A STUDY OF THE INTENTION TO USE ROBO-ADVISORY SERVICES IN MALAYSIA

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CHOW, TAN, & TAN ROBO-ADVISORY SERVICES BFN (HONS) SEPTEMBER 2023

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BY

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

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DECLARATION

We hereby declare that:

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

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

(3) Equal contribution has been made by each group member in completing the FYP.

(4) The word count of this research report is 17915 words.

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Last but not least, all credit goes to our family, friends, and others who directly and indirectly contributed to our study effort but were not named above, for their encouragement and support from the beginning to the conclusion.

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DEDICATION

This study is dedicated to Universiti Tunku Abdul Rahman (UTAR) for giving us the chance to improve and apply the information gained during the three-year finance degree.

Moreover, we would also like to dedicate our study to Dr. Kuah Yoke Chin, our Final Year Project supervisor. Throughout this study, she provided us with invaluable help and direction. Her support has led us to where we are now, and without her intelligent advice, we would struggle to complete our studies on time. We greatly value our esteemed supervisor's efforts.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AUM	Asset Under Management
AVE	Average Variance Extracted
BI	Behavioural Intention to Use Robo-advisory Services
CA	Cronbach’s Alpha
CAGR	Compounded Annual Growth Rate
COVID-19	Coronavirus Disease
CR	Composite Reliability
DOSM	Department of Statistics Malaysia
E-commerce	Electronic Commerce
EE	Effort Expectancy
ETF	Exchange-traded Fund
E-wallet	Electronic Wallet
FC	Facilitating Conditions
Fintech	Financial Technology
HM	Hedonic Motivation
HTMT	Heterotrait-Monotrait Ratio of Correlations

IDT	Innovation Diffusion Theory
M40	Middle 40%
MPCU	Model of Personal Computer Utilisation
PE	Performance Expectancy
PLS-SEM	Partial Least Square Structural Equation Modelling
PV	Price Value
S&P 500	Standard and Poor's 500
SCT	Social Cognitive Theory
SI	Social Influence
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TT	Trust
UTAUT	Unified Theory of Acceptance and Use of Technology Theory

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PREFACE

With the advancement of technology in the financial industry, artificial intelligence has been applied to financial advisory services, namely robo-advisory services, or robo-advisors. Robo-advisor is an automated solution that provides automated portfolio rebalancing using trading algorithms according to passive investment and diversification strategies, featuring advanced customer experience, guiding them through a self-assessment process and shaping their investment behaviour based on investors' expectations.

This study was prompted by the phenomenon that happens among investors. The possibility of robo-advisors replacing portfolio managers in financial advisory services in Malaysia came to the mind of the team members. Therefore, this study was conducted to examine the determinants of the intention to use robo-advisory services in Malaysia. The members anticipated that this study would assist a variety of parties, including robo-advisory firms and researchers.

In addition, the members of this study could also explore and gain knowledge concerning the current development of robo-advisory services in Malaysia. This study aims to present readers and interested parties with a variety of perspectives and the members could also take advantage of this chance to continue researching and studying this topic in their future studies by utilising this report as a reference.

ABSTRACT

In Malaysia, robo-advisory services have become increasingly popular in the financial industry. Hence, this study investigates the factors that determine the intention to use robo-advisory services in Malaysia. The proposed research model is based on the Unified Theory of Acceptance and Use of Technology Theory 2 (UTAUT2). More specifically, the independent variables included in the model are performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and trust. Furthermore, the target respondents for this study are individuals from the M40 income group in Malaysia. A total of 400 responses were collected and analysed through Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS software. The findings demonstrated that performance expectancy, social influence, hedonic motivation, price value, and trust are significant in affecting the behavioural intention to use robo-advisory services in Malaysia, except for effort expectancy and facilitating conditions, which showed an insignificant result. Moreover, this study would contribute to understanding the emergence of robo-advisory services in Malaysia and provide practical and theoretical implications for portfolio managers, robo-advisory firms, and researchers to aid in the future development of robo-advisory services and financial industry in Malaysia.

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This study investigates the factors determining the intention towards using robo-advisors. The evolution, current development and opportunities of robo-advisors are briefly explained. Moreover, factors influencing the behavioural intention to use robo-advisory services are identified in this chapter, along with the research problem, questions, and objectives, as well as the theoretical and practical contribution.

1.1 Research Background

1.1.1 Background of Robo-advisors

In recent decades, with the development of artificial intelligence (AI), experts have utilised AI algorithms to construct predictive models for the stock market and speculate on the evolution of financial pricing (Tsai & Chen, 2022). The advancement of financial technology (fintech) has increasingly been used to assist investors in investment decisions. Based on Gan et al. (2021), due to tremendous market demand for low-cost automated portfolio management, robo-advisors have attracted interest from the financial and academic community.

1.1.2 Evolution of Robo-advisors

After the 2008 financial crisis, financial institutions lost public trust, affecting investors' faith in the financial industry (Shih, 2019). It led to many individuals seeking innovative alternatives to allocate their funds.

Hence, robo-advisory services were initially launched in 2008 in the U.S. (Welsch, 2022) with the earliest introduction of Betterment and Wealthfront, making financial advice solutions more approachable to the public (Fisch et al., 2018). In the initial stages, robo-advisors were thought to be niche products targeted at younger, tech-savvy investors (Deloitte, 2016). However, as their benefits became widely known, a broader range of investors, including senior and high-net-worth individuals, were attracted, along with additional companies joining the market.

Robo-advisors have evolved through four stages of the revolution, beginning with fundamental investment management, and progressing to more recent developments in advanced technology and customised solutions (Fahruri et al., 2022). Firstly, Robo-advisor 1.0, which started in 2008 - 2009, established portfolio allocation with low-cost Exchange-traded Funds (ETFs) based on investing preferences and risk tolerance of investors (Gilmour et al., 2019, as cited in Rachman & Sukmadilaga, 2022). Robo-advisor 2.0 focused on reducing costs, carrying a similar objective to Robo-advisor 1.0. Yet, it offered more personalised services to clients and created more comprehensive financial planning. Following Robo-advisor 3.0, at this stage, robo-advisor predefines investment strategies by implementing more advanced technology into their platforms (Fahruri et al., 2022). The investment choices and portfolio rebalancing suggestions are based on algorithms, allowing more personalised portfolio allocation. Lastly, Robo-advisor 4.0 is the most advanced version due to the implementation of self-learning algorithms and AI to manage more advanced financial modelling and portfolio evaluation (Fahruri et al., 2022). It also provides valuable insights into individual behaviour like preventing losses in a volatile market and leveraging investment with complicated financial instruments without the aid of a portfolio manager (Bernardis, 2020).

Throughout robo-advisors' evolution, it has expanded to many regions, including Canada, the U.K., Australia, Germany, and Asia. Based on Figure 1.1, there is a rising trend in the global users of robo-advisors. The dramatic rise of 50 million year-on-year from 2019 to 2022 manifested that the development of robo-advisors has created a fierce pool of competition between businesses, leading to an increase in its adoption ("Growing competition in the robo-advisory market," 2020). Besides, the sharp rise occurred during and after the pandemic as investors would like to seize the opportunity to profit during this hectic period. For instance, Betterment and Wealthfront recorded double-digit growth in new account openings during the pandemic ("Young investors drove use," 2021).

