian youth, this result reflects the high digital engagement of this demographic. As social media is deeply embedded in their daily lives, perceptions shaped through online interactions, such as product reviews, influence endorsements, or peer discussions, can strongly affect their financial behavior. These can reduce perceived risk and uncertainty surrounding a emerging financial service. Furthermore, the social image associated with using such tools enhances their adoption intention. The perceived popularity and endorsement of robo-advisors within one's digital circle can act as a form of social proof. Moreover, information from social media can impact their decision of whether intend to adopt FRA as their investment source. In this sample, the majority of respondents had high financial literacy but had never used a robo-advisor before, meaning that their adoption intention relies heavily on external cues and social proof to bridge the gap. Therefore, these findings reinforce the idea that SI can extend beyond close family and friends, encompassing wider digital networks that youths actively engage with. SI is a critical driver of positive intentions toward robo-advisors among young Malaysians.

5.2.4 Facilitating Conditions (FC)

Given the results in Appendix 5.1, FC indicates an insignificant relationship with INT, as evidenced by a p-value of 0.087. This suggests that the availability of resources, support systems, or technical assistance does not meaningfully influence Malaysian youths' intention to use FRA. These results diverge from the initial hypothesis and contradict numerous prior studies that identified FC as a key determinant of FRA adoption intention (Bernice et al., 2024; Bajunaied et al., 2023; Roh et al., 2023). Referring to the mean score of items in FC, most respondents already possess the necessary resources and internet access, which aligns with the young, well-educated sample group. They also expressed relatively high confidence in seeking assistance if they encounter difficulties, reflecting their digital familiarity and reliance on online communities or customer support systems. While their specific knowledge of robo-advisor operations remains limited, their general financial literacy and strong technology skills enable them to navigate platforms independently. However, uncertainty still exists regarding how these platforms integrate with their existing digital tools. This combination of self-sufficiency and adaptability may explain why FC exerts little influence on their intention to adopt FRA.

The result can be attributed to the characteristics of participants, who are primarily young people with a considerable degree of digital proficiency and experience with online services. According to findings by Sebastian et al. (2022) and Utomo et al. (2021), these users likely have the skills and confidence required to navigate FRA platforms on their own, which diminishes the importance of needing external assistance or technical help. As a result, the presence or absence of FC may not significantly affect Malaysian youths' FRA adoption intention. Moreover, Venkatesh et al. (2003) indicated that FC is more inclined to lose its relevance when PE and EE are incorporated in the model. This may be because users' expectations for system support and usability are already reflected in their perceptions of the ease of use and usefulness, overlapping with the role of FC.

The study's findings are consistent with research by Nourallah (2023) and Gan et al. (2021), who also found no significant correlation between FC and intention to adopt FRA. Additionally, Kusuma and Kusumawati (2023) noted that unfavourable situations, such as system interruptions, lack of timely help, or operational difficulties, can further erode users' trust in external support, prompting them to rely more heavily on their own abilities when using the platform. Among Malaysian youths, this pattern may be linked to their upbringing in a digital-centric environment, which has fostered self-sufficiency and adaptability when exploring new platforms without formal assistance. As a result, FC plays a minimal role in influencing their adoption intentions. For service providers, this suggests that enhancing platform performance, personalisation, and overall user experience, rather than expanding technical support channels, will be more effective in attracting tech-savvy youths who prioritise independence, speed, and investment returns.

5.2.5 Financial Knowledge (FK)

Appendix 5.1 demonstrates that FK has a significant and positive relationship with INT, as evidenced by a p-value of 0.000. This indicates that Malaysian youths with higher FK are more inclined to use FRA, likely because they possess a clearer understanding of essential financial concepts. Such knowledge is crucial when engaging with digital investment tools. This result aligns with Yi et al. (2023) and Gan et al. (2021), who also discovered that youths with greater FK are more likely to adopt FRA. Besides, Lusardi and Mitchell (2014) describe financial literacy as the ability to make well-informed financial decisions, and this ability can foster confidence in using FRA. In addition, Henager and Cude (2016) highlight that perceived FK or how knowledgeable individuals believe they are can sometimes influence behaviour more than actual knowledge. This may explain why those who view themselves as financially capable are more willing to embrace FRA even if their true literacy is only moderate.

