THE INFLUENCE OF ROBO-ADVISORY SERVICES ON MALAYSIA UNIVERSITY STUDENT'S INVESTMENT INTENTION

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

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PREFACE

This final year project, entitled "The Influence of Robo-Advisory Services on Malaysia University Student's Intention," is the result of months of continuous effort, collaboration, and dedication. It marks the culmination of our undergraduate studies in Banking and Finance and reflects the knowledge, skills, and research capabilities we have developed throughout the program.

This research was carried out to gain deeper insights into the factors influencing university students' willingness to adopt financial technology tools such as robo-advisors. In particular, we explored how trust, ease of use, and perceived risk contribute to or hinder the intention to use these platforms for investment purposes.

The journey of completing this project was filled with both challenges and rewarding moments. It provided us the opportunity to strengthen our teamwork, enhance our analytical thinking, and apply theoretical concepts in a practical context. We hope this study will contribute meaningfully to the growing body of literature on financial technology adoption and serve as a useful reference for future researchers and fintech developers who aim to understand the preferences of younger investors in Malaysia.

ABSTRACT

The emergence of robo-advisory services has transformed the landscape of investment by offering automated, algorithm-driven financial planning with minimal human intervention. As financial technology (fintech) continues to advance, understanding the behavioral intentions of young investors toward these services is crucial. This study investigates the influence of perceived risk, trust, and perceived ease of use on the intention to adopt robo-advisory services among Malaysian university students.

The study adopts the Technology Acceptance Model (TAM) as the theoretical foundation, integrating elements of trust and perceived risk to examine how these factors impact adoption intentions. Data was collected through a structured questionnaire distributed to university students across Malaysia, and a total of 135 valid responses were analyzed using Jamovi statistical software version 2.6.24. Descriptive and inferential analyses, including multiple regression, were employed to determine the relationships among the variables.

The findings reveal that both trust and perceived ease of use have significant positive effects on students' intention to use robo-advisory services. Conversely, perceived risk demonstrates a significant negative relationship, indicating that concerns over data security, financial loss, and technological uncertainty remain barriers to adoption. These results highlight the need for fintech developers and financial service providers to focus on building secure, user-friendly platforms that foster trust and address risk concerns, particularly when targeting young, tech-savvy investors.

This research contributes to the growing body of literature on fintech adoption in emerging markets and offers practical implications for improving the design, communication, and implementation strategies of robo-advisory services in Malaysia. Future research could expand the sample size and explore other demographic groups to enhance generalizability and provide deeper insights into consumer behavior in the digital investment space.

Keywords: Robo-Advisory Services; Perceived Risk; Trust; Ease of Use; Technology Acceptance Model

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1.0 Introduction

This study investigates the intention of Malaysian university students to adopt robo-advisory services for investment purposes. This chapter provides a brief explanation of current trends, their importance, and their relevance to Malaysian university students. In addition, the determinants of the intention of Malaysian university students to make use of robo-advisory investment services are described throughout this chapter, together with research problems, questions, and objectives, as well as theoretical and practical contribution.

1.1 Research Background

"Robo-advisor" refers to any automated investment or financial planning service that targets the general public by providing simple and affordable access to financial information, advice, goods, and services (Berger, 2015). Robo-advisory services, one of the most innovative AI technologies, greatly facilitate individual financial planning. This service is especially good for young investors, such as Malaysian university students who are technology savvy but may not have much experience with finance, since it offers automated, algorithm-based portfolio management and financial planning. However, the use of robo-advisory services is anticipated to increase as the digital landscape changes, particularly among younger, tech-savvy people looking for simple and effective financial planning solutions. This pattern emphasizes how robo-advisors can empower a new generation of investors and democratize access to financial possibilities. Due to their high level of digital literacy and tolerance for new technologies, Malaysian university students are in a good position to utilize these services in order to safeguard their financial prospects. (Yi, Rom, Hassan, Samsurijan & Ebekozien, 2023)

Younger, tech-savvy people are using robo-advisory services more and more since they are affordable and easily accessible. In comparison with traditional financial advisors, robo-advisors remove entry barriers and increase accessibility to financial guidance by providing financial advice at significantly reduced prices and requiring smaller initial amounts. Millennials and Generation Z find this particularly enticing since they are more at Ease with digital solutions and automation and are twice as likely to explore using these services as older generations. Furthermore, younger people with greater financial literacy—those who comprehend complex financial concepts like bond and stock pricing—are more likely to use robo-advisors because they see the benefits of these advanced technology-based advising services. (Isaia & Oggero, 2022).

Robo-advisors use advanced algorithms to manage financial portfolios and provide recommendations to users about investments (Bhatia et al., 2021). Robo-advisors, as opposed to traditional portfolio managers, allow clients with modest starting capital to start investing (D'Acunto, Prabhala, & Rossi, 2019). Additionally, these platforms give customers the benefit of portfolio diversification, which is especially advantageous for people who do not have a lot of expertise or knowledge about investments (Gomber, Kauffman, Parker, & Weber, 2018). When robo-advisory services are available around the clock, investors may access their accounts and make decisions about investments whenever they choose, adding to their convenience and flexibility (Park, Ryu, & Shin, 2016). Robo-advisors not only provide affordable investing options but also a variety of features customized to each user's financial objectives and risk tolerance. These platforms are a great tool for first-time investors who want to manage and grow their wealth because they frequently come with educational materials, customized investment plans, and automatic portfolio rebalancing. (Yi, Rom, Hassan, Samsurijan & Ebekozien, 2023)

Although robo-advisors are relatively new in Malaysia, the industry is growing quickly since there is a huge need for low-cost automated portfolio management solutions (Kuah, Chow, Genevieve, & Tan, 2024). The notion of robo-advisors has attracted significant interest in recent times owing to a growing number of robo-advisor providers within Malaysia's financial industry (Ruslan, Ibrahim, & Abd Hamid, 2022). Currently, the Securities Commission Malaysia (SC) has approved eight licensed robo-advisors, commonly referred to as Digital Investment Managers (DIM), in Malaysia. These include the domestic robo-advisor AkruNow and Airo. My, which partners with Interactive Brokers and Pacific Trustees; Mytheo, a Malaysian-Japanese collaboration; StashAway, which expanded from Singapore; UOBAM Invest, a business-focused robo-advisory by UOB Asset Management; Wahed Invest, a Shariah-compliant platform originating from New York; Kenanga Digital Investing (KDI), which Malaysia's largest independent investment bank supports; and RIA, which was introduced by Amanah Saham Nasional Berhad (ASNB) and features portfolios of their variable funds (Suraya, 2025). While every platform offers something different, the majority of Malaysian robo-advisors invest mostly in exchange-traded funds (ETFs), especially international ETFs. (Smart Investor, 2022). Additionally, there are also two more digital investment platforms, BEST Invest and Versa Asia, which offer Shariah-compliant and ESG unit trusts, PRS, REITs, and gold investments using sophisticated tech-pushed methods. They do not fall under the DIM category. Still, their technology is comparable to that of robo-advisors, and they are notable for providing unit trusts with no sales costs, which is uncommon in Malaysia, where fees can reach 6%. (Suraya, 2025).

Robo-advisors have caused strong competition, which has led to a decrease in costs and forced traditional financial institutions to either embrace robo-advisory platforms or reevaluate their pricing structures in order to stay competitive (Fan & Chatterjee, 2020). In Malaysia, robo-advisors have grown in popularity as more customers use digital financial management tools (Ku & Wang, 2022). The principal objective in Malaysia is to augment the financial literacy of the robo-advisors initiative, specifically for prospective investors who actively pursue high-yield investments and select platforms that are user-friendly and system-orientated (Manaf, Ismail, & Zakaria, 2024). The business, financial markets, and investment systems in Malaysia have all been significantly impacted by the rise of robo-advisory services as a digital investment option (Manaf, Ismail, & Zakaria, 2024). In comparison to traditional advisory services, robo-advisors provide a quicker and more safe option. They charge less for consultations and make use of contactless connectivity (Abraham, Schmukler, & Tessada, 2019). The financial adviser business might go through a revolution with the adoption of robo-advisory, which will ultimately improve Malaysia's digital economy and increase the country's income contribution as well as local and worldwide competitiveness (Manaf, Ismail & Zakaria, 2024).

The COVID-19 epidemic has pushed forward the shift to digital financial management, leading to a rise in the use of robo-advisors. The effectiveness and usability of robo-advisors increased throughout the pandemic as more people became used to managing their finances online. Individuals who participate in digital financial activities, such as online shopping and digital payments, are more likely to employ robo-advisory services than people who participate in non-financial online activities (Isaia & Oggero, 2022). Early in 2020, when the market started to decline, consumers started saving more and searching for simple investment options. Because these younger investors were looking for ways to enhance their financial wellbeing and believed that robo-advisors might help them make better and wiser investment decisions, we can see a surge in the number of people signing up for robo-advisors (Phoon & Koh, 2018).

1.2 Problem Statement

Artificial intelligence (AI) applications in the financial sector are fundamentally transforming the industry landscape, bringing unprecedented opportunities and challenges （Zhang & Lee, 2023). However, Malaysian investors currently face multiple challenges, including limited financial literacy, suboptimal investment portfolios, and heavy debt burdens (Sabri et al., 2021). Studies have shown that many investors lack a basic understanding of financial concepts, resulting in poor investment decisions and an inability to assess risks (Rahman, Isa, Masud, et al., 2021) properly. In addition, high levels of household debt (including credit card debt and personal loans) have severely constrained disposable income and limited investment opportunities (Nazmi, Lye, & Tay, 2024). Although the Malaysian government has actively introduced policies to stabilize the financial market and strive to create a good environment for people to invest (Bank Negara Malaysia, 2022), and the non-governmental organization Agensi Kaunseling dan Pengurusan Kredit (AKPK) is also committed to helping individuals manage their financial situation and advocating the wise use of credit, these problems still exist significantly.

In Malaysia, the adoption rate of robo-advisors is still relatively low (Zheng, 2022). According to Bank Negara Malaysia's Strategic Thrust 2, the Financial Sector Blueprint 2022-2026 proposes key strategies to improve people's financial status, including increasing the popularization of financial literacy, developing courses and materials specifically for investment knowledge, improving the accessibility of financial services, encouraging financial institutions to promote digital investment services such as smart investment advisors, and promoting smart investment advisor-related innovations(BNM, 2022). However, Malaysia's financial literacy level is still lower than that of 26 other countries (BNM, 2022), indicating that people still face many challenges in investment decisions, and the popularization and effective application of robo-advisors are, therefore, limited.

For University students, investment decisions are particularly difficult (Yi et al., 2023). Mohd Kamel and Sahid (2021) highlighted that most Malaysian university students lack basic financial knowledge and find it difficult to accurately assess risks and returns when faced with a variety of investment products, resulting in investment portfolios that are often too concentrated in a specific asset and lack diversification. In this context, robo-advisors using sophisticated algorithms and artificial intelligence to analyze client data, robo-advisors have significantly lowered the barrier to entry for investors, especially millennials, by eliminating the need for intermediaries and providing a low-cost alternative (Karnavat, Namrata, & VR, 2024). However, D'Acunto et al. (2019) found that even if robo-advisors provide low-cost investment advice when university students are deeply involved in financial planning, they still prefer to consult human advisors. Northey et al. (2022) also pointed out that in the complex investment decision-making process, university students rely more on personalized advice, and human advisors have this advantage. Therefore, university students are both interested in and reserved about robo-advisors, and this contradictory attitude has become an important reason affecting their adoption of robo-advisors.

In addition, the Malaysian robo-advisor market has continued to develop in recent years, and the number of companies providing robo-advisor services has continued to grow since 2019 (Gan & Khan, 2021). However, existing research mainly focuses on the technical and legal aspects of robo-advisors, while the acceptance and usage behaviour of university students as a young investor group are less explored (Hohenberger, Lee, & Coughlin, 2019). Moreover, the existing research conclusions on the Trust and acceptance of Malaysian university students on robo-advisor platforms are inconsistent (Yi et al., 2023), further highlighting the need for in-depth research. Moreover, the International Organization of Securities Commissions (IOSCO, 2021) pointed out that the application of robo-advisors in asset management has both risks and opportunities, and its specific impact on Malaysian university students has not yet been fully evaluated.

In summary, the current research on the cognition, acceptance and influencing factors of robo-advisors in investment decisions among Malaysian university students is still insufficient. This study aims to fill this research gap and provide empirical evidence for the promotion and optimization of smart advisors among young investors.

1.3 Research Objectives

1.3.1 General Objectives

This study examines Malaysian university students' investment intentions. The study's primary conclusions state that perceived risk, Trust, and Ease of use are some of the causal elements that influence changes in Malaysian university students' investment intentions. In this study, perceived risk, Trust, and Ease of use are the independent variables, and the intention of Malaysian university students to adopt robo-advisory services for investment is treated as the dependent variable.

1.3.2 Specific Objectives

1. To examine the relationship between Trust and Malaysian university students' investment intentions by using robo-advisory services.
2. To examine the relationship between Ease of use and Malaysian university students' investment intentions by using robo-advisory services.
3. To examine the relationship between Perceived Risk and Malaysian university students' investment intentions by using robo-advisory services.

1.4 Research Questions

The information this topic provides can help us address our concerns about the phenomenon observed in Malaysia. A number of different indicators can impact a Malaysian university student's investment intention. The three main topics of this research will be perceived risk, Trust, and Ease of use.

1. Does trust influence Malaysian university students' investment intentions by using robo-advisory services?
2. Does the ease of use influence Malaysian university students' investment intentions by using robo-advisory services?
3. Does the perceived risk influence Malaysian university students' investment intentions by using robo-advisory services?