<u>**Users of Robo-advisors Globally**</u>

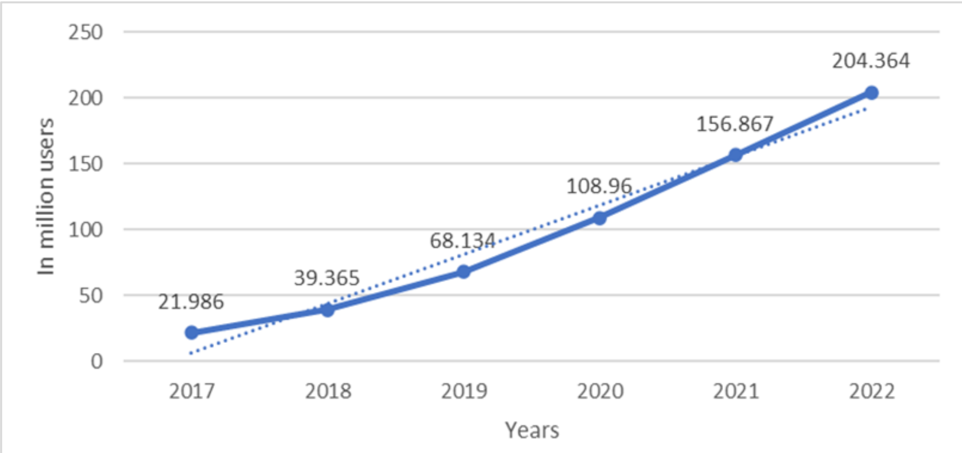

Figure 1.1. Users of robo-advisors globally. Adapted from Statista. (2023a). *Robo-Advisors - Worldwide*.

1.1.3 Current Development of Robo-advisory Services in Malaysia

The growth of robo-advisors in Malaysia is lagging behind that of other peers like Singapore since they just became available in Malaysia in 2017 (KPMG, 2021). They are still comparatively new, but the market is expanding aggressively, driven by enormous market demand for affordable automated portfolio management strategies. Notably, in Malaysia, the financial services industry and researchers have devoted significant attention to robo-advisors in recent years (Ruslan et al., 2022). Securities Commission Malaysia granted permission to several local investing platforms, such as Wahed Invest, Raiz, StashAway, and MyTHEO, to offer robo-advisory services in Malaysia (Ruslan et al., 2022). According to Statista (2023b), there has been a stable increase in users adopting robo-advisors from 2017 to 2022, predicting a continuous increment in the later years. This recent occurrence highlights a trend in Malaysia's fintech industry towards robo-advisors (Gan et al., 2021).

Table 1.1:

List of Robo-advisors Companies Based in Malaysia

Platform	**Launched**	**Methodology**	**Annual Fees**
StashAway	2018	Employing a distinctive investing technique responsive to economic conditions.	0.2% - 0.8%
MyTHEO	2019	Using the company's innovative algorithms to develop functional portfolios that feature integrated risk-based investing and "smart data" methods.	0.5% - 1.0%
Wahed Invest	2019	Using Modern Portfolio Theory, investors' assets are optimised to maximise profit while following Shari'ah law.	0.39% - 0.79%
Akru Now	2020	Investing in a smart portfolio of ETFs that are internationally diversified and low fees.	0.2% - 0.7%

BEST Invest	2020	Using AI and big data technologies, it recommends investment based on a diverse portfolio of Shari'ah-compliant unit trust assets.	0.5% - 1.8%
Raiz	2020	Using an algorithm that evaluates the risk profile of the investor to create a diversified portfolio consisting of Amanah Saham Nasional Berhad trust funds tailored to the investor's preferences.	RM1.5 a month (<RM6k) or 0.3% (>RM6k)
Kenanga Digital Investing (KDI)	2022	Allowing for AI-assisted investing in a range of chosen ETFs that are listed in the U.S. and correspond to the user's preferences.	0.3% (<RM3k) or 0.7% (>RM3k)
Versa	2022	Allowing to invest in two newly launched investment portfolios, a high-risk tolerance in a growth portfolio, and a lower risk tolerance in a moderate portfolio. Partnership with Affin Hwang Asset Management in managing the portfolios.	1%

Note: From Ruslan, R. A. H. M., Ibrahim, M. A., & Hamid, N. H. (2022). Application of artificial intelligence in fintech: The decision of youth

investors to use the robo-advisor platform as micro-investing alternative. *Journal of Entrepreneurship, Business and Economics 2022, 10*(2s2), 38-54.

Statista's report predicts that the robo-advisory industry in Malaysia will continue to expand in the coming years in terms of users and Asset Under Management (AUM) (Statista, 2023b). The market stands at US$16.88 billion in 2022 and is expected to rise at an 11.78% compound annual growth rate (CAGR) between 2023 and 2027 to US$33.39 billion (Figure 1.2). In addition, due to the worldwide enforcement of movement restrictions, the global pandemic has affected numerous industries, including the financial advisory market. Although the portfolio manager still holds a significant share of the market, robo-advisors have emerged as the popular choice for investors seeking advice (Nguyen et al., 2023). Therefore, the number of registered users on robo-advisory platforms in Malaysia witnessed a massive surge from around 23,000 to 200,000 accounts in 2020, reflecting a rise of around 763% (Nguyen et al., 2023).

Asset Under Management in Malaysia's Robo-advisors Market

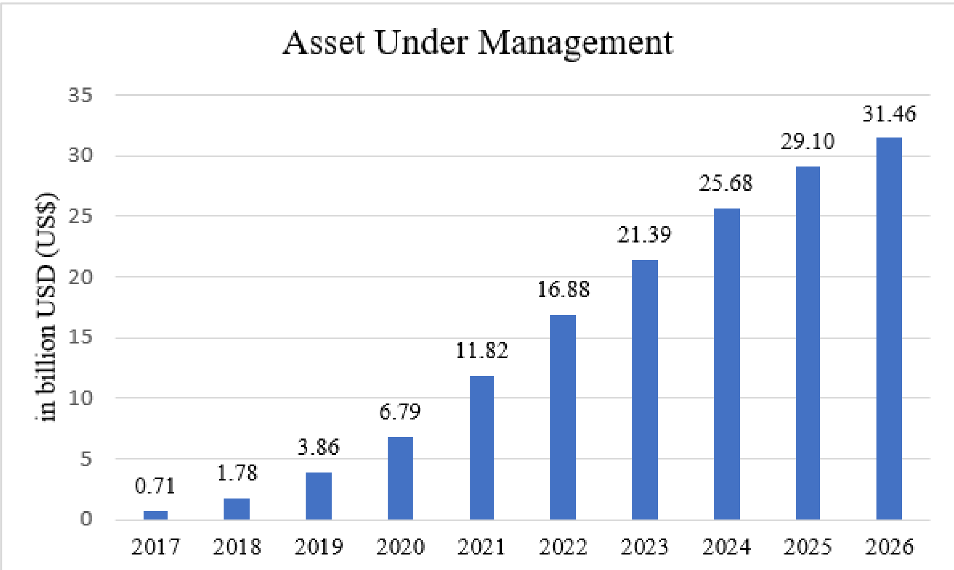

Figure 1.2. Asset under management in the Robo-Advisors market. Adapted from Statista. (2023b). *Robo-Advisors - Malaysia*.

1.1.4 Services Offered by Robo-advisors

Robo-advisors provide automated investment management, financial advice, or financial planning services, targeting the demands of the mass market (Woodyard & Grable, 2018). Robo-advisors require minimal human intervention by utilising self-learning algorithms and AI technology to automatically provide portfolio management to retail investors (Gilmour et al., 2019). There are various services and capabilities provided by robo-advisors, including automatic deposits, tax-loss harvesting, asset allocation, portfolio monitoring, and rebalancing (Fan & Chatterjee, 2020; Bhatia et al., 2022). In addition, to meet the needs of more sophisticated investors, robo-advisors offer innovative features like notifications for market updates, opportunity or risk alarms, data visualisations, and regular portfolio evaluations (Farida & Kohli, 2019). To enhance the trust of users, hybrid robo-advisors are also developed. It employs the robo-advisory platform as a channel for customer interaction while performing consultation and management duties based on the portfolio manager's expertise (Youngmi, 2014, as cited in Sa et al., 2018), allowing a certain degree of human-human interaction.