In contrast, while Brenner and Meyll (2020) and Todd and Seay (2020) observed that individuals with lower FK tend to favour robo-advisors, these findings may vary by context. In Malaysia, FK appears to act as a significant facilitator rather than an obstacle, likely due to an increasing emphasis on financial literacy and digital skills among youths. This aligns with the perspective of Eichler and Schwab (2024), who argue that having a basic understanding of financial principles is essential for making investment decisions, particularly when using platforms that enable automated financial planning. The results suggest that improving financial literacy can play a vital role in encouraging FRA adoption, as financially knowledgeable individuals are more likely to perceive these tools as reliable and efficient for managing investments.

For Malaysian youths, stronger FK builds confidence in using FRA. Growing access to financial education through schools, government initiatives, and online resources equips them with the ability to understand how these platforms work and how to apply them to meet personal goals. This competence helps them interpret financial data, assess risks, and make informed decisions, leading them to view robo-advisors as trustworthy and beneficial tools for managing their finances.

5.3 Implications of the Study

5.3.1 Theoretical Implications

There has been limited research specifically examining the intention to adopt FRA among Malaysian youths, despite FRAs being introduced in Malaysia since 2017. Addressing this gap, this study extends the existing UTAUT model by integrating FK as an additional construct. This extension offers valuable theoretical insights because it incorporates an important domain-specific factor that influences technology adoption in the financial context, thereby enhancing the explanatory power of the model for understanding the intention to adopt FRA. The findings reveal that four out of five independent variables (PE, EE, SI, and FK) have a positive and significant relationship with adoption intention. This suggests that young Malaysians have more intention to adopt robo-advisors when they perceive these technologies as useful, easy to use, socially supported, and when they possess adequate FK.

In contrast, FC showed no significant impact, highlighting an area of ambiguity and identifying a potential gap for future investigation. This finding suggests that, although social networks and digital trends may influence youths' adoption intentions, access to infrastructure or resources does not appear to be a critical determinant. Consequently, the findings of this study provide a solid foundation for future research, both in terms of methodology and results, particularly for studies focusing on individuals aged 18 to 30. Future studies are encouraged to consider incorporating additional constructs such as perceived risks, preferences for customization and control, and transparency, which may provide further insights into the factors that will influence the intention of Malaysia's youth to adopt FRA services.

5.3.2 Practical Implications

5.3.2.1 Researchers

Study on the intention to adopt FRA among Malaysian youths is still in its early stages. The present study, which applies the UTAUT framework with the additional factor of financial knowledge, identifies all factors excluding FC as significant predictors of adoption intention. These results provide future researchers with a reliable basis to refine or extend the model, particularly by further examining why FC are not influential despite their theoretical importance. The strong and consistent effects of the significant variables also suggest they can be prioritised when developing comparative studies across age groups, regions, or countries.

Researchers could also broaden the model by integrating personal attributes, such as risk tolerance, cultural background, or preference for human interaction, to better explain variations in FRA adoption intention. This approach would help build knowledge that is relevant to specific contexts while also making the findings more applicable to a wider range of groups.

5.3.2.2 Financial Institutions

The positive and significant influence of PE and EE suggests that financial institutions must develop and design their FRA platforms to deliver clear value and ensure user-friendliness. Initiatives such as investing in user experience design, providing educational content, and simplifying onboarding processes will be essential to increase the likelihood of adoption among young Malaysians. Furthermore, the demonstrated importance of SI highlights the critical role of social media marketing and peer-driven strategies. Financial institutions should leverage social media platforms, influencers, and peer testimonials to build trust and raise awareness. Given that youth are highly responsive to social media trends, effective online engagement can significantly enhance their intention to adopt FRA.

Moreover, the significant relationship between FK and adoption intention implies that improving financial literacy represents a strategic approach. Collaborations with universities, non-governmental organizations, and government agencies to conduct workshops, webinars, and gamified learning sessions could educate young people about personal finance while simultaneously introducing the benefits of FRA services.