1.5 Significance of Study

This study aims to investigate how robo-advisory services influence the financial decision-making of Malaysian university students, with a particular focus on three key independent variables: perceived risk, Trust, and Ease of use. By examining the impact of these factors on students' willingness to adopt robo-advisors and their investment behaviours, this research seeks to uncover both the practical benefits and potential barriers associated with the adoption of these services. The study holds several significant research implications.

First, the findings will serve as a valuable resource for fintech companies. From a practical perspective, the results can help identify and address user concerns related to robo-advisory services, ultimately improving customer satisfaction and service quality. By conducting an in-depth analysis of perceived risk, Trust, and Ease of use, this study aims to provide actionable recommendations that enable fintech firms to develop robo-advisory platforms better suited to university students' needs. Furthermore, it will offer insights into effective marketing strategies for promoting robo-advisory adoption.

Second, this research fills a gap in existing literature regarding the impact of robo-advisory services on specific demographics while contributing to the broader field of fintech applications. As an exploratory study, it seeks to identify the key factors influencing Malaysian university students' adoption of robo-advisors—an area that has received limited attention in prior research. Additionally, the findings will lay the groundwork for future quantitative studies, leading to more comprehensive and widely applicable conclusions.

Third, the study's findings have the potential to enhance university students' interest and participation in investment activities. By understanding the advantages of robo-advisors, students may be encouraged to explore and utilize these tools, thereby improving their engagement in financial planning and investment management. Gaining proficiency in using robo-advisory platforms can not only stimulate students' interest in investing but also equip them with essential financial skills, fostering long-term financial wellbeing. Increased participation in investment activities at an early stage can contribute to both individual financial security and the overall economic stability of the nation.

Lastly, this research provides valuable insights for policymakers. Beyond contributing to academic knowledge, the study holds practical policy implications. The findings can serve as a foundation for regulators to develop targeted policies and guidelines that protect users' rights while fostering the healthy growth of fintech services. Additionally, this research offers guidance on how robo-advisory platforms can be leveraged as investment and financial management tools for Malaysian university students. Educators and policymakers can use these insights to design targeted interventions and curriculum improvements, equipping students with the necessary financial knowledge to make informed investment decisions early in their financial journey. In turn, this can support both individual financial stability and national economic growth.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

The relevant theory and literature based on the objectives of the research introduced in chapter one will be subjected to analysis. The chapter begins with the topic of the major theory that underpins the research framework. The explanatory variable, dependent variable, and then hypotheses are handled in chapter two. The research sets a conceptual framework of one dependent variable and three independent variables, i.e., Malaysian university students' investment intentions using a robo-advisory service. The relationship among the three determinants and Malaysian university students' intentions to invest using a robo-advisory service will be elaborated using the proposed conceptual framework.

2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) and its extensions serve as a framework for the underlying concept of this research. The Technology Acceptance Model (TAM), first introduced by Davis (1989), examines the relationships between users' attitudes, perceived usefulness, perceived ease of use, and usage intentions to provide a comprehensive framework for understanding how users accept technology (Osman, Alwi, Jodi, Khan, Ismail & Yusoff, 2024). TAM has been extensively implemented in a variety of industries, including education, and posits that perceived usefulness is directly impacted by perceived ease of use (Qahman, Zakaria, Hussin, Samra, Aldaya, Din & Othman, 2023). According to Holden & Karsh (2010), perceived usefulness (PU) measures how much students think utilising AI would improve their performance as investors. They may believe, for example, that AI is a technology that may enhance decision-making and offer superior investment insights. Furthermore, the concept of perceived ease of use (PEOU) relates to the level of simplicity with which students perceive the application of AI for the purposes of investment. Students are more likely to accept AI products if they are easy to use and take less time to learn how to use them. Finally, students' motivation or willingness to employ AI for investing is measured by behavioural intention (BI). It is affected by perceived ease of use as well as perceived usefulness. Students are more likely to adopt AI if they believe it to be practical as well as straightforward to use (Holden & Karsh, 2010). Therefore, TAM is employed in this research to explore how students' perceptions of AI's usefulness and ease of use shape their behavioral intentions to adopt AI for investment purposes. By applying TAM, this study aims to provide insights into the factors driving technology acceptance in the context of AI and investment, offering valuable implications for educators, developers, and policymakers seeking to enhance the adoption of AI tools among students.

2.2 The intention of Malaysian university students to adopt Robo-advisory services for investment purposes.

The dependent variable in this study is the intention of Malaysian university students to adopt robo-advisory services for investment purposes. The intention to adopt refers to the students' willingness and plan to use robo-advisory services for managing their investments. This study aims to fill this gap by investigating the factors influencing the intention of Malaysian university students to adopt robo-advisory services. Understanding these factors can provide insights into the future landscape of financial advisory services and help stakeholders develop strategies to encourage the adoption of these technologies among young investors. The intention of Malaysian university students to adopt robo-advisory services for investment will be influenced by perceived risk, trust, and ease of use.

When robo-advisors were originally introduced to the market, they offered small investors a more affordable way to obtain portfolio management services and financial advice (Fein, 2015). One important aspect of robo-advisors is their ability to provide services at a minimal cost. Automating client data collection and analysis, recommendation creation and execution, and outcome monitoring results in cost reductions (Fulk, Grable, Watkins & Kruger, 2018). These days, robo-advisors offer non-investment money management services like managing savings, tracking expenses, budgeting, mortgage finance, legal counsel, tax advice, and general financial planning guidance. While federal regulators have not yet concluded whether robo-advisory services satisfy the suitability or fiduciary standard, politicians generally agree that automated services could be a way to provide financial advice and services to more people and families (Idzelis, 2016). Meanwhile, it's important that some people have expressed worries over robo-advisors' place in the financial industry. For instance, Fein (2015) conducted a critical analysis of robo-advisors and concluded that their recommendations are not always in the best interests of their clients. Fein stated that the way consumer information is used generally lacks transparency. Customers may pay more for both obvious and hidden costs as a result of this lack of transparency, which may also result in unreported conflicts of interest. Despite the ongoing debate surrounding the fiduciary status of robo-advisory companies, it is evident that more and more customers are accepting the idea of entrusting some or all of their financial management to an automated system (Cutler, 2015). The limited information on the use of robo-advisors indicates that younger consumers with a high level of trust in online platforms are typically the main users of this technologically advanced money management strategy (Pisani, 2016).

There are a number of important legal issues surrounding robo-advisory services. First, it's unclear who is responsible for faulty legal counsel or careless asset management. According to Sanz Bayón & Vega (2018), if problems result from programming faults, the programmer may also be held liable. However, the actual users of the software should bear the majority of the liability. The oversight of their robo-advisors and the overall plan must fall under the control of the participating firms' management bodies. Because robo-advisory services are not yet subject to a specified legal framework, compliance and liability issues arise. The regulatory frameworks that now manage each of the nations where robo-advisors operate might not be sufficient to handle the particular difficulties that come with automated financial advice. In addition, robo-advisors have to manage various legal requirements, such as getting to know their clients, maintaining transparency, and performing suitability evaluations. It might be difficult for other market participants to successfully operate under these regulations without robotic support (Sanz Bayón & Vega, 2018). Furthermore, there are several difficulties in managing enormous amounts of information and the related cybersecurity concerns. To avoid systemic dangers arising from algorithmic trading, effective data control and risk management are absolutely necessary. Moreover, there are uncertainties regarding the suitability of the advice given by robo-advisors due to issues about investors' comprehension of the methods employed by digital guidance tools and how their risk tolerance is determined. Although there are difficulties in the way, robo-advisory services can help make financial planning more accessible to everyone. However, in order to gain users' trust and serve their interests, they need to overcome these legal and regulatory barriers (Sanz Bayón, & Vega, 2018).

2.3 Trust

Trust is a multidimensional notion frequently defined as a belief or expectation based on one's encounters with others and highly influenced by their perceived reliability (Robbins, 2016b). At its root, trust is a psychological condition in which people deliberately accept vulnerability in the belief that others will behave in their best interests or have positive intentions (Rousseau et al., 1998b). Personal beliefs, risk perceptions, and behavioral patterns all have an impact on this cognitive process. Trust is essential in maintaining social order, facilitating smoother social interactions, and encouraging collaboration among individuals and groups (Robbins, 2016).

Furthermore, trust is not fixed; it is influenced by the larger social and cultural context, as well as the attitudes and behaviors of those involved (Simpson, 2012b). For example, an individual's propensity to trust is frequently linked to their prior experiences and the level of their perceived knowledge about the entity or circumstance under consideration. In the case of technology adoption, such as robo-advisors, trust is even more important because users must rely on automated systems to make financial decisions.

Recent research has demonstrated the transferability of trust across contexts. Manaf et al. (2024) claim that trust created in one area can favor trust in other domains, such as robo-advisor acceptance. This implies that if users gain trust in technology in general, they are more inclined to extend that faith to specific applications such as robo-advisory platforms. Additionally, Kwon et al., (2022b) used the idea of "perceived safety" to assess consumers' confidence and sense of security when using robo-advisors. This includes concerns about funds losses, technological breakdowns, and personal information security. Their findings show a high link between trust and acceptance of robo-advisors, implying that people who regard these systems as safe and reliable are more willing to utilize them. Furthermore, Singh & Kumar, (2024) discovered that higher levels of trust in robo-advisors relate to decreased resistance to innovation and increased adoption. This emphasizes the importance of trust as a crucial driver for adopting automated financial advice services.

Trust in robo-advisory services is built on three pillars: perceived privacy protection, firm reputation, and performance efficacy. Performance efficacy is the concept that robo-advisors can improve investing outcomes. When consumers believe these technologies are effective, their trust in the platform grows dramatically. Perceived privacy protection is also important, as effective security measures for personal and financial information increase trust in the service (Yi et al., 2023b). Furthermore, firm reputation plays an important part in shaping trust. Investors are more likely to trust robo-advisors provided by well-known businesses because of their proven track record and resources lower perceived risk. This demonstrates how trust is determined not just by technology itself, but also by the legitimacy and reliability of the institution that supports it.

Perceived privacy protection is an essential component of trust for robo-advisory services. Users are more likely to trust platforms that use strong security to protect their personal and financial information. According to Yi et al., (2023b), effective privacy protection systems increase trust because consumers are certain that their data is secure. This is especially crucial for university students, who may be unwilling to share sensitive information due to their inexperience with financial technologies. Concerns about privacy, such as the possibility of data breaches, financial loss, and identity theft, might harm users' opinions of robo-advisors. To address these issues, robo-advisors must show a strong commitment to privacy protection, which is typically interpreted as fulfilling their fiduciary duty to investors (Lee et al., 2018). When consumers believe their privacy is being prioritized, their trust in the platform grows, resulting in increased adoption rates.

Firm reputation is also an important factor in determining trust in robo-advisory services. Well-established organizations with a demonstrated track record are more likely to win consumer trust because their reputation lowers perceived risk and uncertainty (Aldboush & Ferdous, 2023). For university students who lack the skills to analyze the technical features of robo-advisors, the service provider's reputation serves as an important heuristic for determining dependability. Jin et al. (2021) found that organizations with good reputations are seen as more credible and capable of providing high-quality services. This is especially important in the context of robo-advisors, because consumers trust the platform to handle their money. A positive reputation not only builds trust, but it also encourages long-term loyalty to the service.

Another important component in establishing trust is performance efficacy, or conviction that robo-advisors can improve investing outcomes. When users believe the platform is effective at delivering accurate and reliable results, their trust in the service grows dramatically (Yi et al., 2023b). For university students who may have minimal financial expertise, robo-advisors' ability to simplify difficult investing decisions is critical in establishing confidence. However, questions about the dependability of robo-advisors during periods of market instability could damage trust. According to Bhatia et al., (2021), some investors distrust robo-advisors' capacity to navigate difficult market situations and protect their wealth. Addressing these concerns through clear information and consistent performance is critical to sustaining user trust.

Social impact is key in molding trust and uptake of robo-advisory services. According to Tun-Pin et al. (2019), individuals are more inclined to employ robo-advisors if they obtain positive recommendations from their social networks, which include friends and relatives. Trust serves as a mediator in this interaction, converting social influence into favorable views and intends to use the service. This phenomenon is especially relevant for university students, who are frequently influenced by peer behavior and rely on social proof to make decisions concerning new technology (Jin et al., 2024).

The impact of social influence on technology adoption has been extensively studied in the literature. Solarz & Swacha-Lech, (2021) discovered that social influence had a considerable impact on the adoption of fintech services, especially robo-advisors. The study found that people are more likely to adopt technology if they believe their peers approve it. This is especially true for younger groups, such as university students, who are particularly vulnerable to peer pressure and societal trends (Khoo et al., 2024). Furthermore, trust is an important intermediary between social influence and the use of robo-advisory services. According to Vasquez & San-Jose (2022), trust increases the impact of social influence by lowering perceived risk and uncertainty. When customers believe the suggestions of their social networks, they are more inclined to embrace robo-advisors and use the service. This is especially true for university students, who frequently rely on their social circles for financial advice (Singh & Kumar, 2024).

2.4 Ease of use

Ease of use is a core variable in the Technology Acceptance Model (TAM), defined as the degree to which users believe that using a system requires minimal effort (Davis, 1989). In the field of financial technology, particularly in the application of robo-advisors, Ease of use significantly influences user acceptance and adoption intentions. With the advancement of artificial intelligence and automation technologies, researchers have extensively studied the role of Ease of Use in financial technology services.