Robo-advisors provide portfolio recommendations for investors to aid in decision-making through the risk profiling process (Bhatia et al., 2022). Based on the study of Fein (2015), inexperienced users of the robo-advisory platforms are required to complete an online questionnaire to assess their risk tolerance, investment preferences, personal financial condition, and financial goals. Based on the result, a portfolio is then constructed by the programmed algorithms. Fein (2015) stated further that investors who share identical financial goals often receive comparable portfolio recommendations.

Usually, robo-advisors allocate investors' funds to ETFs, a type of investment fund that holds different asset classes such as stocks, bonds, commodities, and other instruments across various industries and geographies (Guo, 2020). As stated by Santhosh (2018), ETFs are designed to track the performance of a certain benchmark index, such as the S&P 500. He also highlighted that ETFs are an attractive investment alternative for diversification and risk minimisation due to their lower expense ratios and greater liquidity. These features are closely related to the passive investment approach employed by ETFs. Thus, about 55% of robo-advisors in Europe use ETFs as their primary investment vehicle (Kaya, 2017), minimising the costs and risks for investors.

Furthermore, the study of Kaya (2017) shows that robo-advisors employ statistical tools and algorithms to track portfolio performance 24 hours a day. Robo-advisors will automatically rebalance the portfolio for investors when changes in economic conditions result in a deviation from the desired asset allocation level (Kaya, 2017). This helps to reduce the risks involved in the investor's present portfolio structure (Louw, 2018). Besides, at times when investors alter their investment preferences and risk levels, robo-advisors will also automatically adjust the portfolio structure to meet the changing needs of investors (Kaya, 2017).

Other than automated portfolio management services, robo-advisors have gained appeal in part due to the provision of tax-loss harvesting. As stated by Cahn (2017), the goal of tax-loss harvesting is to reduce an individual's tax burden by offsetting capital gains with capital losses. This tactic involves selling some investment assets at a loss to offset or reduce the taxes owed on capital gains and replacing them with identical ones, helping investors lower the tax obligations and rebalance their portfolios simultaneously (Hammer, 2013, as cited in Sidat, 2021).

Additionally, robo-advisors offer a range of financial services, such as credit planning, retirement planning, and cash flow management. According to Muñoz-Leiva et al. (2017), numerous robo-advisors help keep track of the user's financial activities and offer recommendations. Some have been successful in lowering credit card defaults by notifying users to pay on time (Mazar et al., 2018). Moreover, they help keep track of the users' credit scores and assess the results periodically (Faloon & Scherer, 2017, as cited in Chhatwani, 2022). An analogous procedure applies to retirement planning, in which the robo-advisors outline the total investment amount required depending on the investor's financial status and consumption requirements (Arya et al., 2013).

1.2 Research Problem

Portfolio managers are important in wealth management. However, robo-advisors were made possible by the development of fintech (Kraiwanit et al., 2022). Due to the transformations experienced by the world, people are now living in a technological era, and the growing popularity of robo-advisors has threatened the position of portfolio managers in the market. There has been a lively debate about how robo-advisors compare to portfolio managers, and robo-advisors have grown in popularity since 2008 (Fan & Chatterjee, 2020).

Recently, robo-advisors have been widely used to aid investors in constructing investment decisions and building varied investment portfolios, as well as frequently compared with portfolio managers. The usage of robo-advisors for wealth management has several advantages over portfolio managers. Firstly, they help to make investing selections specified to the client's financial goals, financial condition, and risk level. Robo-advisors would deliver services the same as portfolio managers and may outperform through mathematical algorithms and AI. Under certain guidelines, they are more objective-oriented and less emotionally controlled, resulting in unbiased and profitable investment outcomes (Au et al., 2021). Based on personal investing preferences, robo-advisors will automatically generate a suitable asset allocation plan (Kaya, 2017; Phoon & Koh, 2018; Fan & Chatterjee, 2020). Hence, individual investors' portfolios are customised and maintained properly by automated programmed algorithms to reduce the majority of risks caused by human factors.

Furthermore, robo-advisors can also help to bring down the cost of financial consultancy services, saving on fixed expenditures such as pricey portfolio managers pay (Abraham et al., 2019). Hence, robo-advisors may be able to cut the minimum investment requirements by charging 0.25% of the assets managed, whilst the charges of portfolio managers do not go below 0.75% and can reach 1.5% (EY, 2015, as cited in Abraham et al., 2019). Additionally, based on Gan et al. (2021), portfolio managers in Malaysia charge expertise fees and commissions for their services, whereas robo-advisors charge fees yearly ranging from 0.2% to 1% of the portfolio's value and provide services anytime, anywhere. Given the negative impact of higher fees on returns, this is a significant cost-efficiency benefit of robo-advisors. Nonetheless, some robo-advisors adopt a more active strategy to invest, resulting in higher costs (Napach, 2017, as cited in Fisch et al., 2018).

Although Malaysia's robo-advisory market shows substantial potential, there are still concerns regarding the dependability of robo-advisors to deliver comparable or better advisory services than portfolio managers since it evaluates customers' financial positions using a restricted risk assessment (The Financial Industry Regulatory Authority, 2016). First, robo-advisors may not understand customers the way the portfolio managers do through many encounters, targeted inquiries, and stronger connections (Abraham et al., 2019). Based on the information it has, robo-advisors can make recommendations and manage the account, but "one-size-fits-all" questions may be too vague and limited to comprehend customers' financial condition and expectations. They could not receive the same level of tailored advice as portfolio managers who understand their financial situation deeply.

Second, there are limited investment choices. Robo-advisors can build tailored portfolios, but if users cannot enter their preferences or situations into the service, they would not be able to provide advice based on that information. Many of these algorithms may not be able to filter out specific assets that conflict with a customer's morals, including equities in the cigarette, alcohol, or fossil fuel industries. Additionally, these assessments presume that people with comparable risk profiles will provide the same responses to the same subjective questions, which may or may not be accurate (Kaya, 2017). Hence, when using a robo-advisor, users may not be able to select or avoid certain assets. They can still be constrained to a selection of preselected funds even among those that allow them to personalise the investments or allocation within their portfolios.

Third, robo-advisors also lack a customer-advisor relationship, such as assisting customers in defining their financial objectives, counselling during a bearish market, and dealing with potential changes in their lives (Accenture, 2015, as cited in Abraham et al., 2019). There could be portfolio managers available to help with matters other than financial ones. Hence, it is reasonable if individuals are reluctant to use robo-advisory services. While this technology is rising in popularity among investors; hence, its usage intention in Malaysia will be investigated in this study.

While robo-advisors present a particularly intriguing instance to examine how clients accept or shun AI-enabled services, the absence of empirical research concerning low market penetration is all the more regrettable (Flavián et al., 2022). There are numerous studies about robo-advisory services that have been conducted based in different regions. Sidat (2021), for example, investigated the factors influencing South African financial planners' intentions to adopt robo-advisors while Zhang et al. (2021) studied the differences between portfolio managers and robo-advisors in the U.S. Nonetheless, there are only a few studies examining the determinants of the usage intention regarding robo-advisory services in Malaysia. For instance, Gan et al. (2021), Ruslan et al. (2022), Nourallah (2023) and Nguyen et al. (2023).