5.3.2.3 Policy Makers

Policy makers can play a pivotal role in fostering greater adoption of FRA among the youth demographic. Based on the study findings, enhancing FK among youths should be a top priority. The results indicate that youths with higher FK exhibit a stronger intention to use FRAs. However, the research also highlights a critical challenge: Malaysian youths generally possess lower FK and hold misconceptions regarding investment amounts and associated risks. This presents a notable contradiction, as FRAs are promoted as tools to simplify and broaden access to investing, particularly for youths with limited financial literacy.

This discrepancy suggests that policy makers, including the SC and BNM, should shift their focus beyond merely ensuring the availability and accessibility of FRA platforms. Instead, they should adopt a more aggressive approach to improving foundational financial literacy among youths. Addressing this knowledge gap can also help narrow the disparity between Malaysia's OECD International Network on Financial Education (OECD/INFE) financial literacy scores and the OECD average (Bank Negara Malaysia, n.d.-d).

5.4 Limitations of the Study

Firstly, this research did not incorporate other potentially significant variables such as trust, perceived risk, and perceived cost. While these variables are important in general adoption intention, they were not prioritised here because they do not directly address the core issue faced by Malaysian youths, who are digitally adept but often financially inexperienced. In this context, financial knowledge was chosen as the key extension to the UTAUT framework, as it more meaningfully captures the gap between digital readiness and financial capability. Previous studies have reported inconsistent findings on the role of financial knowledge, further justifying its inclusion as a focal construct (Brenner & Meyll, 2020; Gan et al., 2021; Piehlmaier, 2022; Qadoos & AbouGrad, 2025). Moreover, in Malaysia, many young people are confident with technology but struggle with financial literacy, making this variable particularly relevant to understanding their adoption intention (Nourallah, 2023). Hence, this study confines its scope to this specific area, while acknowledging that the model may not capture the full breadth of other factors influencing adoption intention.

Furthermore, the data collected in this study is cross-sectional, meaning that the data was gathered at a single point in time. Therefore, it is difficult to track changes in Malaysian youths' intention to adopt FRA over time, especially as FRA platforms develop with new features, regulatory changes, or market awareness. This restricts the study's capacity to identify long-term adoption patterns or the influence of technological advancements on users' intentions toward FRA.

Additionally, the study targeted only respondents aged 18 to 30, using quota sampling across Malaysian regions. Although this focus allows for a detailed exploration of youth perspectives, it may not represent the views of older generations or institutional investors, who may have different motivations, risk appetites, or access to financial tools.

5.5 Recommendations for Future Research

The first recommendation is that future research could expand the current framework by incorporating moderating variables such as age, gender, or investment experience to better understand how these individual characteristics influence the intention to adopt FRA. Including these moderating effects within the UTAUT2 model may provide more targeted insights, especially in customising robo-advisory services for different user segments. Besides, future research could integrate other potentially significant variables to provide a more comprehensive understanding of the factors influencing adoption intention. This would complement the present study by broadening the scope of analysis and capturing dimensions that were beyond the focus of this research.

In addition, longitudinal studies should be considered to examine how perceptions, attitudes, and intentions evolve over time. Since the digital financial environment is always changing with new regulations, technological updates, and market conditions, it would be more accurate and dynamic to track changes in users' intentions over time. Such an approach could also help identify patterns of continued use versus discontinuation, thereby offering practical implications for both fintech providers and policymakers in designing long-term strategies for user engagement.

Lastly, future research should extend the sampling frame to study the intention to adopt FRA in other demographics and group representations, such as age, investment backgrounds, and income levels. Younger users may adopt FRA due to convenience, digital familiarity, or lower entry barriers; older generations or institutional investors may emphasize trust, security, regulatory compliance, and portfolio performance. By incorporating these diverse perspectives, future researchers could explore meaningful comparisons across groups, identify unique drivers and barriers for each segment, and develop more targeted strategies to promote robo-advisor adoption across different markets and investor categories.

5.6 Chapter Summary

In conclusion, the relationship between INT and various factors is discussed thoroughly in this study. With the exception of FC, all factors are crucial to the intention to adopt FRA, according to the 384 responses gathered from Malaysian youths and run by SmartPLS. The main findings and implications are also provided, along with limitations and recommendations for further research. By identifying the variables influencing the intention to adopt FRA in Malaysia, it can be said that the objective of the research has been met.