Studies have shown that Ease of use has a significant impact on the adoption of robo-advisors. Fan and Chatterjee (2020) found that the convenience of information retrieval and an intuitive user interface enhance user trust, thereby increasing adoption willingness. Sabir et al. (2023) further confirmed that a higher level of Ease of use leads to greater acceptance of technology, thereby increasing the usage frequency of robo-advisors. Additionally, Figà et al. (2022) highlighted that Generation Z, and female users rely more on Ease of use when adopting robo-advisors, as they may have relatively less financial knowledge and investment experience. The study found that these groups are more inclined to choose robo-advisors with intuitive interfaces and automated functions, while complex processes or technical jargon can be adoption barriers. Therefore, optimizing user interfaces, providing guided investment advice, and reducing operational complexity can enhance acceptance among these groups.

Ease of use not only influences user acceptance but also plays a crucial role in perceived usefulness. Ku and Wang (2022) demonstrated that Ease of use and perceived control have a significant positive impact on perceived usefulness, which in turn increases investors' willingness to use robo-advisors. Similarly, Menon (2021) found that perceived usefulness is a key factor influencing user attitudes in wealth management. Wu and Gao (2021) conducted a study with 207 participants, using Structural Equation Modeling (SEM) to test hypotheses and examine the relationship between Ease of use, perceived usefulness, and adoption intention. Their study first conducted reliability and validity tests, followed by Maximum Likelihood Estimation (MLE) to analyze path relationships between variables. The final results indicated that perceived usefulness plays a dominant role in the decision to adopt robo-advisors, with a positive impact. Seiler and Fanenbruck (2021) further quantified this impact, finding that a 1% increase in perceived usefulness (e.g., enhanced privacy protection) led to a 0.57% increase in adoption intention.

Various studies have employed different methods and theoretical models to explore the impact of Ease of Use on the intention to adopt robo-advisors. For example, Ramesh et al. (2023), using TAM, found that user interface friendliness and AI capabilities are key factors in enhancing Ease of use. Blanche et al. (2023), applying the Stimulus-Organism-Response (S-O-R) model, discovered that younger users are more likely to recommend robo-advisors compared to older users, while male users generally exhibit greater confidence in using these services. Additionally, Gaspar and Oliveira (2024) found that Ease of use influences investors' risk aversion behaviour and indirectly affects investment decisions. Improving user experience, optimizing interface design, and enhancing system intelligence can boost user trust and increase the adoption rate of robo-advisors.

The role of Ease of use varies across different markets. In developing countries, Gan et al. (2021) examined the adoption of robo-advisors among Malaysian consumers during the COVID-19 pandemic. They found that the crisis accelerated demand for convenient online financial services, with Ease of use being a crucial factor in adoption. Nain and Rajan (2023) revealed that India's robo-advisory market is still in its early stages, with users prioritizing convenience, time efficiency, and transparency. In developed countries, Méndez et al. (2022) described the challenges robo-advisors face in penetrating the Latin American financial market, emphasizing that Ease of use is a key factor influencing market penetration. Hammer (2021) analyzed the regulatory framework in Europe and Germany, highlighting the importance of user-friendly interface design in building user trust. Additionally, Yi et al. (2023) focused on millennial adoption behaviours, finding that Ease of use and Trust are the primary drivers for this demographic to adopt robo-advisors.

2.5 Perceived Risk

Perceived risk, defined as the uncertainty individuals experience regarding potential negative outcomes of their decisions, plays a crucial role in the adoption of new financial technologies (Featherman & Pavlou, 2003). In the context of robo-advisory services, perceived risks—including potential financial losses, lack of consumer protection, and data privacy breaches—significantly influence investor intentions (Ryu, 2018). Understanding these risks is essential to assessing how they shape individuals' willingness to adopt robo-advisory financial services.

Perceived risk can be categorized into multiple dimensions, each representing a distinct aspect of potential adverse outcomes. Performance risk pertains to the extent to which individuals trust robo-advisors to consistently and accurately perform their intended functions (Lee, Lee, & Eastwood, 2003). A higher perceived performance risk is linked to concerns that robo-advisors may fail to meet users' expectations, leading to financial losses and diminished confidence in the technology (Dietvorst, Simmons, & Massey, 2015). Investors may hesitate to use robo-advisors if they perceive a high probability of inaccurate recommendations or algorithmic failures, much like how consumers avoid unreliable products. Im et al. (2008) further emphasized that technological failures erode users' trust in emerging financial tools, thereby slowing adoption.

Financial risk, another significant factor, relates to the perception of uncertainty and potential monetary losses associated with robo-advisory services (Holtgrave & Weber, 1993). Investors may fear that these services could introduce greater financial volatility compared to traditional investment methods. Similarly, privacy risk has emerged as a critical concern, particularly regarding data protection and the potential loss of control over personal information. The increasing reliance on robo-advisors exacerbates these concerns, as such platforms collect and utilize sensitive personal data (Smith, Dinev, & Xu, 2011). Users may feel vulnerable if financial records, contact details, or other personal identifiers are mishandled or accessed by unauthorized parties (Eeuwen, 2017). Such concerns undermine investor trust and satisfaction, as Shankar et al. (2003) found that privacy and security apprehensions negatively affect user confidence in digital financial services.

Beyond performance, financial, and privacy risks, psychological risk also plays a vital role in shaping investor perceptions. This form of risk arises from concerns about losing autonomy in financial decision-making (Stone & Grønhaug, 1993). Investors accustomed to human advisors may feel uneasy relying on automated systems, particularly after witnessing errors in algorithmic predictions (Dietvorst et al., 2015). This apprehension is more pronounced among individuals who prioritize personal control over their financial choices. However, younger investors, having grown up in a digital-first environment, tend to value convenience over direct control (Lee & See, 2004). The widespread adoption of digital payment solutions such as Touch 'n Go and GrabPay has further normalized technology-driven financial interactions, gradually reducing psychological resistance to robo-advisory services (Bank Negara Malaysia [BNM], 2020).

As digital adoption accelerates, understanding how young investors perceive risk in robo-advisory services becomes increasingly important. Malaysian university students generally perceive lower risk due to their longer investment horizons and greater capacity to absorb financial losses (Brooks et al., 2018). However, this perception contrasts with Malaysia's broader cultural preference for financial stability (Hofstede, 1980), which heightens concerns about robo-advisors' reliability, data security, and transparency. While younger generations are highly familiar with digital technology, their limited investment experience creates a paradox:

they trust robo-advisors for their efficiency but may overlook risks such as algorithmic bias and data misuse (Yi et al., 2023).

To mitigate these risks, robo-advisory platforms employ various strategies aimed at enhancing security, transparency, and reliability. Robust cybersecurity measures and increased transparency in algorithmic decision-making can help alleviate privacy concerns (Faloon & Scherer, 2017). Additionally, diversification algorithms assist in managing financial volatility (Fisch et al., 2020), while customizable risk profiles enhance personalization and mitigate apprehensions regarding algorithmic decision-making (Glaser et al., 2019). Hybrid advisory models that incorporate both human expertise and algorithm-driven insights further balance automation with user control, addressing psychological risk factors (Belanche et al., 2019). By implementing these measures, robo-advisory services can foster greater trust and acceptance among potential users.

In conclusion, perceived risk is a pivotal factor influencing investor attitudes toward robo-advisory services. While these services enhance efficiency and data-driven decision-making, concerns related to performance, financial security, privacy, and psychological factors continue to shape adoption behaviors. Younger investors, despite their digital proficiency, remain cautious due to Malaysia's cultural preference for financial stability and trust in traditional systems. Addressing these concerns through regulatory measures, enhanced transparency, and hybrid models integrating human oversight is essential for fostering investor confidence. By understanding the role of perceived risk in shaping investor intentions, this study underscores the need for robo-advisory solutions that not only leverage technological advancements but also prioritize trust, security, and user confidence in an evolving financial landscape.

2.6 Hypotheses Development

2.6.1 Trust

Existing literature shows that trust strongly increases the chances of robo-advisory service use among young investors. If users view such systems as trustworthy, transparent, and capable of providing correct financial advice, they will be more likely to use them despite possible risks (Belanche et al., 2019; Duan & Liu, 2020). Empirical evidence in various contexts always verifies such association, with evidence that trust reduces perceived financial risk while maximizing trust in algorithmic advice (Jung et al., 2020; Bhatia et al., 2021). It is particularly strong among college students, who value institutional legitimacy and system security in assessing automated investment tools (Larosiliere & McHaney, 2021). These findings collectively substantiate the proposed hypothesis:

H_1: Trust has a significant relationship with the Malaysian university students' investment intentions by using robo-advisory services.

2.6.2 Ease of use

Ease of use is important for customers who adopt robo-advisor financial advisory services. When investors judge a platform to be user-friendly, they also tend to perceive it as having higher utility and value and lower risk (Hanif et al., 2024). Intuitive interfaces and clearly communicated system functionality are key factors that promote investor acceptance of robo-advisors (Rani et al., 2024). Ease of use factors such as customization, capabilities, and control over robo-advisors also influence user acceptance (Wu & Gao, 2021). These findings confirm the following hypotheses:

H_1: Ease of use has a significant relationship with the Malaysian university students' investment intentions by using robo-advisory services.

2.6.3 Perceived risk

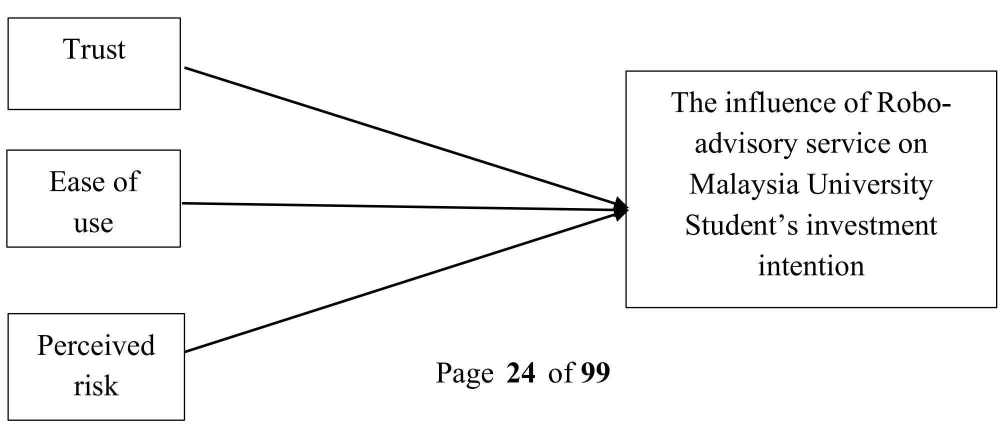
This study highlights the significant role of perceived risk in shaping investor attitudes toward robo-advisory services. While technological advancements continue to enhance efficiency and accessibility, concerns related to performance, financial security, privacy, and psychological factors remain key barriers to adoption. Given these considerations, further empirical research is necessary to quantify the relationship between perceived risk and investor intentions.

Based on the literature review and theoretical framework, this study proposes the following hypothesis:

H_1: Perceived risk has a significant relationship with the Malaysian university students' investment intentions by using robo-advisory services.

2.7 Conceptual Framework

Figure 1.1: Proposed Conceptual Framework



This conceptual framework is introduced to study the influence of robo-advisory on Malaysia University student's investment intention. This conceptual framework includes three independent variables which are trust, ease of use and perceived risk. Based on the mentioned research, we can assume that all these independent variables will play a significant role on Malaysia University Student investment using robo-advisory. Thus, this framework will be applied to verify whether it is true or not. Hence, hypotheses will then be formed on the basis of this framework in the following section.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter outlines the research methodology employed to investigate the influence of AI-based robo-advisory services on the investment decisions of Malaysian university students. The methodology is designed to address the research objectives and ensure the reliability and validity of the findings. This chapter includes details on the research design, sampling design, data collection methods, and proposed data analysis method.

3.1 Research Design

This study employs a quantitative research approach to examine the influence of trust, perceived ease of use, and perceived risk on the intention to use robo-advisory services for investment decisions. This approach is particularly suited for capturing measurable data that can reveal the relationships between these factors and their impact on Malaysian university students' investment behaviours. By analysing these relationships statistically, the study aims to provide empirical evidence of how these factors shape investment decision-making processes (Watson, R., 2015).

To gather the necessary data, this study utilizes a survey questionnaire that captures students' perceptions of trust, ease of use, and risk associated with robo-advisory tools, along with their intention to use these services for investment decisions. The questionnaire consists of structured questions with Likert scale responses, enabling participants to indicate their level of agreement or disagreement with various statements. This method facilitates the collection of standardized data from a large sample, ensuring the reliability and generalizability of the results to the broader population of Malaysian university students (Roopa, S., & Rani, M. S., 2012).

3.1.1 Sampling Design

3.1.1.1 Target Population and Respondents

The target population for this study comprises Malaysian university students who are potential users of AI-based robo-advisory services. This group was chosen for their likely familiarity with technology and their potential interest in innovative financial tools, making them an ideal demographic for examining the adoption of such services. By selecting a broad sample across the country, this study aims to capture a comprehensive view of the population's intentions towards robo-advisory services, thus providing valuable insights for service providers and related organizations. Additionally, this approach ensures a diverse sample that reflects the varied perspectives and characteristics of the broader student population (Ingram, H., & Schneider, A., 1991).

3.1.1.2 Sampling frame and location

The sampling frame for this study includes Malaysian university students enrolled in both public and private universities across the country. It focuses on students in business, finance, economics, and related fields, as they are more likely to have an interest in investment decisions and technology (Acharya, A. S., Prakash, A., Saxena, P., & Nigam, A., 2013). Data was collected from multiple locations, including both urban centres and rural areas such as Kuala Lumpur, Penang, Kedah, and Perlis.