From the perspective of the models used in past studies, the Unified Theory of Acceptance and Use of Technology theory (UTAUT), Technology Acceptance Model (TAM), and Theory of Planned Behaviour (TPB) have always been adapted to explain human behaviour (Pramatari & Theotokis, 2009; Hess et al., 2010; Zhou et al., 2010; Yoo et al., 2012; Lian & Yen, 2014, as cited in Venkatesh et al., 2016). However, only fewer prior studies have employed the extended model, UTAUT2, as the baseline model for their research (Nourallah, 2023; Md. Sharif Hassan et al., 2023; Rabaa'i, 2021). The UTAUT2 modifications enhance the variation clarified in behavioural intention (increased by 18% to 74%) and technological usage (increased by 12% to 52%) (Venkatesh et al., 2012). Additionally, since UTAUT1 is more concerned with the technology adoption within an organisation, UTAUT2 is preferable to examine the adoption in a more consumer-oriented context (Venkatesh et al., 2012). Hence, UTAUT2 will be employed in this study.

Furthermore, cognitive and non-cognitive dimensions of trust are involved in how people interact with AI-based services (Ferrario et al., 2020). In terms of cognitive trust, it requires preliminary trustability for humans to play their faith in AI to accomplish particular tasks, while non-cognitive trust indicates people's desire to believe in AI. Also, Hoff and Bashir (2015) found agreement across earlier empirical research on how people's long-term inclination to trust and characteristics of automated services, such as performance, influence that propensity. Yet, Nourallah (2023) stated that UTAUT neglected the trust perspective. Hence, Venkatesh et al. (2016) stated that considering the 'trust' viewpoint in the UTAUT is important for research. Also, Jung et al. (2018) assessed the demands for robo-advisors from the consumer's perspective and found that trustability is a major driver influencing consumer attitudes towards robo-advisors. Thus, the variable of trust is included in this study.

In short, the UTAUT2 model will be applied in this study with a variable eliminated, which is a habit as the target respondents of this study are people with an understanding of robo-advisors and may not have used robo-advisors before. In addition, the variable of trust is crucial in examining one's intention towards using robo-advisors, according to several previous research (Gan et al., 2021; Nourallah et al., 2022; Nourallah, 2023).

1.3 Research Questions

RQ1: Is there a significant relationship between performance expectancy and behavioural intention to use robo-advisory services?

RQ2: Is there a significant relationship between effort expectancy and behavioural intention to use robo-advisory services?

RQ3: Is there a significant relationship between social influence and behavioural intention to use robo-advisory services?

RQ4: Is there a significant relationship between facilitating conditions and behavioural intention to use robo-advisory services?

RQ5: Is there a significant relationship between hedonic motivation and behavioural intention to use robo-advisory services?

RQ6: Is there a significant relationship between price value and behavioural intention to use robo-advisory services?

RQ7: Is there a significant relationship between trust and behavioural intention to use robo-advisory services?

1.4 Research Objectives

1. To analyse the relationship between performance expectancy and behavioural intention to use robo-advisory services.
2. To analyse the relationship between effort expectancy and behavioural intention to use robo-advisory services.
3. To analyse the relationship between social influence and behavioural intention to use robo-advisory services.
4. To analyse the relationship between facilitating conditions and behavioural intention to use robo-advisory services.
5. To analyse the relationship between hedonic motivation and behavioural intention to use robo-advisory services.
6. To analyse the relationship between price value and behavioural intention to use robo-advisory services.
7. To analyse the relationship between trust and behavioural intention to use robo-advisory services.

1.5 Research Significance

1.5.1 Portfolio Manager

This study acknowledges portfolio or fund managers to analyse and assess investors' financial behaviour and attitude towards robo-advisory services. There will be a better understanding of the factors behind the public's intention to adopt robo-advisors and to re-evaluate their current market position in the financial services industry as people nowadays tend to compare conventional financial advice solutions with digital financial advice solutions in terms of various aspects. For example, performance, convenience, cost, and so on. Thus, this study would assist portfolio managers in developing investment products and strategies that align with the expectations of modern retail investors. This will further help them modify the pricing strategy and innovate value-added benefits to the customers to maintain the competitiveness of conventional financial advice solutions through differentiation.

1.5.2 Robo-advisory Firms

This study will provide some suggestions to the robo-advisory firms in Malaysia for enhancing the quality of existing robo-advisory services. Throughout the study, the robo-advisory firms will be able to identify the factors that influence the behavioural intention to use robo-advisors. Hence, they can improve their robo-advisory applications by addressing the concerns and expectations of potential investors, which may in turn increase the future usage of robo-advisory services in Malaysia. Besides, this study also presents a basic idea for players who intend to enter the robo-advisory market of Malaysia.

1.5.3 Researchers

By including one additional factor, trust (TT), in the UTAUT2 model, the study's methodology will provide a more in-depth view of the intention to use robo-advisory services in Malaysia. This would help researchers comprehend the motivation behind Malaysians' use of robo-advisory services and further recognize the problems hindering their potential usage. They might therefore use this study as a guide and apply the concepts as the basic framework of their associated research subjects in the future. It is believed that this will generate further solutions or ideas that could support the future development of robo-advisors in Malaysia.

1.6 Conclusion

In conclusion, chapter one provides a quick overview of the determinants regarding the intention towards using robo-advisors and focuses on the research overview, as well as the significance of the study. An in-depth study will be discussed in the subsequent chapters based on the research objectives.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

The analysis of relevant theories and literature, which follow the objectives of the study that have been discussed in chapter one, will be examined. The explanation of the key hypotheses that support the research framework opens this chapter. The second chapter examines the dependent and explanatory factors, followed by the hypotheses. A conceptual framework is established for this study, consisting of seven independent variables and one dependent variable—behavioural intention to use robo-advisory services in Malaysia. The connection between the seven determinants and the intention towards using robo-advisors will be further explored using the proposed conceptual framework.

2.1 Review of Relevant Theory

2.1.1 Unified Theory of Acceptance and Use of Technology 1

Venkatesh, Davis, and Morris presented the Unified Theory of Acceptance and Use of Technology (UTAUT) in 2003 to provide a comprehensive model that combines alternative behavioural viewpoints on user and innovation adoption (Momani, 2020). It explains the user's desire to accept technology and how people could use it in the future (Milani, 2019). Venkatesh et al. (2003) mentioned that the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), the TPB-TAM model, the Theory of Reasoned Action (TRA), the Model of Personal Computer Utilisation (MPCU), the Motivational Model, Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT) are the eight models used to develop UTAUT. However, based on a thorough analysis and evaluation of studies on the models, the UTAUT model is the most effective for accessing technological adoption, which can explain 70% of the variation in user intention (Chao, 2019). Therefore, researchers frequently use UTAUT as an analytical framework (Williams et al., 2015).

UTAUT, in particular, is the extension of TAM by including two more components, which are facilitating conditions and social influence (Milani, 2019). Based on Figure 2.1, UTAUT includes four core components (Figure 2.1) that serve as the direct contributing factors of behavioural intention together with another four moderators, including age, gender, experience, and willingness to use.

Performance expectancy is critical as it reflects the capacity of technology to provide advantages and enhance performance to the users, while effort expectancy is the convenience of using technology (Venkatesh et al., 2003). Individuals may respond positively to the intention of using technologies if it is perceived as handy and straightforward, which will lead to the consumer being more likely to adopt and use the technology (Sair & Danish, 2018).

Besides that, in terms of social influence, when someone believes that technology is socially acceptable, they are inclined to adopt and use it, especially towards the opinions of external sources such as friends and hierarchical superiors, or internal sources such as personal beliefs and values (Afonso et al., 2012, as cited in Ayaz & Yanartas, 2020). Lastly, facilitating conditions refer to the extent to which an individual assumes the presence of organisational and technological infrastructure to enable the utilisation of the technology (Venkatesh et al., 2003). Hence, lack of direction, incomplete details, and few resources may deter people from embracing technology. However, according to empirical findings, a direct impact of facilitating conditions on usage behaviour is observed rather than on behavioural intention (Venkatesh et al., 2003).