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APPENDICES

Appendix 3.1: Youth Population Distribution Across Malaysia's Regions in 2024

STATISTIK **POPULASI PENDUDUK BELIA (15-30 TAHUN) MENGIKUT ETNIK** DI MALAYSIA BAGI TAHUN 2024

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BIL	NEGERI	ETNIK					BUKAN WARGA NEGARA	JUMLAH
		MELAYU	BUMIPUTERA LAIN	CINA	INDIA	LAIN-LAIN		
1	Johor	613.4	15.1	318.2	66.4	7.9	193.7	1,214.6
2	Kedah	485.6	0.7	66.5	37.3	6.7	48.8	645.5
3	Kelantan	541.2	7.6	10.4	2.0	2.5	15.3	578.9
4	Melaka	204.3	2.7	45.9	15.4	1.3	27.2	296.7
5	Negeri Sembilan	190.1	6.8	55.1	39.9	1.4	32.6	325.8
6	Pahang	319.6	28.9	63.5	16.6	2.2	36.7	467.5
7	Perak	397.6	25.9	145.3	72.3	2.6	65.1	708.7
8	Perlis	81.9	0.6	6.1	2.5	1.4	3.9	96.4
9	Pulau Pinang	198.8	1.5	161.6	41.3	3.1	87.4	493.7
10	Sabah	95.7	634.1	67.8	1.8	10.5	457.5	1,267.5
11	Sarawak	177.6	328.9	134.2	1.5	1.4	48.2	691.8
12	Selangor	954.1	18.2	387.4	178.9	14.3	287.3	1,840.2
13	Terengganu	330.0	1.0	5.0	0.9	0.5	14.9	352.4
14	WP.Kuala Lumpur	187.2	4.5	164.9	41.8	2.3	70.1	470.8
15	WP.Labuan	6.2	14.2	2.3	0.3	0.2	3.9	27.1
16	WP.Putrajaya	20.0	0.4	0.2	0.2	0.1	1.2	22.0
JUMLAH KESELURUHAN (2024)		**4,803.4**	**1,091.0**	**1,634.2**	**519.0**	**58.3**	**1,393.6**	**9,499.6**
JUMLAH KESELURUHAN (2023)		**4,801.5**	**1,088.8**	**1,628.2**	**518.9**	**60.0**	**1,219.3**	**9,316.7**

Nota:
1.Anggaran Penduduk Pertengahan Tahun berasaskan data Banci Penduduk dan Perumahan Malaysia 2020.
2.Hasil tambah mungkin berbeza kerana pembundaran.

Sumber: Jabatan Perangkaan Malaysia (2024).

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Appendix 3.2: Measurement Items of Variables

Variables	Items	References
Performance Expectancy	PE1: I would find financial robo-advisor useful for financial decision-making. PE2: Using financial robo-advisor would increase my possibility of accomplishing things that are important to me. PE3: Using financial robo-advisor would help me accomplish financial goals faster. PE4: Using financial robo-advisor would increase my financial profits.	Venkatesh et al. (2003); Gan et al. (2021)

Effort Expectancy	EE1: I believe it would be easy for me to learn how to use a financial robo-advisor. EE2: I think my interactions with the financial robo-advisor would be clear. EE3: I expect that the financial robo-advisor would be easy to use. EE4: It would be easy for me to become skillful in using financial robo-advisor. EE5: I believe I could develop proficiency in using the financial robo-advisor without much difficulty.	Venkatesh et al. (2003); Gan et al. (2021)
Social Influence	SI1: The people who are important to me would support my use of a financial robo-advisor. SI2: Those who influence my behavior would encourage me to use a financial robo-advisor. SI3: People whose opinions I value would prefer that I use a financial robo-advisor. SI4: Financial robo-advisor users are generally seen as having a strong reputation.	Venkatesh et al. (2003); Gan et al. (2021)
Facilitating Conditions	FC1: I have the necessary resources (such as a smartphone or computer	Venkatesh et al. (2003); Gan et al. (2021)

	with internet access) to use a financial robo-advisor. FC2: I possess the required knowledge to operate a financial robo-advisor. FC3: The financial robo-advisor is compatible with the other technologies I use. FC4: I can seek assistance from others if I encounter difficulties while using a financial robo-advisor.	
Financial Knowledge	FK1: I have a good understanding of the financial market. FK2: I am knowledgeable about the stocks I trade, including their business and financial conditions. FK3: I stay informed about major economic news that affects the stock market. FK4: I have a solid foundation of financial knowledge.	Gan et al. (2021)
Intention to Adopt Financial Robo-Advisors	INT1: I intend to use financial robo-advisor in the next 6 months. INT2: I predict I would use financial robo-advisor in the next 6 months. INT3: I plan to use financial robo-advisor in the next 6 months. INT4: I intend to use financial robo-advisor for managing investments.	Venkatesh et al. (2003); Gan et al. (2021); Nazmi et al. (2024)