3.1.1.3 Sampling element

The sampling element for this study consists of individual Malaysian university students, primarily those enrolled in undergraduate programs related to finance, business, economics, and technology. These students were selected based on their likely engagement with financial investment and technology. Furthermore, students with reliable internet access and devices such as smartphones, tablets, or computers were targeted to facilitate their participation in the online survey. This approach ensured the collection of data from a diverse and representative sample, capturing various perspectives on the influence of robo-advisory services in investment decision-making (Singh, R., & Mangat, N. S., 2013).

3.1.1.4 Sampling Technique

This study employs a combination of snowball and convenience sampling techniques to effectively gather data from Malaysian university students. Snowball sampling is used to identify respondents who are relevant to the study, particularly those familiar with robo-advisory services for investment purposes. This technique begins with selecting a few participants within the target population who meet the study's criteria. These initial respondents are then encouraged to refer to other potential participants within their network who also fit the criteria. This approach is particularly effective in accessing a specific subset of students who may be difficult to identify through conventional sampling methods, thereby enhancing the relevance of the data collected while minimizing survey costs (Goodman, L. A., 1961).

Simultaneously, convenience sampling is utilized to capture a broader range of student participants. This approach involves selecting respondents based on their availability and willingness to participate, primarily through online university groups. The key advantages of convenience sampling are its cost-effectiveness and efficiency, which allows the researcher to quickly gather data from a large number of students. Additionally, this method provides easy access to participants, ensuring a diverse sample that includes not only those deeply involved with robo-advisory services but also those who can offer valuable insights from a more general perspective (Sedgwick, P., 2013).

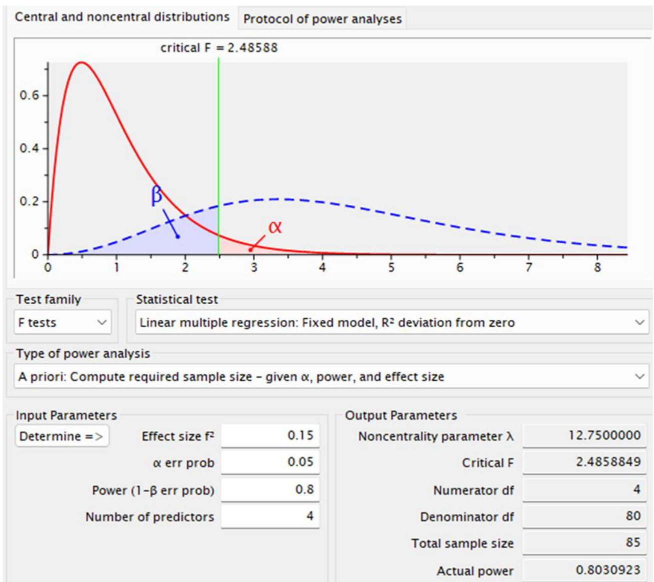
3.1.1.5 Sampling size

This study utilizes the G*Power method to determine the appropriate sample size. The research hypothesis aims to investigate the influence of trust, perceived ease of use, and perceived risk on the intention to use AI-based robo-advisory services among Malaysian university students. Given this objective, a multiple linear regression model is selected as the appropriate statistical test, using the "f test" under the test family (Kang, H., 2021).

Before conducting the G*Power analysis, key input parameters must be established, including effect size, significance level (α), statistical power (1-β), and the number of predictors. Effect size represents the magnitude of the relationship between variables, while the significance level (α) is set at 0.05, indicating a 5% probability of rejecting a true null hypothesis (Type I error). Statistical power (1-β) is set at 0.80, reducing the risk of failing to detect a true effect (Type II error). The number of predictors in this study is four, corresponding to the four independent variables (Kang, H., 2021).

For the f test, Cohen (1988) suggests effect sizes of 0.02 (small), 0.15 (medium), and 0.35 (large). In this study, a medium effect size of 0.15 is selected. Accordingly, the parameters entered into the G*Power calculation include an effect size of 0.15, α of 0.05, power of 0.80, and four predictors. The resulting total sample size output is 85, indicating that at least 85 respondents are required for the study.

Figure 2.1: Sample Size Calculated by G*Power 3.1.9.7



However, to account for potential non-compliance or incomplete responses, a dropout rate of 20% is considered. Using the formula below, the adjusted sample size is calculated:

$$N^D = \frac{N}{1-d}$$

N: sample size before considering drop-out rate

d: the expected drop-out rate

N^D: sample size after considering drop-out rate

Applying this formula:

$$N^D = \frac{85}{1-d} = 106.25$$

Therefore, the final target sample size is rounded up to approximately 110 or more respondents. This ensures a more robust dataset, enhancing the reliability and generalizability of the study's findings (Kang, H., 2021).

3.2 Research Instruments

A questionnaire works effectively as a data collection tool, especially in quantitative research. It's a quick and simple way to get a lot of information from a lot of people in a short amount of time. As a result, the questionnaire's design is essential to guaranteeing the validity, consistency, and generalizability of the data gathered. The questionnaire's validity will be increased by using a sample drawn from earlier studies. Many question formats are frequently used, including multiple-choice, dichotomous, scaled, and pictorial. Both multiple-choice questions will be used in this study.

3.2.1 Questionnaire

The questionnaire will be designed in a Google form with only English language. We used the English language as our main language because it is an international language, and it is used for our main communication in study. By having a conceptual framework with three independent variables, which are perceived risk, trust, and ease of use of robo-advisory, and one dependent variable of investor intention of robo-advisory service for investment purposes, the questionnaire consists of three sections including the demographics section. To determine the characteristics of respondents and divide them into groups, the first section of the demographics section uses single-select multiple-choice questions. For the second and third sections, the respondents are asked to rate the degree of exposure to perceived risk, their degree of acquired robo-advisory service skills, their trust in robo-advisory service, and their satisfaction with robo-advisory service as an investment purpose based on various five-point Likert scales, for example (1-strongly agree, 5-strongly disagree) (Roopa& Rani, 2012).

3.2.2 Pilot test

Before a study or survey is fully implemented, a pilot test is a small-scale, early trial done to detect potential problems and improve the technique (*The Practice of Social Research*, n.d.). Before any data is collected, it is usually necessary to do 30 to 50 subgroup pilot tests to see whether there are any common misconceptions or potential confusion that could prevent respondents from taking the survey. To reduce errors, it is common practice to solicit helpful input during the pilot test phase. This allows for the modification of questions, the removal of unclear words, and the restructuring of long sentences or statements (Kim et al., 2017). Before starting our questionnaire, pilot test was also included, and the relevant results were collected.

3.3 Constructs Measurement (Scale and Operational Definitions)

Construct measurement is the most important for research work. According to the research, construct measurement is needed to establish whether findings and results are valid or not.

3.3.1 Nominal Scale

A nominal scale provides a measurement scale that classifies data without creating a quantitative relationship between the categories. It is used to categorize variables into discrete, non-overlapping groupings, with each category being unique and lacking any intrinsic order (Stevens, 1946). For example, gender is often measured using a nominal scale, which categorizes individuals into groups such as "male," and "female," without implying any ranking or numerical value (Velleman & Wilkinson, 1993). Now, the nominal scale is being used to support the research in distinguishing gender, as demonstrated below.

Example of nominal scale:

Your gender:
(   ) Male   (   )Female

3.3.2 Ordinary Scale

An ordinal variable is like a nominal variable, except the data points are arranged in a clear order. (Mishra et al., 2018). An ordinal scale is a level of measurement in which the order of values is important yet the disparities between them are not always equal. This scale is used in Section A and is used to measure the age group provided.

An interval scale is a measurement scale with equal intervals between its values, which allows for meaningful comparisons of differences. Unlike other scales, it lacks a real zero point, hence zero does not represent the complete absence of the measured attribute. This scale allows addition and subtraction but not multiplication or division since the absence of an absolute zero point renders such operations invalid (Stevens, 1946; Velleman and Wilkinson, 1993). This scale is used in Sections B and C and the question is provided by the Five Likert scale to answer the question related to dependent variables and independent variables.

Example of Ordinal scale:

Your age: (   )18-20   (   )21-24   (   )25-28

3.3.3 Interval Scale

An interval scale is a measurement scale with equal intervals between its values, which allows for meaningful comparisons of differences. Unlike other scales, it lacks a real zero point, hence zero does not represent the complete absence of the measured attribute. This scale allows addition and subtraction but not multiplication or division since the absence of an absolute zero point renders such operations invalid (Stevens, 1946; Velleman and Wilkinson, 1993). This scale is used in Section B and C and the question is provided by the Five Likert scale to answer the question related to dependent variable and independent variables.

Table 3.1: Example of interval scale

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am likely to use Robo-advisory services for my investment needs in the future.	1	2	3	4	5

3.4 Questionnaires Designing

There are three parts to the questionnaires: Section A, Section B, and Section C. Section A consists of demographic variables that ask for personal information from the targeted respondent. It consists of five questions in total; the nominal scale measures gender, university, education level, and faculty, while the ratio scale measures age and income level.

Section B comprises 21 questions for pre-determined determinants, i.e., perceived risk of applying robo-advisory services, trust with respect to using robo-advisory services, and ease of use of robo-advisory services. The measurement instrument applied for this section is the Likert scale, for which the response has to be selected between 1 and 5 based on the agreement or disagreement degree. The questionnaire has five options: 1 for "Strongly Disagree," 2 for "Disagree," 3 for "Neutral," 4 for "Agree," and 5 for "Strongly Agree."

The dependent variable in Section C is an investor's intention to employ a robo-advisory service for investment purposes. There are seven questions in this section. The scale of measurement was the Likert scale, which is an interval scale. 1 to 5 is the range of the scale. Like in Section B, the numbers 1 through 5 represent "Strongly Disagree," "Disagree," "Neutral," "Agree," and "Strongly Agree." The reliability of the questions is explained using SPSS 26.0 software after the data has been collected via the questionnaire.

3.5 Data Processing

Data processing refers to the process of systematic conversion of raw data into useful information through several steps. It begins with data collection; whereby raw data are received from various sources. Subsequently, data checking confirms whether the data are accurate, complete, and consistent by detecting errors or missing values. Data editing is done next, whereby errors or inconsistencies in the data are corrected. Data coding subsequently transforms raw data into predetermined structures or numeric codes, which can be analyzed easily. Lastly, the process of converting data into a structured or digital format for processing is known as data transcription. These procedures make data clean, categorized, and ready for analysis, allowing organizations and researchers to extract meaningful information and make informed decisions (Isah et al., 2019).

3.5.1 Data Collection

In this study, the questionnaire will be sent to the students at various Malaysian universities by sending the link to the questionnaire and providing the link on the university platform for the students to fill in the information. The purpose of the questionnaire is mainly to obtain information to explain the factors that influence students at University Malaysia's intention to use robo-advisory services for investment purposes. The questionnaire will be answered through an online mode between July and October.

3.5.2 Data Checking

Data checking is the procedure of verifying that data collected is accurate, complete, and consistent before analysis. After a pilot test, data checking is necessary to identify errors, missing digits, or inconsistencies in the data set. This phase allows the issues to be recognized in the data collection process and the adjustment of methodologies and tools before upscaling to the entire study. Through upfront data quality, avoid costly errors, save money and time, and generate more accurate and meaningful results in the main study (Barchard et al., 2019).

3.5.3 Data Editing

Data editing is required after data checking because data checking reveals deficiencies, inconsistencies, or missing numbers, whereas data editing corrects and enhances these. It is used to correct errors, achieve consistency in data formats, and improve overall data quality. Data editing makes the dataset accurate, complete, and ready for analysis by cleansing and standardizing it. This stage is crucial for converting raw, error-ridden data into a consistent and usable format so that accurate insights and informed decision-making can take place (Hoogland et al., 2011).

3.5.4 Data Coding

Data coding is subsequently done. Data coding transforms raw data, such as text answers or categories, into pre-established numerical codes or formats for analysis. It summarizes complex or unstructured data, making it consistent and allowing efficient processing. Data coding is the process of giving targeted respondents' answers numerical codes. The numerical codes are subsequently entered into Jamovi. Responses are coded 1 through 5, but 99 represents a missing value. Data coding involves placing altered data into numeric digits or other symbols (Adu et al., 2021).

Table 3.2: Answer of Section a Demographic Information

Question	**Label**	**Data Type**	**Coding**
1	Age	Numeric	Actual age value (e.g., 21, 22, 23...)
2	Gender	Categorical	1 = Male

			2 = Female
3	Race	Categorical	1 = Malay 2 = Chinese 3 = Indian 4 = Others
4	Education Level	Categorical	1 = Foundation 2 = Diploma 3 = Bachelor's 4 = Master's 5 = PhD 6 = Others
5	State	Categorical	1 = Johor 2 = Kedah 3 = Kelantan 4 = Melaka 5 = Negeri Sembilan 6 = Pahang 7 = Perak 8 = Perlis 9 = Pulau Pinang 10 = Sabah 11 = Sarawak 12 = Selangor 13 = Terengganu 14 = Kuala Lumpur
6	Monthly Allowance	Numeric	Actual allowance value in RM (e.g.,

			RM2,001- RM4,000...)
7	Source of Funds for Investment	Categorical	1 = Savings 2 = PTPTN 3 = Parents 4 = Investment 5 = Salary
8	Do you have investment experience?	Categorical	1 = Yes 2 = No
9	Have you ever used robo-advisory services?	Categorical	1 = Yes 2 = No

Table 3.3: Answer of Section B to Section E

	Label	Coding
Section B	Dependent Variable: The influence of the robo-advisory service on Malaysia University students' investment intention	1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree
Section C, D, and E	Independent Variable: • Ease of Use • Trust • Perceived Risk	1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

3.5.5 Data Transcribing

Finally, data transcription is completed. Transcribing data converts raw data into useful information. The data is processed using Jamovi software.