Research Model of UTAUT

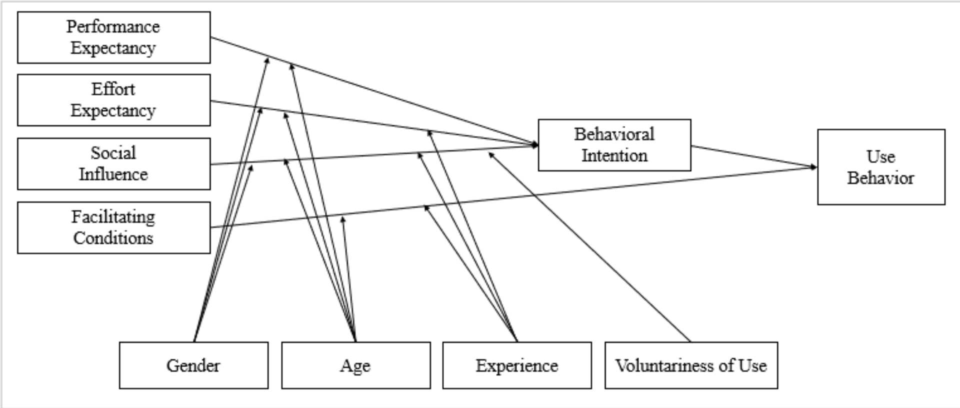

Figure 2.1. Research model of UTAUT. Adapted from Venkatesh, V., Morris, M. G., Davis, B. G., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

2.1.2 Unified Theory of Acceptance and Use of Technology 2

Despite the widespread use of the UTAUT model, questions have been raised about its ability to explain the adoption of technology (Chao, 2019). Thus, the original UTAUT has been extended to form UTAUT2, which was developed to explain and predict users' acceptance and utilisation of technology (Venkatesh et al., 2012). It emphasises individual viewpoints in technological adoptions, sustaining better at describing variations in users' technical intentions (Huang & Kao, 2015). Nevertheless, Figure 2.2 has included additional components underlying UTAUT's theoretical context, such as hedonic motivation, habit and price value. These three additional components provide better insights into the determinants that influence users' adoption and utilisation of technology, taking both hedonic and utilitarian, automatic behaviour and cost considerations into account (Venkatesh et al., 2012). Additionally, UTAUT1 is more concerned with the technology adoption within an organisation while UTAUT2 is developed to examine the adoption in a more consumer-oriented context (Venkatesh et al., 2012).

Hedonic motivation can refer to the enjoyment or pleasure gained from utilising technology. Several studies (Brown & Venkatesh, 2005; Childers et al., 2001; Heijden, 2004; Thong et al., 2006, as cited in Venkatesh et al., 2012) have highlighted hedonic motivation as an essential determinant in technology acceptability and usage in the consumer context. The more the anticipated fun and enjoyment components from technology usage, the more likely customers will adopt the technology (Sebastian et al., 2022).

Besides, habit, as defined by Limayem et al. (2007) and Venkatesh et al. (2012), refers to which customers automatically adopt technology or technological products. It means that the consumer uses technology at a level of comfort and familiarity, which may lead to continuing usage and behavioural intention (Huang & Kao, 2015). There are three criteria comprising the components such as previous behaviour, reflex behaviour, and individual experience, and it has directly affected decision-making on the technology (Huang & Kao, 2015). According to prior studies on habitual intentions, technological usage is significant in fostering behavioural intention changes (Sebastian et al., 2022).

Price value, as described by Dodds et al. (1991, as cited in Venkatesh et al., 2012), pertains to the cognitive balancing act between the perceived benefits of technologies and the monetary expenses associated with their use. This component evolved from perceived value, frequently viewed as a significant predictor of buying behaviour that may impact the intention of using a system (Huang & Kao, 2015). People always seek to maximise the net profit, which implies that if the adoption and use of technology may generate favourable outcomes, it may provide a favourable sensation and impact to users (Sebastian et al., 2022).

In the studies that have tested the model, the additional components enable the model to build a predictive capability, which boosts its potential for anticipating user adoption by up to 74% (Venkatesh et al., 2016, as cited in Sebastian et al., 2022). Thus, UTAUT2 is highly effective at predicting user behaviour and providing insightful information into the components that drive and inhibit technology adoption and use (Huang & Kao, 2015).

<u>Research Model of UTAUT2</u>

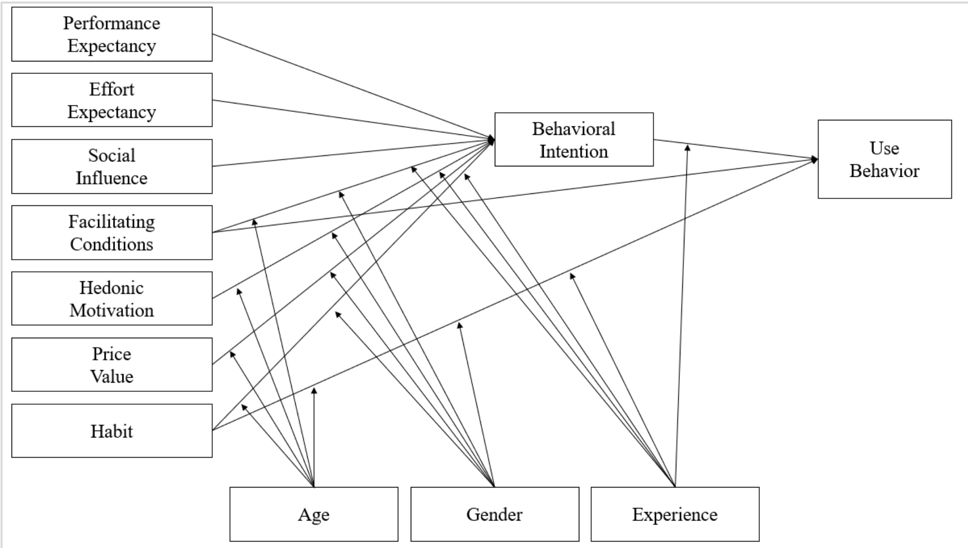

Figure 2.2. Research model of UTAUT2. Adapted from Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly, 36*(1), 157-178.

2.2 Review of Variables

2.2.1 Behavioural Intention to Use Robo-advisory Services in Malaysia

Behavioural intention is regarded as a personal evaluation of the likelihood of a specific behaviour (Fishbein & Ajzen, 1975). It is also concerned with whether users of a particular technology will stick with or abandon the service provider (Zeithaml et al., 1996). To put it simply, behavioural intention refers to how likely someone perceives himself or herself to be involved in certain behaviours or embrace technology.

During the digitalization, financial technology solutions such as e-wallets, digital banking, and robo-advisors have gained significant prominence. The emergence of robo-advisors gives investors an alternative advisory solution to portfolio managers due to their unique features. Compared to portfolio managers, robo-advisors provide investors who lack financial resources with the opportunity to start investing at a low initial cost (Gomber et al., 2018; D'Acunto et al., 2019). Yet, investors who lack knowledge or experience in investments can enjoy the benefit of portfolio diversification through robo-advisory solutions (Gomber et al., 2018). Furthermore, robo-advisory services are available 24/7, which provides great convenience and flexibility to investors (Park et al., 2016).

The recent COVID-19 pandemic has fastened the pace of digitalization globally, which in turn has enhanced the popularity of robo-advisors among consumers (Isaia & Oggero, 2022). The emergence of robo-advisors gives rise to research opportunities to examine determinants that impact the intention to embrace robo-advisory services.