	INT5: Using financial robo-advisors for managing investments is something I would do. INT6: My intention is to use financial robo-advisors rather than any human financial advisors.	

Appendix 3.3: Survey Questionnaire Permission Letter

UNIVERSITI TUNKU ABDUL RAHMAN *DU012(A)*
Wholly owned by UTAR Education Foundation *(200201010564(578227-M))*

9 April 2025

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 them to conduct their research at your institution. All information collected will be kept confidential and used only for academic purposes.

The students are as follows:

Name of Student	Student ID
Lim Ching Er	2104773
Kung Sing Ya	2205813
Liew Wei Zen	2105758
Teoh Keat Yee	2105015

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

Thank you.

Yours sincerely,

……………………………….

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

Kampar Campus : Jalan Universiti, Bandar Barat, 31900 Kampar, Perak Darul Ridzuan, Malaysia.
Tel:(605) 468 8888
Sungai Long Campus : Jalan Sungai Long, Bandar Sungai Long, Cheras, 43000 Kajang, Selangor Darul Ehsan, Malaysia
Tel:(603) 9086 0288
Website : https://www.utar.edu.my

Appendix 3.4: Survey Questionnaire

UTAR
UNIVERSITI TUNKU ABDUL RAHMAN
Wholly owned by UTAR Education Foundation
(Co. No. 578227-M)
DU012(A)

UNIVERSITI TUNKU ABDUL RAHMAN
FACULTY OF BUSINESS AND FINANCE

BACHELOR OF FINANCE (HONOURS)

QUESTIONNAIRE

Dear Participants,
We are Bachelor of Finance (Honours) final-year students from Universiti Tunku Abdul Rahman (UTAR), and currently doing final-year project related to the "**Investigating the Intention to Adopt Financial Robo-Advisors in Malaysia**". The purpose of this questionnaire is to examine the determinants of the intention to adopt financial robo-advisors in Malaysia.

Financial robo-advisors (FRA) are automated portfolio management solutions that are driven by artificial intelligence (AI) algorithms. FRA providers in Malaysia are StashAway, MYTHEO, Wahed Invest, Akru Now, BEST Invest, Raiz, Kenanga Digital Investing, and Versa.

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 your cooperation in answering all the questions as it is crucial to us to complete our research study and achieve its objectives.

This questionnaire consists of TWO (2) sections:
Section A: Screening Questions and Demographic Information
Section B: Determinants of Intention to Adopt Financial Robo-Advisors

Your identity and responses will be kept private and strictly confidential. All information obtained from the survey is solely for academic research purposes. If you have any enquiries regarding this questionnaire, please email to kelseylim125@1utar.my. Thank you for your contribution and participation.

PERSONAL DATA PROTECTION STATEMENT

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

Notice:

1. The purposes for which your personal data may be used are inclusive but not limited to:-
   - For assessment of any application to UTAR
   - For processing any benefits and services
   - For communication purposes
   - For advertorial and news
   - For general administration and record purposes
   - For enhancing the value of education

- For educational and related purposes consequential to UTAR
- For the purpose of our corporate governance
- For consideration as a guarantor for UTAR staff/ student applying for his/her scholarship/ study loan

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

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

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

Consent:

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

2. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations

or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

3. You may access and update your personal data by writing to us at kelseylim125@1utar.my.

Acknowledgment of Notice

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

Section A: Screening Questions and Demographic Information

Subsection 1: Screening Questions

1. Age
   - o 17 and below **Thank you for your participation*
   - o 18 – 24
   - o 25 – 30
   - o 31 and above **Thank you for your participation*