3.6 Data Analysis

The methodical application of logical and statistical methods to the extraction and interpretation of relevant information from data to support well-informed decision-making is known as data analysis (Van de Vijver& Leung,1997). Therefore, data analysis is the process needed to proceed after collecting all the information data.

3.6.1 Descriptive analysis

The part of statistics known as descriptive analysis is concerned with enumerating and characterizing a dataset's key characteristics. To give a thorough picture of the data, it makes use of graphical representations, measures of variability, and central tendency (Sidel et al., 2018). In this study, the demographic part (section A) uses descriptive analysis. The information is utilized to determine the frequency and provide an explanation of the percentage of respondents who selected strongly disagree, disagree, agree, agree, and highly agree as their response options.

3.6.2 Scale Measurement

3.6.2.1 Validity and Reliability

To investigate whether the results of the survey can be relied upon, it is therefore necessary to use reliability tests. The purpose of reliability testing is to ensure that measurements are consistent and repeatable. This is crucial for clinicians to assess the accuracy and dependability of a measurement tool or method, allowing us to confidently make clinical decisions, track patient progress, and evaluate treatment outcomes (Bruton et al., 2000). Internal consistency is one of the primary measures of reliability. It defines how much all that is on a scale is quantifying the same characteristic. Internal consistency is typically assessed using Cronbach's alpha coefficient. Besides, higher levels of Cronbach's alpha, which range from 0 to 1, suggest better internal consistency. Based on the table shown, a scale above 0.9 means that it is excellent and reliable, above 0.8 is good, above 0.7 is acceptable, above 0.6 is questionable, above 0.5 is poor reliability, and below 0.5 is determined as unacceptable (Bruton et al., 2000).

Table 3.4: Cronbach's Alpha

Cronbach' Alpha	Internal Consistency
$\alpha \geq 0.9$	Excellent Reliable
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor Reliable
$0.5 > \alpha$	Unacceptable

Source: Bruton, Conway& Holgate,2000

3.6.3 Preliminary Data Screening

3.6.3.1 Multicollinearity

Multicollinearity is detected in the research. When independent variables in a regression model have a high degree of correlation, it becomes difficult to isolate their individual effects, a phenomenon known as multicollinearity. This may complicate the analysis and perhaps produce misleading results by resulting in unstable and incorrect coefficient estimates (Murtazashvili & Wooldridge, 2016). So, we have found the problem before the regression is conducted. To see whether the multicollinearity problem happened we had used the correlation coefficient and variance inflation factor to calculate it.

First, the correlation coefficient is calculated by using Jamovi software. Potential multicollinearity is indicated by a high absolute value (e.g., above 0.7 or 0.8) of the pairwise correlation between independent variables (Gujarati & Porter, 2009). Secondly, we calculate the variant inflation factor using Jamovi software too. The factor greater than 10 indicates high multicollinearity (Neter et al., 1983).

3.6.3.2 Correlation analysis

The second preliminary data screening is conducted for correlation analysis. To identify any statistically significant relationships between two variables, correlation analysis will be performed. A correlation coefficient is a singular figure that indicates a relationship between two variables being examined. For the research, the perceived risk, trust, and ease of use of robo-advisory services by using Pearson's Correlations (ŞahiN & Aybek, 2019). A person's correlation coefficient shows that the two variables are related. All these characteristics include a linear relationship, independent variables, and consistently distributed variables.

3.6.3.3 Exploratory Factor Analysis

We need to use Exploratory Factor Analysis (EFA) once data is collected to discover underlying relationships between variables and classify them into a smaller number of unobserved factors. EFA plays a crucial role in establishing data structure, dimension reduction, and theory building. The process entails numerical data, a big sample size, and reasonably related variables (Hooper, 2012). EFA generates **factors, factor loadings** (the size of correlations between factors and variables) as an example: Loadings range from -1 to 1, and larger absolute sizes (e.g., >0.4 or <-0.4) indicate a strong correlation, and **communalities** (variation in variables explained by factors), as an example; Large communalities (close to 1) indicate that the factors represent the variable well, while low values indicate the variable is poorly represented by the factors. These results help to condense information, reveal underlying patterns, and inform future research or theory development (Yong & Pearce, 2013).

3.6.4 Normality

Final initial screening of data is performed for the normality test. A normality test is a statistical process that determines whether a dataset has a normal distribution. It determines whether the sample data deviates significantly from a normal distribution, which is critical when using various statistical methods that presume normality. These tests look at the distribution's shape, skewness, kurtosis, and how well it approaches a theoretical normal distribution (Shapiro & Wilk, 1965; An, 1933)

The method to measure the normality test it can look at Kurtosis. Kurtosis determines the "tailedness" of the distribution. A kurtosis near 0 implies normality (Shapiro & Wilk, 1965). Second, the skewness measures the distribution's asymmetry. A skewness around 0 implies normality (Shapiro & Wilk, 1965). Besides, if the data is regularly distributed, the Q-Qplot will show data points forming a straight line (An, 1933). The last step is to verify the histogram. In normally distributed data, the histogram is usually symmetrical as well as bell-shaped. The frequency of the curve is at its highest in the center, tapering towards the ends (An, 1933).

3.6.5 Inferential Analysis

Inferential analysis is the most critical data analysis. The group of statistical analysis known as inferential analysis is used for drawing a conclusion regarding a population on the basis of a data sample (Russo, 2004). It states that the population parameter which is unknown is approximated using the statistics of the given population by conducting a research study. Hence, from the data of a sample of 120 students at different Universities of Malaysia, one can make a conclusion regarding the intention of the investor to use a service of a robo-advisor for investment. The multiple linear regression analysis is an inferential technique that is employed within the research for studying the relationship between the dependent variable, investor's intention of using a service of a robo-advisory for investment, and the independent variable, perceived risk, trust on the service of a robo-advisor, and ease of use of a service of a robo-advisor.

3.6.5.1 Multiple Linear Regression Analysis

A multiple linear regression model is a statistical method for predicting a dependent variable's value based on two or more independent variables (Montgomery & Runger, 2010). Because three criteria were selected for this study, this strategy can therefore be used in this investigation.

Following the regression analysis, the model will be assessed using the correlation matrix, coefficients table, and model summary table. The Correlation Matrix enables the detection of multicollinearity before performing the regression by displaying the correlations between each pair of independent variables (ŞahiN & Aybek, 2019). The following is the coefficient table, this table displays the estimated coefficients (β) for each independent variable, together with their standard errors, t-values, and p-values, indicating the importance and impact of each predictor on the dependent variable (Neter et al., 1983). Lastly is the model summary table, where we check R square. It is measuring how much of the dependent variable's variability is explained through the independent factors (Neter et al., 1983).

The equation for the multiple linear regression is

$$WAI_i = \beta_0 + \beta_1 PR_i + \beta_2 TR_i + \beta_3 EOU_i + \mu_i$$

Where:

WAI_i = Investor's intention to use robo-advisory services for investment

PR_i = Perceived risk

TR_i = Trust

EOU_i =Ease of use

μ_i = Error term

There will be multiple linear regression analysis according to the given formula. The hypothesis in chapter two suggests that the independent variables on the right side of the equation have a considerable impact on the dependent variable on the left side.

3.6.5.2 Coefficient Table

A coefficient table is required for the report because it enables the analysis and interpretation of the links between each of the independent variables (trust, perceived risk, ease of use) and the dependent variable (intention to use robo-advisors). Because the study includes continuous independent variables, regression analysis is the most appropriate method, and the coefficient table provides a concise summary of the findings. It shows the unstandardized coefficients (B), which show how much the dependent variable changes for every one unit increase in each independent variable, as well as the standardized coefficients (β), which allow comparing the relative importance of each variable (ŞahiN & Aybek, 2019). The table's p-values indicate statistical significance for each relationship ($p < 0.05$). For instance, if the independent variable "trust" coefficient is 0.45 with a p-value < 0.05, it indicates that increased trust significantly improves the intention to utilize robo-advisors.

3.7 Conclusion

To summarize, this study aims to analyze the Malaysia University students' intention to use robo-advisory services for investment based on three variables which are perceived risk and trust, and ease of use. This study aims to identify which content factors have the most impact on the investment intentions of Malaysia University students. Before the actual test, a pre-test and pilot test were conducted. During the real test, 100 students from the University of Malaysia were given questionnaires to gather primary data. Furthermore, the acquired data will be analyzed and explained in depth using the technique presented in this chapter, leading to the transition to Chapter 4.

Chapter 4: Data Analysis

4.0 Introduction

This chapter presents the findings of the study, derived from data collected from 155 respondents and analysed using *Jamovi* v.2.6.24 software (The jamovi project, 2024). The analysis evaluates the influence of perceived ease of use, trust, and perceived risk on the intention to robo-advisory services among Malaysian university students.

The chapter begins with a reliability analysis to assess the internal consistency of the measurement items. This is followed by descriptive statistics summarizing the dataset's characteristics. A Pearson correlation analysis is then conducted to evaluate the strength and direction of the relationships among the key constructs—perceived ease of use, trust, perceived risk, and intention to use robo-advisory services. The correlation coefficients provide initial insights into how strongly these variables are associated, helping to validate the theoretical model prior to regression analysis.

Subsequently, exploratory factor analysis (EFA) is carried out to verify the underlying factor structure and ensure that the observed items effectively represent the intended constructs. This step also assesses the dimensionality and construct validity of the instrument. After confirming these relationships, multiple linear regression analysis is conducted to examine the influence of the independent variables on the dependent variable.

By systematically presenting these findings, this chapter provides a comprehensive understanding of the factors influencing the adoption of robo-advisory services, offering insights into the role of perceived risk, trust, and ease of use in shaping investment decisions.

4.1 Pilot Test: Reliability Analysis

To assess the internal consistency of the survey instrument, Cronbach's alpha (α) was calculated for each construct. A Cronbach's alpha value above 0.70 is generally considered acceptable for reliability. while values above 0.90 indicate excellent internal consistency (Nunnally & Bernstein, 1994). Referring to Table 4.1, the Cronbach's alpha value for the constructs ranges from 0.91 to 0.98, indicating high reliability.

Table 4.1

Reliability Analysis (Cronbach's Alpha)

Construct	Cronbach's α
DV	0.911
Ease of Use	0.941
Trust	0.925
Perceived Risk	0.926
Overall Model	0.979

4.2 Descriptive Analysis

A total of 155 responses were collected for this study. However, after filtering out respondents who lacked investment experience, had never used robo-advisors, and had no intention of adopting them in the future, 134 qualified respondents remained. The descriptive analysis of these respondents provides insights into their demographic characteristics, financial background, and investment behaviour.

According to Table 4.2, the majority of respondents are fall within the 22-25 age group (59.0%), followed by 18-21 years (38.1%), and a small portion aged 26-28 (3.0%). Gender distribution is balanced, with 50% male and 50% female respondents. Regarding ethnicity, 97.0% are Chinese, 2.2% Indian, and 0.7% Malay, reflecting the demographic composition of the sample.

Regarding education level, 93.3% are undergraduate students, with a small proportion holding diploma, foundation, master's, or PhD qualifications. The respondents are from various states across Malaysia, with the highest representation from Selangor (25.4%), Perak (19.4%), and Johor (17.2%).

For financial background, 81.3% receive a monthly allowance of RM0-RM2000, followed by 14.9% in the RM2001-RM4000 range. The main sources of investment funds include parents (45.5%), savings (26.1%), salary (11.9%), PTPTN (11.9%), and direct investments (4.5%). This suggests that a significant portion of student investors rely on family support and personal savings for their investment activities.

Investment behaviour indicates that 60.4% of qualified respondents have prior investment experience, while 43.3% have used robo-advisory services before. The filtering process ensures that the final sample consists of individuals who are actively engaged in investment and have firsthand exposure to robo-advisors, making them suitable for analysing the factors influencing the intention to adopt such tools.

Table 4.2

Respondent's Demographic Profile

Characteristics	Category	Frequency	Percentage
Age	18-21	51	38.1%
	22-25	79	59.0%
	26-28	4	3.0%

Gender	Female	67	50.0%
	Male	67	50.0%
Race	Chinese	130	97.0%
	Indian	3	2.2%
	Malays	1	0.7%
Education Level	Diploma	4	3.0%
	Foundation	2	1.5%
	Master	1	0.7%
	Phd	1	0.7%
	SPM	1	0.7%
	Undergraduate	125	93.3%
State	Johor	23	17.2%
	KL	1	0.7%
	Kedah	10	7.5%
	Melaka	4	3.0%
	Negeri Sembilan	10	7.5%
	Pahang	3	2.2%
	Penang	13	9.7%
	Perak	26	19.4%
	Perlis	2	1.5%
	Sarawak	7	5.2%
	Selangor	34	25.4%
	Terengganu	1	0.7%

Monthly Allowance	RM0 - RM2000	109	81.3%
	RM2,001 –RM4,000	20	14.9%
	RM4,001– RM6,000	2	1.5%
	RM6,001– RM8,000	1	0.7%
	RM8,001 and above	2	1.5%
Source of Fund Investment	Investment	6	4.5%
	PTPTN	16	11.9%
	Parents	61	45.5%
	Salary	16	11.9%
	Savings	35	26.1%
Investment Experience	No	53	39.6%
	Yes	81	60.4%
Prior Use of Robo-Advisor for Investment	No	76	56.7%
	Yes	58	43.3%

4.2.1 Usage of Robo-Advisory Platforms

According to Table 4.3, The analysis of robo-advisory platform usage among qualified respondents reveals that MooMoo is the most widely used platform, with 33.8% of respondents utilizing it. StashAway follows, with 11.8% of respondents using it individually, and additional users combining it with other platforms. Best Invest is also notable, often used together with StashAway (5.9%) or alongside MooMoo (4.4%).