According to Venkatesh et al. (2012), numerous factors can influence an individual's willingness to embrace technology. As an extension to the robo-advisory context, platform-specific variables, or characteristics of robo-advisors, such as price, level of enjoyment provided, ease of use and benefits given, can influence consumers' intentions to adopt robo-advisors. From a psychological perspective, factors like habit and peer influence may affect the behavioural intention towards using robo-advisors. Also, sociodemographic variables like age, gender and personal experiences could have a direct or indirect impact on an individual's intention to adopt robo-advisors.

2.2.2 Performance Expectancy (PE)

Performance expectancy means the degree to which a person expects that using the application will help them perform better at work (Venkatesh et al., 2003). Multiple research has revealed that performance expectancy is critical in affecting consumers' decisions to adopt technology. Since understanding a degree of self-benefit is a justification for adopting technology, if consumers believe such services will benefit them, they will use them more frequently (Yeh et al., 2022). The same goes for the robo-advisors.

From the study conducted by Gan et al. (2021), consumers' perception of robo-advisory services' ability to help with managing their finances and investments may have an impact on their propensity to use them. The study by Gan et al. (2021) revealed that the usage intention regarding robo-advisors among Malaysians is positively and significantly connected to performance expectancy. Moreover, based on Nourallah (2023), using robo-advisors without experiencing major problems will provide young retail investors with a pleasant image and increase their trust in this technology. The result of the study among Malaysian and Swedish revealed a positive correlation between performance expectancy and initial trust in robo-advisors. Chan et al. (2022) also illustrated a positive and significant association between performance expectancy and usage intention of fintech services. Based on the statement mentioned above, the higher the level of performance expectancy, the more likely they intend to adopt it. The results are similar to the study conducted by Oliva et al. (2019) and Phuong et al. (2022).

However, there is a different point of view from the studies of Rizkiana (2020) and Putra et al. (2022). They revealed that performance expectancy is insignificant in affecting the intention to use fintech payment services. Megadewandanu et al. (2016) also claimed that performance expectancy shows insignificant results in the intention of using fintech services. This could mean that even if the service improves consumers' performance, it does not guarantee usage.

Multiple research stated that performance expectancy is significant in determining the usage intention towards robo-advisors. Thus, the hypothesis is formed as follows:

H_0: Performance expectancy has no significant relationship with the behavioural intention to use robo-advisory services.
H_1: Performance expectancy has a significant relationship with the behavioural intention to use robo-advisory services.

2.2.3 Effort Expectancy (EE)

Effort expectancy implies the extent of comfort or ease involved with which the technology is used (Venkatesh et al., 2003). They further added that this variable is likely to be significant during the initial implementation but will become insignificant in the longer term and post-adoption usage.

In the study conducted by Nourallah (2023) based in Sweden and Malaysia, only in Malaysia did effort expectancy have a positive and significant impact on early confidence towards robo-advisors, highlighting how ease of use is important to Malaysians. Thus, consumers will perceive more user-friendly robo-advisors with less effort needed, encouraging them to trust the technology. According to the findings of Milani (2019), those who think that robo-advisors are complicated to use and comprehend are less inclined to have favourable attitudes towards robo-advisors and vice versa, implying a positive and significant correlation. The findings are consistent with Aseng (2020) and Senyo and Osabutey (2020).

Nevertheless, there are also findings providing an opposite viewpoint. To further illustrate, Gan et al. (2021) found that effort expectancy is insignificant in explaining the robo-advisor’s adoption. Also, utilising the model provided by Zhou et al. (2010), effort expectancy showed an insignificant association with adopting fintech services. It is in line with Butarbutar et al. (2022) and Shamsurin Ahmad et al. (2021). This may clarify why, despite the user's perception that the services are simple to use and take little effort, it is not important in predicting the adoption of the services.

According to previous studies, there has been a favourable yet substantial association between effort expectancy and the intention towards utilising FinTech. Hence, the hypothesis is formed as follows:

H_0: Effort expectancy has no significant relationship with the behavioural intention to use robo-advisory services.
H_2: Effort expectancy has a significant relationship with the behavioural intention to use robo-advisory services.

2.2.4 Social Influence (SI)

Another important variable that influences people’s acceptance of technology is social influence. According to Venkatesh et al. (2003) and Venkatesh et al. (2012), social influence pertains to the extent of an individual's belief that significant people feel a specific technology should be used. The focus of this study has been on people’s perceptions of how significant others, like family members, relatives and friends think they should embrace robo-advisory services during the technological adoption process. It is also mentioned in UTAUT that this variable is positively correlated to technology adoption (Venkatesh et al., 2012). Literature has shown that it positively influences an individual's behavioural results (Fishbein & Ajzen, 1975; Taylor & Todd, 1995, as cited in Belanche et al., 2019).

According to Yeh et al. (2022), social influence positively influences the attitude in using robo-advisors, consequently, significantly influencing the intention of adopting robo-advisors. Thus, social influence, such as thoughts and remarks from friends or famous figures, may affect the attitudes of users.

Mohammad Husam Odeh (2019) stated that social influence is examined to be an important determinant of technology, demonstrating a significant positive correlation between social influence and the intention towards adopting financial information systems. People are affected not only by the advantages of fintech but also due to the user community within the user's social circle (Chuang et al., 2016, as cited in Shamsurin Ahmad et al., 2021). The result aligns with the outcomes studies of Gerlach and Lutz (2019) and Soodan and Rana (2020), as cited in Gan et al. (2021). Thus, while making such usage decisions, consumers are influenced by the expectations of others.

However, there are different viewpoints on the concept of social influence. Khan et al. (2017, as cited in Milani, 2019) determined that social influence is insignificant in explaining the behavioural intention in adopting fintech services. The study by Shamsurin Ahmad et al. (2021) similarly concluded that there is no correlation between social influence and the acceptance of fintech payment services, which is consistent with the studies of Chen et al. (2019) and Alalwan et al. (2017).

Since the robo-advisory services provide automated financial guidance, the opinions of others appear to be an important part of moulding people's initial faith in robo-advisors, contributing to the adoption of the services. Given that people from various cultures may not behave the same way when it comes to following peer views, it is suggested that social influence and intention towards using robo-advisory services are positively significant.

H_0: Social influence has no significant relationship with the behavioural intention to use robo-advisory services.

H_3: Social influence has a significant relationship with the behavioural intention to use robo-advisory services.

2.2.5 Facilitating Conditions (FC)

The perception of organisational and technological infrastructure as existing to assist system utilisation is measured by the concept of facilitating conditions (Venkatesh et al., 2003). Kamaghe et al. (2020, as cited in Ambarwati et al., 2020) highlighted that a lack of direction, motivation, and support, as well as a lack of proper knowledge and resources, may deter people from embracing technology. It implies that various facilitating circumstances, such as training and assistance, may be offered without charge inside the organisation and are consistent among users who are more inclined to adopt the technology (Mansour et al., 2021).

Facilitating conditions is one of the primary components of behavioural intention towards adopting technologies (Mansour et al., 2021). Rahmen et al. (2020, as cited in Gan et al., 2021) discovered that facilitating conditions affect intention and actual behaviour to embrace mobile financial services. It mentioned that robo-advisors provide services with no human assistance, creating facilitating conditions that may attract people to use the platforms (Gan et al., 2021). Based on Yeh et al. (2022), various researchers (Chawla & Joshi, 2019; Chatterjee & Bhattacharjee, 2020) proposed that facilitating conditions positively impact behavioural intention in terms of technical infrastructure. As a result, the study of robo-advisors based on UTAUT research has shown a positive impact on behavioural intention influenced by facilitating conditions (Yeh et al., 2022). Consequently, it indicates that technological and organisational infrastructure is user-friendly and adaptive, leading to a positive evaluation which may build greater usage intentions (Ghazali et al., 2018, as cited in Yeh et al., 2022). Kiranga and Chotiyaputta (2021) also found a positive relationship in the context of mobile banking in Pakistan.