Subsection 2: Demographic Information

1. Gender
   - o Female
   - o Male

2. Region
   - o North Region (Kedah, Perlis, Pulau Pinang, Perak)
   - o South Region (Melaka, Johor)
   - o Central Region (Selangor, Kuala Lumpur, Negeri Sembilan)
   - o East Region (Kelantan, Terengganu, Pahang)
   - o East Malaysia (Sabah, Sarawak)

3. Highest academic qualifications
   - SPM / O-level
   - STPM / UEC / A-level / Diploma / Certificate
   - Bachelor's Degree
   - Master's Degree
   - PhD
   - Professional Certificate
   - None of the above

4. Do you have any investment experience in the options below?
   - Mutual funds
   - Stocks/Bonds
   - Derivatives
   - Cryptocurrencies
   - NFT
   - Real estate property
   - P2P lending
   - Equity crowdfunding
   - None of the above

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

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

Section B: Determinants of the Intention to Adopt Financial Robo-Advisors

Note: In following sections, scale 1 indicates that you strongly disagree with the statement and 5 indicates that you strongly agree with the statement.

[Strongly disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Strongly agree = 5]

Subsection 1: Performance Expectancy

		1	**2**	**3**	**4**	**5**
PE1	I would find financial robo-advisor useful for financial decision-making.	□	□	□	□	□
PE2	Using financial robo-advisor would increase my possibility of accomplishing things that are important to me.	□	□	□	□	□
PE3	Using financial robo-advisor would help me accomplish financial goals faster.	□	□	□	□	□
PE4	Using financial robo-advisor would increase my financial profits.	□	□	□	□	□

Subsection 2: Effort Expectancy

		1	**2**	**3**	**4**	**5**
EE1	I believe it would be easy for me to learn how to use a financial robo-advisor.	□	□	□	□	□
EE2	I think my interactions with the financial robo-advisor would be clear.	□	□	□	□	□
EE3	I expect that the financial robo-advisor would be easy to use.	□	□	□	□	□
EE4	It would be easy for me to become skillful in using financial robo-advisor.	□	□	□	□	□
EE5	I believe I could develop proficiency in using the financial robo-advisor without much difficulty.	□	□	□	□	□

Subsection 3: Social Influence

Note: In the statements below, "people" refers specifically to individuals or communities on social media (e.g. influencers, groups you follow).

		1	2	3	4	5
SI1	The people who are important to me would support my use of a financial robo-advisor.	☐	☐	☐	☐	☐
SI2	Those who influence my behavior would encourage me to use a financial robo-advisor.	☐	☐	☐	☐	☐
SI3	People whose opinions I value would prefer that I use a financial robo-advisor.	☐	☐	☐	☐	☐
SI4	Financial robo-advisor users are generally seen as having a strong reputation.	☐	☐	☐	☐	☐

Subsection 4: Facilitating Condition

		1	2	3	4	5
FC1	I have the necessary resources (such as a smartphone or computer with internet access) to use a financial robo-advisor.	☐	☐	☐	☐	☐
FC2	I possess the required knowledge to operate a financial robo-advisor.	☐	☐	☐	☐	☐
FC3	The financial robo-advisor is compatible with the other technologies I use.	☐	☐	☐	☐	☐
FC4	I can seek assistance from others if I encounter difficulties while using a financial robo-advisor.	☐	☐	☐	☐	☐

Subsection 5: Financial Knowledge

		1	2	3	4	5

FK1	I have a good understanding of the financial market.	☐	☐	☐	☐	☐
FK2	I am knowledgeable about the stocks I trade, including their business and financial conditions.	☐	☐	☐	☐	☐
FK3	I stay informed about major economic news that affects the stock market.	☐	☐	☐	☐	☐
FK4	I have a solid foundation of financial knowledge.	☐	☐	☐	☐	☐

Subsection 6: Intention to Adopt Financial Robo-Advisors

		1	**2**	**3**	**4**	**5**
BI1	I intend to use financial robo-advisor in the next 6 months.	☐	☐	☐	☐	☐
BI2	I predict I would use financial robo-advisor in the next 6 months.	☐	☐	☐	☐	☐
BI3	I plan to use financial robo-advisor in the next 6 months.	☐	☐	☐	☐	☐
BI4	I intend to use financial robo-advisor for managing investments.	☐	☐	☐	☐	☐
BI5	Using financial robo-advisors for managing investments is something I would do.	☐	☐	☐	☐	☐
BI6	My intention is to use financial robo-advisors rather than any human financial advisors.	☐	☐	☐	☐	☐