A smaller proportion of respondents reported using Bybit (1.5%), Octa (1.5%), OctaFX (1.5%), Touch 'n Go (1.5%), and Webull (1.5%). Additionally, some respondents employ multiple platforms, including Best Invest + StashAway (5.9%), StashAway + MooMoo (5.9%), and StashAway + OctaFX (1.5%), indicating that a subset of investors prefer diversifying their robo-advisory services.

Table 4.3

Robo-Advisory Platform being used

	Frequency	Percentage (%)
Akru	3	4.4%
Akru;Best Invest	1	1.5%
Akru;MooMoo	1	1.5%
Akru;StashAway;MooMoo	1	1.5%
Best Invest	10	14.7%
Best Invest;MooMoo	4	5.9%
Best Invest;StashAway	4	5.9%
Best Invest;StashAway;MooMoo	3	4.4%
Bybit	1	1.5%
MooMoo	23	33.8%
MooMoo;Octa	1	1.5%
Octa	1	1.5%
StashAway	8	11.8%

4.3 Validity Assessment

4.3.1 Pearson Correlation Matrix

In this study, Pearson’s correlation is used to assess validity, as it is appropriate for Likert-scale variables with five or more response categories (e.g., ease of use, trust, and perceived risk). According to Cohen’s (1988) rules of thumb for interpreting correlation coefficients, values of $r = 0.10$, $r = 0.30$, and $r = 0.50$ represent small, medium, and large effect sizes, respectively. In this study, all correlations exceeded $r = 0.85$, indicating very strong relationships (Field A., 2024).

As shown in Table 4.4, the correlation analysis reveals strong positive relationships among the study variables. A significant correlation exists between intention to use robo-advisor and ease of use ($r = 0.860$, $p < .001$), trust ($r = 0.876$, $p < .001$), and perceived risk ($r = 0.852$, $p < .001$). However, the unexpected positive relationship between perceived risk and adoption intention requires further analysis to determine its underlying causes.

Table 4.4

Pearson Correlation Matrix

Constructs		DV	Ease of Use	Trust	Perceived Risk
DV	Pearson's r	—			
	df	—			
	p-value	—			
Ease of Use	Pearson's r	0.860	—		
	df	132	—		
	p-value	<.001	—		
Trust	Pearson's r	0.876	0.941	—	
	df	132	132	—	
	p-value	<.001	<.001	—	

Perceived Risk	Pearson's r	0.852	0.886	0.881	—
	df	132	132	132	—
	p-value	<.001	<.001	<.001	—

4.3.2 Coefficient

The econometric model used in this study is specified as follows:

$$WAI_i = \beta_0 + \beta_1 PR_i + \beta_2 TR_i + \beta_3 EOU_i + \mu_i$$

Where:

- Y represents the intention to use robo-advisory tools,
- PR_i denotes perceived ease of use,
- TR_i denotes trust,
- EOUi denotes perceived risk,
- β_0 is the intercept,
- β_1, β_2, β_3 are the regression coefficients,
- μ_i is the error term.

Thus, the estimated regression equation is:

$$WAI_i = 0.409 + 0.133X_1 + 0.422X_2 + 0.321X_3 + \mu_i$$

According to Table 4.5, the results reveal that trust was identified as the strongest predictor of intention to use robo-advisory services for investment decisions ($\beta = 0.422$, SE = 0.1147, t = 3.68, $p < .001$). According to Cohen’s (1988) effect size guidelines, a standardized coefficient (β) of 0.10 is considered small, 0.30 is medium, and 0.50 is large. With a β value of 0.422, trust falls between a medium and large effect size, indicating a substantial positive impact on adoption intention. Furthermore, the significance level ($p < .001$) confirms that this relationship is highly significant.

Similarly, perceived risk exhibited a significant positive relationship with the intention to use robo-advisory services ($\beta = 0.321$, SE = 0.0882, $t = 3.64$, $p < .001$). Based on Cohen's (1988) classification, a β value of 0.321 represents a medium effect size. The high statistical significance ($p < .001$) suggests a strong and reliable association between perceived risk and adoption intention.

In contrast, ease of use was not a significant predictor of adoption intention ($\beta = 0.133$, SE = 0.1113, $t = 1.19$, $p = 0.235$), as the p-value exceeds the 0.05 significance threshold. The β value of 0.133 indicates a small effect size, implying that ease of use has only a weak influence on the dependent variable. The lack of statistical significance suggests that while ease of use may contribute to a positive perception of robo-advisory services, it does not directly impact users' intention to adopt them.

Table 4.5

Model Coefficients - DV

Predictor	Estimate	SE	t	p
Intercept	0.409	0.1309	3.12	0.002
Ease of Use	0.133	0.1113	1.19	0.235
Trust	0.422	0.1147	3.68	<.001
Perceived Risk	0.321	0.0882	3.64	<.001

4.4 Factor Analysis

4.4.1 Exploratory Factor Analysis (EFA)

According to Table 4.6 to 4.10, the suitability of the dataset for EFA was verified using Bartlett's Test of Sphericity ($\chi^2 = 2457$, $p < .001$), confirming that the correlation matrix significantly deviates from an identity matrix (Field, 2018). Additionally, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was 0.960 overall, exceeding the recommended threshold of 0.8 (Kaiser, 1974), which suggests that the dataset is highly suitable for factor analysis. The MSA values for individual items ranged from 0.899 to 0.985, with all surpassing the minimum acceptable value of 0.5. This confirms that each variable demonstrates sufficient correlation with the others, further supporting the appropriateness of EFA.

All items exhibited strong factor loadings (> 0.7), indicating a strong representation of the underlying construct. Additionally, uniqueness values were below 0.5 for most items, suggesting that they are well-explained by the factor. Similar to PCA findings, Ease of Use (EOU), Trust, and Perceived Risk (PR) items loaded onto a single factor, implying they may collectively measure a broader construct rather than distinct dimensions.

Model fit assessment produced the following results: RMSEA = 0.0801 (90% CI: 0.0676 - 0.0937), indicating acceptable fit (Hu & Bentler, 1999); TLI = 0.919, surpassing the 0.9 threshold for acceptable fit; and a significant Chi-Square Test ($\chi^2 = 353$, $p < .001$), which is common in large samples. The Bayesian Information Criterion (BIC) was -573, where lower values indicate better model fit. Given these findings, a one-factor solution is suggested.

Table 4.6

EFA's Assumption Checks

Test	χ^2	df	p
Bartlett's Test of Sphericity	2457	210	<.001

Table 4.7

KMO Measure of Sampling Adequacy

	MSA
Overall	0.960
EOU1	0.970
EOU2	0.963
EOU3	0.968
EOU4	0.967
EOU5	0.962
EOU6	0.956
EOU7	0.963
T1	0.911
T2	0.971
T3	0.965
T4	0.957
T5	0.962
T6	0.967
T7	0.953
PR1	0.899
PR2	0.955
PR3	0.967
PR4	0.976
PR5	0.985
PR6	0.956
PR7	0.957

Table 4.8

EFA's Factors Loading

	Factor 1	Uniqueness
EOU1	0.824	0.321
EOU2	0.877	0.232
EOU3	0.767	0.411
EOU4	0.819	0.329
EOU5	0.807	0.349
EOU6	0.806	0.350
EOU7	0.832	0.308
T1	0.699	0.511
T2	0.834	0.305
T3	0.844	0.288
T4	0.771	0.406
T5	0.757	0.426
T6	0.804	0.354
T7	0.728	0.470
PR1	0.647	0.582
PR2	0.757	0.426
PR3	0.767	0.412
PR4	0.778	0.395
PR5	0.790	0.376
PR6	0.772	0.404
PR7	0.735	0.460

Note. The 'Maximum likelihood' extraction method was used in combination with a 'promax' rotation

Table 4.9

EFA's Factor Statistics

Factor	SS Loadings	% of Variance	Cumulative %
1	12.9	61.4	61.4

Table 4.10

Model Fit Measures

	RMSEA 90% CI				Model Test		
RMSEA	**Lower**	**Upper**	**TLI**	**BIC**	**χ^2**	**df**	**p**
0.0801	0.0676	0.0937	0.919	-573	353	189	<.001

4.5 Inferential Analysis

A multiple linear regression model was constructed to investigate the effects of perceived ease of use, trust, and perceived risk on the intention to use robo-advisor. As shown in Table 4.11, the results indicate a strong relationship between the predictors and the dependent variable, with an R-squared (R^2) value of 0.798, demonstrating a substantial model fit.

Furthermore, the F-test result of 172 ($p < .001$) confirms that the overall regression model is statistically significant, indicating that at least one of the independent variables significantly predicts the intention to use robo-advisors. These findings suggest that ease of use, trust, and perceived risk play a crucial role in influencing respondents' adoption intention.

The R^2 value of 0.798 indicates that 79.8% of the variance in adoption intention is explained by the independent variables. The adjusted R^2 of 0.794 accounts for the number of predictors in the model, confirming that the results remain robust even after adjusting for potential overfitting. According to Cohen's (1988) guidelines for effect size interpretation, an R^2 value above 0.70 suggests a large effect size, reinforcing the strong predictive power of the model.

These findings suggest that the selected independent variables—such as ease of use, trust, and perceived risk—play a crucial role in influencing respondents' adoption intention. However, further analysis, such as examining the standardized regression coefficients, is necessary to determine the relative importance of each predictor.

Table 4.11

Overall Model Test

Model	R	R^2	Adjusted R^2	F	df1	df2	p
1	0.894	0.798	0.794	172	3	130	<.001

4.5.1 Assumption Testing

The Durbin–Watson test was conducted to assess autocorrelation in the regression model. As shown in Table 4.12, the Durbin–Watson statistic was 1.94, with a p-value of 0.672, indicating no significant autocorrelation in the residuals. Since the DW statistics are close to 2, this suggests that the assumption of independent residuals is satisfied.

Collinearity statistics were performed to examine multicollinearity among the predictor variables. Table 4.13 reports the Variance Inflation Factor (VIF) values for ease of use (10.06), trust (9.67), and perceived risk (5.11) indicate potential multicollinearity concerns. According to Kutner et al., 2005, a VIF above 10 suggests severe multicollinearity, while values between 5 and 10 indicate moderate multicollinearity. Additionally, the tolerance values, which are the inverse of VIF, were all below 0.2, further confirming the presence of multicollinearity.

The Shapiro-Wilk normality test was conducted to assess whether the residuals followed a normal distribution. As presented in Table 4.14, the test yielded a statistic of 0.918 with a p-value of <.001, indicating a significant departure from normality. Since a p-value below 0.05 suggests that the residuals deviate from a normal distribution, this result implies that normality assumptions may not be fully met.

Table 4.12
Durbin–Watson Test for Autocorrelation

Autocorrelation	DW Statistic	p
0.0271	1.94	0.696

Table 4.13
Collinearity Statistics

	VIF	Tolerance
Perceived Risk	5.11	0.1957
Trust	9.67	0.1035
Ease of Use	10.06	0.0994

Table 4.14
Normality Test (Shapiro-Wilk)

Statistic	p
0.918	<.001

Chapter 5: Discussion and Conclusion

5.0 Introduction

This chapter reports a summary of the findings of the study and a last look at the statistical analyses and their suitability relative to the objectives and hypotheses of the research. It ascertains to what degree results support the theoretical framework, considers academic and practical implications, and openly recognizes methodological weaknesses. Besides, practical recommendations are presented to close noted gaps, and recommendations for further research aim at building on the contributions of the study while conducting a fair evaluation of the accomplishments and limitations of the study with the view of informing future research endeavors.

5.1 Summary of Inferential Testing

Table 5.1 Summary of Inferential Testing

Variable	T-statistic	Probability	Results
Trust	3.680	< 0.001	Significant
Ease of Use	1.190	0.235	Insignificant
Perceived Risk	3.640	< 0.001	Significant
R-squared	0.798		
Adjusted R-squared	0.794		
Durbin-Watson Statistic	1.940		
F-statistic	172.000		

Prob (F-statistic)	< 0.001

The multiple linear regression analysis indicated significant relationships between the independent variables (trust, ease of use, perceived risk) and the intention to adopt robo-advisory investment tools among Malaysian university students. Trust showed up as the strongest predictor ($\beta = 0.422$, $p < 0.001$), followed by perceived risk ($\beta = 0.321$, $p < 0.001$), both indicating statistically significant and positive impacts on adoption intention. On the other hand, ease of use ($\beta = 0.133$, $p = 0.235$) performed not significantly influence intention, suggesting its role may be nearby in this context.

The model successfully explained 79.8% of the variance in adoption intention ($R^2 = 0.798$, Adjusted $R^2 = 0.794$). The overall regression model was highly significant ($F = 172.000$, $p < 0.001$), indicating the collective relevance of the predictors. Hypothesis tests indicated no autocorrelation (Durbin-Watson = 1.94) with sufficient normality in residuals, though multicollinearity was found among predictors (VIFs > 5).

5.2 Discussion on Finding

5.2.1 Trust

H_1: Trust has a significant relationship with the Malaysian university students' investment intentions by using robo-advisory services.

The findings showed a high positive correlation between trust and behavioral intention to adopt robo-advisory services for investment purpose ($\beta = 0.422$, $p < 0.001$). This is consistent with core theories of trust in technology adoption (Gefen et al., 2003; McKnight et al., 2002) and recent empirical studies on automated financial platforms. For example, Lee and See (2004) define trust as users' perception of the reliability and security of a system, which becomes critical in risky situations such as investment decisions. This study's findings are also corroborated by Morana et al (2020), who confirmed that transparency in algorithmic decision-making has a direct positive influence on confidence, increasing adoption intention by users of robo-advisory websites.