Nonetheless, Venkatesh et al. (2003) discovered that effort expectancy has full mediation over the impact of facilitating conditions on behavioural intention. To simplify, facilitating conditions would become predictive of intention in the absence of effort expectancy. For example, facilitating conditions do not drive a customer towards utilising fintech digital payment services (Kurniasari et al., 2022). Additionally, Gan et al. (2021) also found an insignificant association between facilitating conditions and intention towards using robo-advisors in Malaysia.

The studies mentioned above have reported conflicting results regarding the effect of facilitating conditions towards the behavioural intention of using robo-advisors. Hence, the hypothesis is formed as follows:

H_0: Facilitating conditions have no significant relationship with the behavioural intention to use robo-advisory services.
H_4: Facilitating conditions have a significant relationship with the behavioural intention to use robo-advisory services.

2.2.6 Hedonic Motivation (HM)

Hedonic motivation, as defined by Brown and Venkatesh (2005), is the satisfaction one derives from using technology and is a major component in affecting technological adoption. Traditionally, the primary hedonic variable has been thought to be perceived enjoyment (Van der Heijden, 2004). Lee et al. (2005) defined perceived enjoyment as how much a person enjoys using a technology despite the potential performance repercussions and added that perceived enjoyment can be explained from an intrinsic motivational perspective. Thus, hedonic motivation can be conceptualised as perceived enjoyment or intrinsic motivation (Venkatesh et al., 2012).

Venkatesh et al. (2012) applied UTAUT2 to examine factors influencing consumers' behavioural intentions in using technology and discovered that hedonic motivation positively and significantly impacts such intentions. Likewise, Thong et al. (2006) stated that perceived enjoyment significantly influences the users' continued information technology usage intentions. Equivalent results were obtained while focusing on digital transactions, showing an important correlation to the behavioural intention in adopting mobile banking (Baptista & Oliveira, 2015; Boonsiritomachai & Pitchayadejanant, 2017) and mobile commerce (Zhang et al., 2012). In recent related research, Nourallah (2023) stated a positive association between hedonic motivation and preliminary confidence in robo-advisors, which is consistent with the findings of Hohenberger et al. (2019).

On the contrary, Wardani et al. (2021) found that hedonic motivation does not exhibit a significant correlation towards embracing financial technology. It does not directly impact the intention to use technology (Zhang & Li, 2004; Venkatesh et al., 2002). Despite this, hedonic motivation is still important due to its indirect influence on the adoption and usage of technology.

Numerous studies referenced above come with inconsistent findings. This can be a result of the fact that those investigations were conducted in various contexts or under different circumstances. Yet, robo-advisors are still considered a newly developed technology and research on the impact of hedonic motivation is limited. Thus, these contradictory findings encourage further investigation of the connection between hedonic motivation and the intention to utilise robo-advisors.

H_0: Hedonic motivation has no significant relationship with the behavioural intention to use robo-advisory services.
H_5: Hedonic motivation has a significant relationship with the behavioural intention to use robo-advisory services.

2.2.7 Price Value (PV)

Price value denotes the balance consumers strike between the perceived benefits of technology and the financial expense incurred in their utilisation (Venkatesh et al., 2012). It is an essential theoretical component of the expanded model of UTAUT, referring to UTAUT2, since people pay money to utilise technology in the consumer environment. When a user considers that the advantages of embracing technology outweigh the expenses incurred for its usage, it shows a positive association between the perceived value and the intention towards utilising certain technology (Venkatesh et al., 2012). Evaluating the price value helps determine the extent of consumers' openness to accept new technologies (Venkatesh et al., 2012).

Based on past studies, price value significantly influences consumers' behavioural intentions (Mohammed Al-Hawari & Ward, 2006; Lee, 2006; Ho & Ko, 2008; Gerrard et al., 2010, as cited in Fatima et al., 2021). Also, Iqbal et al. (2003, as cited in Mohammed Al-Hawari & Ward, 2006) stated that one of the most important variables of automated service is price. The findings proved that pricing has been included as another element that may impact overall consumer impressions of automated service quality (Mohammed Al-Hawari & Ward, 2006).

Zeithaml (1988) stated that if consumers make fewer tradeoffs, they perceive a better value in the good or service. Based on Singh and Kaur (2017, as cited in Bhatia et al., 2021), robo-advisors can even serve customers with low or no account balances, something portfolio managers cannot. Furthermore, it has been noticed that the costs charged by robo-advisors are lower than those charged by portfolio managers as robo-advisors provide a reduced yearly advisory service for them. Likewise, Wardani et al. (2021) indicated that price value positively influences the behavioural intention towards using financial technologies.

Moreover, researchers have revealed price value to be a key predictor of utilitarian value (Dwivedi et al., 2011, as cited in Fatima et al., 2021). From an investor's viewpoint, robo-advisors are certainly a cost-effective choice for mass and wealthy investors since the services are available even to existing investors who cannot afford skilled portfolio managers and to new investors who may have limited income (Bhatia et al., 2021). Hence, when customers pay less for perceived advantages, they place a higher value on innovation (Islam, 2013). Thus, consumers tend to adopt robo-advisors if they believe it is useful in terms of cost through high perceived value.

Despite that, Sa et al. (2018) found that the expenses associated with robo-advisors do not affect the perceived ease but the perceived usefulness, subsequently influencing the intention towards utilising robo-advisors. This means that it is determined to be beneficial if it is affordable, more economical than existing asset management services, and worth the cost of payment (Sa et al., 2018). However, the cost is considered not significant in the proposed framework. Also, the findings of Sani and Koesrindartoto (2019) are consistent with those of Sa et al. (2018). This implies that the cost level will not affect the intention of consumers to utilise robo-advisors.

Studies referenced above reach varied findings. There are no uniform conclusions, most likely because those studies were conducted under distinct contexts or with different study aims from the beginning. Because of the availability of disputes and two-way assertions, the relationship between price value and behavioural intention towards utilising robo-advisory services is being further investigated in this study.

H_0: Price value has no significant relationship with the behavioural intention to use robo-advisory services.
H_6: Price value has a significant relationship with the behavioural intention to use robo-advisory services.

2.2.8 Trust (TT)

Rousseau et al. (1998) indicated trust as a psychological condition that underlies behaviour rather than the behaviour itself. Based on the period before and after a service is adopted, trust could be distinguished into preliminary and ongoing trust (Lee & Choi, 2011). Preliminary trust means the propensity to trust other people in the absence of prior information or knowledge (Lee & Choi, 2011), whereas ongoing trust is seen as trust depending on experience, which is founded on continuous encounters between customers and service providers (Urban et al., 2009).

In the context of FinTech, trust is a key determinant that influences fintech services adoption (Hu et al., 2019; Jüngera & Mietznerb, 2020), particularly at the early stage of building trust (Bhatia et al., 2020). According to Lee and Kim (2020), initial trust is developed based on the stimulus offered by fintech innovation. In addition, it can also be founded on the brand image of the fintech providers (Bhatia et al., 2020).

Numerous past studies have shown that trust motivates one's intention towards technology usage in the context of digital banking (Sharma & Sharma, 2019; Kaabachi et al., 2017; Chong et al., 2010) and e-wallets (Bui & Bui, 2019; Singh & Sinha, 2020). Consistent results were also obtained in a series of e-commerce-related studies, indicating that consumers' trust drives their online purchase intention (Chang & Chen, 2008; Jadil et al., 2022). Collectively, these findings indicated that trust motivates the behavioural intention to use modern technologies. Thus, trust should also have an identical impact in the context of robo-advisory.