Appendix 4.1: Central Tendency (Mean)

	Items	Mean Value
PE1	I would find financial robo-advisor useful for financial decision-making.	**4.435**
PE2	Using financial robo-advisor would increase my possibility of accomplishing things that are important to me.	4.286
PE3	Using financial robo-advisor would help me accomplish financial goals faster.	4.221
PE4	Using financial robo-advisor would increase my financial profits.	4.286
EE1	I believe it would be easy for me to learn how to use a financial robo-advisor.	4.310
EE2	I think my interactions with the financial robo-advisor would be clear.	4.292
EE3	I expect that the financial robo-advisor would be easy to use.	4.336
EE4	It would be easy for me to become skillful in using financial robo-advisor.	**4.362**
EE5	I believe I could develop proficiency in using the financial robo-advisor without much difficulty.	4.219
SI1	The people who are important to me would support my use of a financial robo-advisor.	4.120

SI2	Those who influence my decisions would encourage me to use a financial robo-advisor.	4.169
SI3	People whose opinions I value would prefer that I use a financial robo-advisor.	4.167
SI4	Financial robo-advisor users are generally seen as having a strong reputation.	**4.292**
FC1	I have the necessary resources (such as a smartphone or computer with internet access) to use a financial robo-advisor.	**4.737**
FC2	I possess the required knowledge to operate a financial robo-advisor.	4.018
FC3	The financial robo-advisor is compatible with the other technologies I use.	4.081
FC4	I can seek assistance from others if I encounter difficulties while using a financial robo-advisor.	4.409
FK1	I have a good understanding of the financial market.	4.062
FK2	I am knowledgeable about the stocks I trade, including their business and financial conditions.	4.003
FK3	I stay informed about major economic news that affects the stock market.	**4.104**
FK4	I have a solid foundation of financial knowledge.	3.984
INT1	I intend to use financial robo-advisor in the next 6 months.	3.935

INT2	I predict I would use financial robo-advisor in the next 6 months.	4.010
INT3	I plan to use financial robo-advisor in the next 6 months.	4.005
INT4	I intend to use financial robo-advisor for managing investments.	4.263
INT5	Using financial robo-advisors for managing investments is something I would do.	**4.286**
INT6	My intention is to use financial robo-advisors rather than any human financial advisors.	3.987

Note. Developed by the authors.

Appendix 4.2: Outer Loadings

	PE	EE	SI	FC	FK	I
PE 1	0.798					
PE 2	0.764					
PE 3	0.732					
PE 4	0.795					
EE 1		0.706				
EE 2		0.717				
EE 3		0.729				
EE 4		0.732				
EE 5		0.744				
SI 1			0.701			
SI 2			0.746			
SI 3			0.727			
SI 4			0.759			
FC 1				0.752		
FC 2				0.742		
FC 3				0.712		
FC 4				0.711		
FK 1					0.822	
FK 2					0.826	
FK 3					0.790	

FK 4	0.778	
INT 1		0.744
INT 2		0.885
INT 3		0.846
INT 4		0.839
INT 5		0.722
INT 6		0.762

Note. Developed by the authors.

Appendix 5.1: Summary of significance of results

Hypothesis Testing	Result (Significance at P-Value ≤ 0.05)	Consistency with Predicted Results
H_1: There is a positive relationship between performance expectancy (PE) and intention to adopt financial robo-advisors (INT).	0.000	Consistent
H_1: There is a positive relationship between effort expectancy (EE) and intention to adopt financial robo-advisors (INT).	0.027	Consistent
H_1: There is a positive relationship between social influence (SI) and intention to adopt financial robo-advisors (INT).	0.043	Consistent
H_1: There is a positive relationship between facilitating conditions (FC) and intention to adopt financial robo-advisors (INT).	0.087	Inconsistent
H_1: There is a positive relationship between financial knowledge (FK) and	0.000	Consistent

intention to adopt financial robo-advisors (INT).		

Note. Developed by the authors.