The importance of trust in reducing perceived risks is especially important in this scenario. Bhatia et al. (2022) discovered that trust reduces financial vulnerability among users by 45% because credible systems alleviate concerns about algorithmic bias or faults (Belanche et al., 2019). Similarly, (Nourallah, 2022) stressed that younger investors, such as university students, value trust over simplicity of use, equating trustworthy platforms with lower risk of financial loss—a tendency replicated in this study's sample. For example, the prevalence of MooMoo (50.2% usage) and StashAway (27.6% usage) among respondents demonstrates the impact of institutional reputation on trust-building.

Cultural variables amplify the link. In Malaysia's high uncertainty-avoidance culture (Hofstede, 1984), customers gravitate toward systems that reduce perceived risks, such as data breaches or financial mismanagement. This is consistent with Jung et al. (2020), who identified ethical design and transparency as key drivers of trust in robo-advisors, particularly among risk-averse groups. Furthermore, Lourenço et al. (2020) discovered that trust mediates the relationship between perceived algorithmic competence and adoption intention, with users who believe robo-advisors are competent being 58% more inclined to adopt them—a finding that is consistent with the regression results of this study.

The high impact of trust in this study implies that students connect trustworthy robo-advisory technology with lowered sensitivity to financial losses, hence corroborating the risk-reduction hypothesis (Pavlou, 2003).Developers and politicians may capitalize on these results by placing high value on transparency (e.g., illuminating how algorithms operate), keeping data secure, and adopting ethical design principles in order to establish trust.

5.2.2 Ease of use

H_0: Ease of use has insignificant relationship between influences Malaysian students' intention to use robo-advisors service.

Based on the result from the analysis, according to the Pearson's correlation analysis, the results show that there is a certain positive correlation between two variables ($r = 0.860$, $p < .001$), indicating that the higher the perceived ease of use, the stronger the willingness to use robo-advisory services among Malaysian university students. However, the regression analysis gives a different conclusion: the t-statistic of ease of use is 1.19, which is less than 1.65, and the p-value is 0.235, which is greater than 0.05, indicating that after controlling other factors, perceived ease of use has no significant effect on the willingness to use robo-advisory services among Malaysian university students. This deviates from the original hypothesis of this study.

The results of this study are somewhat different from the classic assertion of Ease of Use in the Technology Acceptance Model (TAM). Davis (1989) and other scholars generally believe that Ease of Use will directly or indirectly affect users' willingness to use. However, the results of this study are similar to the empirical results of some literature, that is, Ease of Use does not necessarily have a significant impact on the intention to use. For example, according to Kueniawan (2020), Ease of use is not a significant moderating factor in the acceptance of information systems technology by users. In addition, the data used in the study by Shortt et al. (2018) were extracted from two formative studies and four summative medical device studies conducted between 2011 and 2014. The results showed that there was a weak correlation between perceived difficulty and task failure scores (= 0.271, $p < 0.001$), the results show that perceived ease of use is not a reliable indicator of true usability. Besides, Pickering et al. (2020) questioned the conclusion that the technology acceptance model and its derivative models positioned perceived ease of use (sometimes mediated by perceived usefulness) as the main indicator of adoption intention, so they followed up in their research to explore repeatability and generalizability. Through a secondary review of the results of the testing and validation activities, the results of the study found that post-hoc measurement of perceived ease of use was less important to participants than their focus on task-oriented usefulness. A contradictory relationship was found between the quantitative measurement of perceived ease of use and the qualitative review of perceived usefulness comments in three sites in Italy, Spain, and the United Kingdom. Moreover, in Nugroho et al. (2018)'s study on the impact of perceived usefulness and perceived ease of use on students' mandatory e-learning usage performance, it was found that perceived ease of use did not affect students' performance, with a P-value of 0.4466. Based on the hypothesis test, it was concluded that perceived ease of use does not affect users' performance when there is an obligation to use the implemented system. Additionally, in order to study technologies that are new to users, Tiainen et al. (2013) investigated the use of motion control devices in a virtual environment. The experiment was conducted by organizing a user test in which participants browsed virtual shopping items by walking or using the device to control movement. The analysis showed that there was no correlation between the actual use of the device and ease of use. Those conclusions are similar to the conclusion of our study that ease of use has no significant effect on the willingness of the intention to use robo-advisory services among Malaysian university students.

One possible reason for the insignificant effect of ease of use on the adoption of robo-advisory by Malaysian university students as proposed by Davis (1989) in the classic technology acceptance model (TAM), perceived ease of use usually indirectly affects the intention to use through perceived usefulness (PU). Although PEOU helps to form a positive attitude of users towards the system, its impact on behavioral intention is often achieved by enhancing PU. In a context where users already have some experience in using digital financial tools, the ease of use of the system may have been taken for granted, and its effect is relatively weakened.

Next, recent studies have pointed out that trust and perceived usefulness are often more predictive than perceived ease of use in the process of accepting artificial intelligence technology. Choung, David, and Ross (2022) found that although PEOU contributes to the formation of trust and PU, it does not have a significant impact on behavioral intention itself. In the context of robo-advisors, students are more likely to view it as an AI-driven financial decision-making tool. When evaluating their intention to use, they are more concerned about whether the system is trustworthy and whether it really helps with financial management, rather than whether the interface is simple.

Furthermore, users' expectations and past experience with technology may also affect their emphasis on perceived ease of use. Yi and Choi (2023) pointed out that users' familiarity with the digital environment and expectations of new technologies significantly affect their adoption intention. For most Malaysian university students, they are usually digital natives with high digital literacy, so when evaluating technology adoption, they pay more attention to the functionality and reliability of the system rather than the basic ease of use.

In summary, these findings are consistent with other empirical research results, further questioning the view that PEOU is generally decisive in various situations. Research shows that in more complex or familiar technology environments, especially when involving AI or financial instruments, perceived ease of use may no longer be a key influencing factor in adoption intention.

5.2.3 Perceived Risk

H_1: Perceived risk has a significant relationship with the Malaysian university students' investment intentions by using robo-advisory services.

Based on the result from the analysis, it indicates that the perceived risk has a significant positive influence on the intention to use robo-advisory services among Malaysian university students. The t-statistic for perceived risk is 3.64, which is more than 1.65, and the p-value is less than 0.001, which is lower than 0.05. These results prove that the relationship between the perceived risk and the intention of Malaysian university students to adopt robo-advisory services for investment purposes is positive and significant. Besides that, the positive correlation ($r = 0.852$, $p < .001$) suggests that students who recognize potential risks may still be more likely to use robo-advisors, possibly due to an awareness of the risk-return trade-off in financial investments.

According to the study's findings, Malaysian university students' intention to use robo-advisory services is significantly positively impacted by perceived risk. According to Nguyen, Chew, Muthaiyah, Teh, & Ong (2023), perceived risk has no significant relationship with the Malaysians behavioural intention to accept robo-advisors. However, this finding deviates from conventional expectations, where higher risk perception typically discourages adoption. However, a number of psychological and financial factors help to explain why younger people are still more likely to use robo-advisory services even though they are aware of the risks.

Firstly, risk-return awareness is one of the main causes of this condition. Students at universities, especially those majoring in business, economics, or finance, have an academic knowledge of the basic trade-off between risk and reward. They are able to understand that increased risk is frequently linked to greater potential benefits because they have been exposed to investment principles through their coursework. As a result, when they are making investing decisions, they are more likely to take measured risks (Lusardi & Mitchell, 2014). Given this perspective, robo-advisory services become an attractive choice because these students are prepared to accept a certain amount of risk in order to achieve financial benefit.

Secondly, knowledge of technology and trust in artificial intelligence (AI) are also important determinants. The younger age group is more accepting of AI-driven services because they grew up in a time of rapid technology growth (Jareño et al., 2023). University students are more likely to trust data-driven, algorithm-based financial services than older investors who could be wary of technology and prefer human financial counsellors. Because they think machine learning algorithms and automated decision-making can effectively optimise their investments and minimise human mistakes, their trust in AI reduces their worries about perceived risks (Kaya, 2023).

Furthermore, a key factor in investment behaviour is the concept of loss aversion, which suggests that individuals fear losses more than they value similar profits. In contrast to older investors, university students generally show lower levels of loss aversion. They have a longer investing horizon and fewer financial obligations, such as house payments or family costs, which is the main reason behind this. Despite being aware of the risks, individuals might be more likely to use robo-advisors because they have more time to recover from possible losses. Loss aversion is one behavioural bias that has been shown to have a major influence on investing decision-making. Despite their wide adoption, robo-advisory services do not always remove investors' fear of loss bias (Bhatia, Chandani, Divekar, Mehta & Vijay, 2022).

In addition, students' preference for robo-advisory services is influenced by their lack of awareness about alternative investments. Many university students lack the knowledge or self-assurance necessary to handle investments on their own. By providing automated portfolio management based on users' risk limitations, robo-advisors simplify the investing process. Students may still view robo-advisory platforms as safer and easier to use than traditional financial advisors or manual investment management, even if they are aware of the risks

(Oehler, Horn & Wendt, 2022). Young investors find these services appealing because they offer individualised investment suggestions without requiring a high level of financial literacy.

Moreover, students' investment behaviour is further influenced by peer recommendations and social influence. Peers, social media, and financial influences all have a big impact on university students. Even though people are aware of the possible risks, they can feel more comfortable using robo-advisory services if their friends or trusted online communities recommend them (Barber & Odean, 2021). Investment decisions are greatly influenced by the impact of testimonials, success stories, and online discussions, particularly for younger people who actively seek out approval from society before adopting new financial technologies.

Additionally, the cost-effectiveness of robo-advisory services is another important consideration. A significant initial cash outlay is necessary for many traditional investment options, which may be prohibitive for university students with limited financial resources. Robo-advisors, on the other hand, usually offer lower initial commitment requirements, enabling customers to begin with small amounts. For students who wish to start investing without making significant financial commitments, this reduces the perceived financial risk involved, making it more approachable and attractive (Bhandari & Deaves, 2006). The minimal initial commitment makes those risks easier to accept, even if they are acknowledged.

Besides that, an additional factor contributing to students' use of robo-advisory services is behavioural bias, specifically overconfidence. The ability of young investors to understand and manage investing risks may be overestimated. In addition, they might believe that the algorithms used by robo-advisors automatically reduce financial risks, which would cause them to undervalue potential drawbacks and concentrate more on rewards. Because people believe they can effectively utilise these platforms despite the inherent risks, they use robo-advisory services more frequently as a result of this cognitive bias. Research shows that overconfident investors are more likely to use robo-advisors because they believe they have the financial knowledge to use these automated platforms to maximise profits (Piehlmaier, 2022).

Lastly, one of the main reasons university students look into investing opportunities is the desire for financial independence. Early financial security and wealth accumulation are goals for many young individuals. With robo-advisory services, they can enter the world of investing easily and affordably, gaining practical experience without needing to have a lot of prior knowledge. They use robo-advisory services more frequently because their desire to become financially independent and accumulate wealth exceeds any worries they may have about perceived risks (Lusardi & Mitchell, 2014).

In conclusion, the results of this study indicate that Malaysian university students are not discouraged from adopting new financial technology, despite the accepted view that perceived risk will prevent such adoption. Their favourable investment intention towards robo-advisory services is influenced by a number of factors, such as risk-return awareness, technological familiarity, reduced loss aversion, limited knowledge of alternative investments, social influence, affordability, overconfidence, and aspirations for financial independence. These findings show that in order to promote more adoption and engagement with digital investing platforms, financial institutions and robo-advisory companies have to adapt their marketing and instructional tactics according to the different behavioural preferences of young investors.

5.3 Implication of Study

The findings of this research explain how trust plays a role in shaping Malaysian university students' intention to utilize robo-advisory services to invest. It is clear from the regression findings that there is a positive and significant influence of trust on adoption intention, in a way that the more the students perceive robo-advisors to be safe, trustworthy, and associated with reputable companies, the more the usage. This is reiterated by Yi et al. (2023), who clarified that the strongest antecedents of trust in robo-advisors are performance efficacy, corporate reputation, and perceived privacy protection. The students will more readily trust such online platforms if they believe their personal and financial data are well protected and they can rely on the provider. In addition, trust plays the role of a mediator between social influence and user behavior; positive peer reviews strengthen trust and, subsequently, adoption intention (Singh & Kumar, 2024). For university students, most likely to take the cue from their peers when trying out new financial tools, this is of paramount importance. To address concerns associated with algorithmic decision-making and give students a proper concept of how robo-advisors operate, teachers and education policymakers need to think about implementing fintech literacy in schools (Kwon et al., 2022). Apart from confidence building, the programs will lead to young investors interacting more and confidently with the utilization of robo-advisory services.

This study presents an empirical challenge to the applicability of the Technology Acceptance Model (TAM) in the emerging financial technology sector. Traditionally, TAM emphasizes "perceived ease of use" and "perceived usefulness" as the core variables that influence the willingness to adopt technology (Davis, 1989). However, among Malaysian university students, although there is a positive correlation between perceived ease of use and the willingness to use Robo-Advisors after controlling for other factors, the regression analysis shows that its effect is not significant ($p > 0.05$), which is contrary to the assumptions of TAM. Therefore, future theoretical models should start from a broader perspective and integrate factors such as behavioral finance, risk psychology, and digital trust to improve the explanatory power and predictive power of financial technology tool adoption behavior. For example, studies have shown that trust, risk perception, and financial knowledge are key factors affecting the willingness to adopt Robo-Advisors (Tan et al., 2023). In addition, studies have also found that perceived risk, customer education, and company reputation have a significant impact on users' adoption intention (Zhou et al., 2024). The inclusion of these factors helps to build an acceptance model that is more in line with specific situations and enhances the explanatory and predictive power of the theory.

The practical significance of this study is that it provides useful insights for developers and promoters of Robo-Advisors services. Although "perceived ease of use" is generally considered to be the core variable that drives technology adoption intention in the TAM model, this variable does not significantly affect the intention to use among Malaysian university students. This finding has important implications for the service development and promotion strategies of robo advisors. Specifically, the designers and promoters of Robo-Advisors should pay more attention to enhancing users' trust in the platform, the security of the service, and the transparency of investment returns, rather than just focusing on the simplicity of technical operations (Liu et al., 2021). □

Next, with the continuous development of financial technology, Robo-Advisors have gradually entered the mainstream market, but there are significant differences in its acceptance in different countries and cultural backgrounds. For the emerging market of Malaysia, studies have shown that when users choose to use Robo-Advisors, in addition to ease of use, they also pay more attention to other factors, such as the regulatory transparency and risk control mechanism of the platform (Nguyen et al., 2022). Therefore, when designing products, Robo-Advisors operators should consider how to increase users' willingness to adopt by strengthening financial education, enhancing users' trust in financial technology, and providing clearer expectations of investment returns. Moreover, research also shows that understanding users' behavioral characteristics and investment experience can help service providers more accurately target the market and develop personalized service plans (Jung et al., 2020). These practical strategies help overcome the impact of insufficient "perceived ease of use" and thus increase the popularity of Robo-Advisors.

Perceived risk and intention to use robo-advisory service by Malaysian university students have a strongly positive relationship, which is of utmost significant to both financial service provides and policymakers. It is a piece of received wisdom that perceived risk acts as an inhibitor for technology adoption, but this study shows otherwise with these young, tech-savvy investors.

Firstly, this finding indicates that Malaysian students at universities are likely to be well-informed regarding risk and return and, consequently, are capable of explaining risks as a means to future returns. It affirms a hypothesis that financial literacy, and specifically understanding of the return-risk trade-off, influences investment decisions (Lusardi & Mitchell, 2014). Financial and robo-advisory firms should therefore frame their promotional materials around confirming this hypothesis by emphasising calculated risks and future returns which accrue as a result of investments through digital channels.

Secondly, the positive impact of perceived risk indicates that education for investment does not eliminate perceived risk. Instead, educators and robo-advisory websites should highlight enhancing financial literacy to make risk manageable and inherent to investment decision-making. Research indicates that financial literacy significantly impacts investment decision-making as it enhances investors' ability to make good decisions and adapt well to perceived risks (Balagobei & Prashanthan, 2021). Moreover, AI-driven robo-advisors facilitate risk management, as these automatically monitor portfolio performance and rebalance them instantaneously to align with investors' financial targets and targeted risk, limiting prolonged loss and building investor trust.

Third, with regard to this discovery, there is a potential for robo-advisory firms to segment and target young investors based on behavioural profiles, i.e., increased overconfidence and decreased loss aversion. These types of behaviours can increase investment risk tolerance, especially if combined with explainable algorithmic models and user-friendly interfaces. More overconfident investors will find robo-investment platforms suitable, confident that they would be able to leverage the platforms to their benefit (Bhandari & Deaves, 2006).

Finally, studies indicate there is a requirement for understanding of environmental and cross-generational drivers of investment behaviours. Robo-platforms need to tap into social influence and digital engagement strategies—i.e., peer reviews, endorsements, and active-learning education through game-like features—common to younger investors, who not only do not shun risks but perhaps are drawn to them as an integral component of financial advancement. Investor behaviour at an individual level is heavily impacted by peer behaviours and social pressures (Barber & Odean, 2001).

In conclusion, this study presents a balanced picture of the determinants of the intention of Malaysian university students to use robo-advisory services. In contrast to traditional assumptions of the Technology Acceptance Model (TAM), perceived ease of use is not a main driver of adoption among the case of this group. Instead, trust and perceived risk are more important determinants. Trust—built on corporate reputation, data privacy, and peer influence—is the most important in promoting the adoption of robo-advisors. Contrary to their expectation, perceived risk, otherwise a resistance determinant of adoption, is positively related to investment intention among these financially literate, tech-savvy students. This suggests a mindset change among investors whereby informed risk is being accepted as a pathway to return.

The findings suggest that fintech innovators, educators, and policymakers must take a different direction. Instead of striving to make user interfaces even simpler, greater efforts must be put into building trust, familiarizing users with financial instruments, and minimizing privacy and security concerns. Furthermore, incorporating behavioural finance elements and leveraging peer influence can enhance adoption significantly. By shaping services along the behavioural traits of young investors and incorporating interactive, gamified learning mechanisms, robo-advisory websites can more effectively address the needs of this emerging market segment. Finally, a comprehensive approach incorporating trust, financial knowledge, and social interaction will be key to enhancing the take-up and long-term viability of robo-advisory services in Malaysia.

5.4 Limitation of study

Although this study provides useful information about the adoption of robo-advisory services by Malaysian university students, it should be noted that it has a number of limitations. These limitations point to potential directions for future research in order to offer a greater understanding of investment intentions within the framework of financial services powered by artificial intelligence (AI).

This study primarily focuses on university students in Malaysia, which limits the generalizability of the findings to other demographics, such as working professionals, retirees, and individuals with varying levels of financial experience (Sabir, Ahmad, Ahmad, Rafiq, Khan & Noreen, 2023). University students tend to be younger, more tech-savvy, and may have different investment behaviours compared to older, more experienced investors who depend on traditional financial advisory services. Additionally, investment decisions are also heavily influenced by variables including long-term financial objectives, disposable income, and employment stability, which may differ among age groups and professional backgrounds.

In addition, the data collected in this study are based on survey respondents' self-reported answers. Self-reporting is a popular technique in behavioural research, however it might add biases, such as social desirability bias, recall bias, and misreading survey questions (Belanche, Casaló & Flavián, 2019). Respondents might give answers that they think are socially acceptable instead of ones that correctly reflect how they really invest or how they view robo-advisors. Furthermore, some participants could not know enough about or have enough experience with robo-advisory services, which could cause inconsistent answers.

Additionally, the study employs a cross-sectional research strategy, which means that data was collected at a single point in time (Yi, Rom, Hassan, Samsurijanm & Ebekozien, 2023). Although this method gives a quick overview of university students' investing intentions, it ignores how their attitudes, actions, and preferences might change over time. Dynamic factors including changes in the economy, technological breakthroughs, regulatory changes, and changes in the level of financial literacy all have an impact on investment decisions. A longer-term study that follows users would give a greater understanding of how these variables change and affect the adoption of robo-advisory services.

Moreover, the study focuses on three important independent variables that influence investment intention: perceived risk, trust, and ease of use. Although these variables are important, additional factors, including income level, risk tolerance, prior investment experience, financial literacy, and regulatory awareness, should improve our knowledge of the adoption of robo-advisors (Figà-Talamanca, Tanzi & D'Urzo, 2022). While people with higher salaries could have different investing choices than students with fewer financial resources, those with greater financial understanding, for instance, might feel more comfortable using robo-advisory platforms. Besides that, the influence of psychological and behavioural factors, such as decision-making biases and risk perceptions, may provide deeper understandings of user adoption.

Finally, the study does not adequately take into consideration differences in the accessibility, features, and regulatory environment of various robo-advisory platforms (Cardillo & Chiappini, 2024). Several robo-advisory services in Malaysia provide unique features, investment plans, and cost structures that could affect students' preferences and adoption behaviours. Additionally, the worldwide robo-advisor business is changing quickly due to regional differences in market development, legal frameworks, and user trust. If these market variations are not taken into account, the study's conclusions might not apply to other situations where robo-advisory firms are more well-established or have different business models.

5.5 Recommendations for Future Research

Although this study provides valuable insights into the acceptance of robo-advisory services by Malaysian university students, it still has certain limitations. To improve the comprehensiveness and application value of the study, future research can be improved in the following aspects.

First, expand the scope of the research subjects and improve the generalizability of the results. This study mainly targets Malaysian university students, who are generally younger and familiar with technology, but their investment experience, financial status and long-term financial goals may be significantly different from other groups in society. Therefore, future research can be extended to investors of different age groups and professional backgrounds, who may have different investment behaviors and views on robo-advisory services. For example, working people may pay more attention to the return rate and cost-effectiveness of investment, while retirees may pay more attention to stability and risk control of investment. In addition, the culture, economic level and degree of financial market development in different regions may also affect investors' acceptance of robo-advisory services, so cross-regional or cross-cultural research is also a direction worth exploring. For instance, compare the similarities and differences between university students in other Southeast Asian countries and Malaysian university students in the acceptance of robo-advisory services, or examine the behavioral patterns of mature markets such as Europe and the United States and emerging markets like Southeast Asia and Africa when adopting robo-advisory services.

Second, adopt multiple data collection methods to reduce self-report bias. This study mainly relies on self-report data from questionnaires, which may lead to social expectation bias, recall bias, and bias in understanding the questionnaire. Therefore, future research can adopt multiple data collection methods, such as interviews, experiments, or behavior tracking, to improve the accuracy and reliability of the data. For example, this study can explore the attitudes and concerns of Malaysian university students who fill out the questionnaire by interviewing each student to supplement the shortcomings of quantitative research. Besides, by collecting actual investment transaction data of those Malaysian university students with investment experience, they can more accurately analyze their use of robo-advisory services and investment preferences.

Moreover, add longitudinal research design to analyze the dynamic changes in Malaysian university students' investment attitudes. Since this study adopts a cross-sectional research design, it can only capture user attitudes at a specific point in time, and investors' acceptance of robo-advisory services may change over time, changes in the market environment, and technological advances. Therefore, future research can adopt a longitudinal research method to regularly track users' investment behavior and attitude changes. For instance, study the long-term impact of financial market fluctuations, policy adjustments, and new technology applications on investor acceptance in Malaysia. And the experimental method can be used to observe the behavioral changes of these Malaysian university students after long-term use of robo-advisory services, such as from initial distrust to gradual acceptance, or giving up the use due to some negative experiences. These longitudinal studies may help analyze the lagged effects caused by changes in external factors from a long-term perspective.

Furthermore, increase the research independent variables to build a more comprehensive investment decision-making framework. This study mainly examines the impact of perceived risk, trust and ease of use on investment willingness. Although these variables are important, investment decisions are usually affected by more complex factors. So future research can further introduce more variables. For example, risk tolerance represents the different tolerance of different investors to market fluctuations, which may affect their acceptance of robot advisors. Next, investors with rich investment experience may be more inclined to use traditional investment methods, while inexperienced investors may be more willing to accept robo-advisory services, so investment experience can be used as a independent variable. Additionally, financial knowledge describes the degree of understanding of financial markets and investment tools, which may affect the user's trust and dependence on robo-advisory services. Besides, psychological and behavioral may also be a factor that investors' decision biases (such as overconfidence and loss aversion) affect their use of robo-advisory services. By incorporating these variables, future research can more accurately analyze the acceptance of robo-advisory services by different types of investors and provide more targeted marketing recommendations.

Finally, analyse different platforms used by robo-advisory services, consider into market and technology factors. As the robo-advisory market continues to develop, there are differences among platforms in terms of investment strategies, charging models, personalized services, and technological maturity. Therefore, future research can compare the characteristics of different robo-advisory platforms, analyze which features are most attractive to users, and explore the impact of market competition on user adoption intentions. It is also possible to study the regulatory environment in different countries or regions and analyze how policies affect the development of robo-advisory services. For example, some countries have strict regulations on automated investment advice, while other countries may allow greater freedom, which may affect user trust and adoption. Moreover, the impact of technological innovation can be examined, such as how advances in artificial intelligence and machines can improve the performance of robo-advisory and enhance user confidence. By analyzing robo-advisory services on different platforms, future research can have a deeper understanding of the market acceptance of robo-advisory services and provide more practical advice for policymakers, financial institutions, and technology companies.

5.5 Conclusion

This research explored the impact of robo-advisory services on the investment intention of Malaysian university students based on three determinants: perceived risk, trust, and ease of use. The results indicated that trust was the strongest predictor of adoption intention, demonstrating its critical role in mitigating financial fears and building confidence in automated systems. Contrary to conventional theories like the Technology Acceptance Model (TAM), it was surprisingly discovered that perceived ease of use had no significant effect on the students' intention. This implied that the modern, tech-savvy generation valued reliability and performance more than functional ease. Contrary to expectations, the perceived risk was positively linked to the intention to adopt, which meant that the students were aware of the risk-return trade-off and were ready to accept robo-advisors despite the inherent disadvantages.

The implications of the research are far-reaching. To build trust, fintech developers must increase transparency in their algorithmic decision-making processes, provide strong data security, and emphasize the legitimacy of their institutions. Policymakers should emphasize financial literacy programs and create regulatory frameworks that not only safeguard users but also encourage innovation. Educators can incorporate robo-advisory technologies into their syllabuses, providing students with hands-on investment skills that are in line with Malaysia's vision for a digital economy.

Although robust in several respects, the research had limitations; it was centered on university students and used a cross-sectional design. Future research would ideally cover a wider range of participants, use longitudinal analyses, and look at other variables, including financial literacy, risk tolerance, and behavioral bias. Filling in these knowledge voids will enable stakeholders to better adapt robo-advisory services to the changing needs of investors and thereby promote inclusive financial engagement and economic resilience.

Lastly, the research fills a much-needed void in knowledge regarding young investors and their use of AI-based financial services and instruments with effective insights set to empower a new breed of financially literate and tech-literate persons in the changing Malaysian investment scene.

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