By extending the UTAUT model, Nourallah (2023) found that preliminary trust positively affects the intention towards using robo-advisors via a survey conducted among young retail investors in Malaysia and Sweden. She further elaborated that young retail investors are willing to trust robo-advisors even in the absence of prior experience. Correspondingly, Wang and Pradhan (2020) and Bruckes et al. (2019) showed a positive association between preliminary trust and intention regarding the use of robo-advisors among seniors and respondents with a basic understanding of robo-advisors respectively. Customers tend to trust and use robo-advisors if they perceive that they are trustworthy and effective.

Furthermore, Gan et al. (2021) proved that trust positively and significantly affects the intention towards utilising robo-advisors in Malaysia using the UTAUT model, aligning with the results of Nourallah et al. (2022). Nevertheless, some doubted the accuracy of their findings since both studies were conducted during the COVID-19 pandemic. One could argue that the close contact restrictions during the pandemic may have increased people's willingness to trust robo-advisors as a substitute for portfolio managers, motivating the usage of robo-advisors (Gan et al., 2021). Other than that, Oehler et al. (2022) stated that there is no linkage between consumers' decisions to adopt robo-advisors and their level of trust, but this finding may be due to the lack of familiarity with robo-advisors among their respondents.

Most previous studies discussed above have shown a positive relationship between trust and the intention to use robo-advisors. Thus, hypotheses are developed with the expectation that trust has a significant impact on the behavioural intention to use robo-advisors.

H_0: Trust has no significant relationship with the behavioural intention to use robo-advisory services.
H_7: Trust has a significant relationship with the behavioural intention to use robo-advisory services.

2.3 Proposed Theoretical Framework

Proposed Conceptual Framework

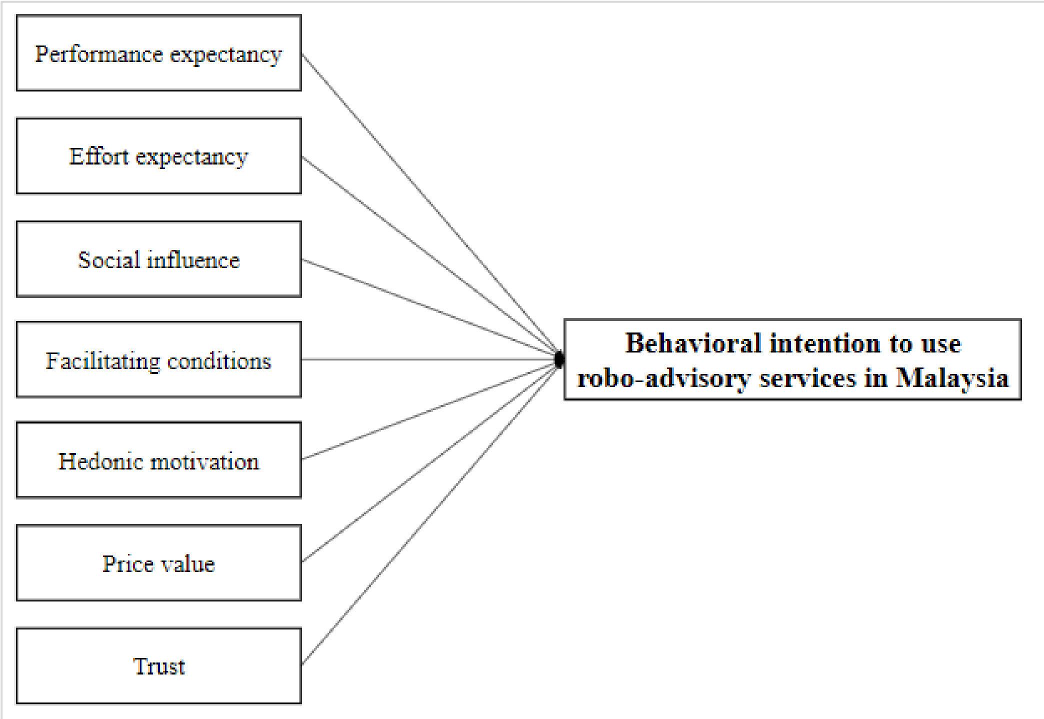

Figure 2.3. The proposed conceptual framework. Developed for the study.

The modified version of UTAUT, which is the UTAUT2, is applied in this study and the figure above is the theoretical framework of factors affecting the behavioural intention to use robo-advisory services in Malaysia. There are seven factors mentioned in the UTAUT2 model; however, six of them will be used with an external independent variable, which is Trust. The factor of Habit from the original UTAUT2 model is not applicable as the study focuses on people who have not used robo-advisors before. Therefore, the seven determinants in Figure 2.3 are used to investigate how they influence the behavioural intention to use robo-advisory services in Malaysia.

2.4 Conclusion

Chapter two covers a review of past studies and relevant theories. The intention to employ robo-advisory services in Malaysia and the link between each independent variable and that intention has been examined. Aside from that, the theoretical framework and hypotheses to be applied in this study have been developed and presented. Therefore, the subsequent chapter will emphasise the research methodology and data analysis.

CHAPTER 3: METHODOLOGY

3.0 Introduction

Chapter three presents the research design and methodologies applied in this study. All of them are utilised to achieve the study's objectives and respond to the research queries outlined in the first chapter.

3.1 Research Design

Research design implies the organisation of parameters for gathering and analysing data, intending to balance economy and method with relevance to the research objectives (Jahoda et al., 1951, as cited in Akhtar, 2016). It serves as a guide for gathering, evaluating, and interpreting information and data (Akhtar, 2016). Hence, it implies a structured strategy with detailed processes that allow researchers to test the hypothesis and achieve the study's objectives, as well as guarantee that pertinent and valuable data is gathered and positively affects the research's efficacy.

3.1.1 Descriptive Research

In this study, descriptive research is chosen as the research method applied. It is a type of analysis that focuses on outlining the features of the population or issue under the study rather than asking "why" it occurs (Manjunatha, 2019). Its importance is based on the idea that through observation, analysis, and description, the respective issues can be resolved, and practices may be made better. Thus, surveys are used to gather a large scale of data by distributing questionnaires to numerous respondents and the SmartPLS software is employed for data analysis.

3.2 Data Collection Method

3.2.1 Primary Data

This study focuses on gathering primary data. Primary data is unpublished information that was obtained directly from a source that has not been altered by anyone (Taherdoost, 2021). Hence, various techniques are used to obtain and compile primary data for a certain purpose. Based on Kabir (2016a), primary data is more trustworthy and reliable since humans have not modified it; thus, its validity is higher than that of secondary data. These features are crucial for some research methodologies where the information used must be tailored to a particular issue and cannot be obtained from published sources (Taherdoost, 2021).

To gather primary data, various survey distribution methods are utilised to obtain responses from the M40 population located in urban and big cities, such as Kuala Lumpur, Johor and Penang, with higher average household income. By conducting surveys, the data can be obtained instantly and exported into specialised statistical tools for further analysis. After receiving sufficient responses, the data is compiled and analysed using SmartPLS software through Partial Least Square Structural Equation Modelling (PLS-SEM).

3.3 Sampling Design

Based on Kabir (2016b), sample design implies the strategies to be utilised for selecting sampling from the target population and the formula for computing sample statistics, which are used to determine the population's characteristics. In other words, based on Singh (2019), sampling is the process of choosing representative samples from a group to estimate and anticipate the outcome of the population and to find the elusive piece of information (Singh, 2019).

3.3.1 Target Population

The sampling process starts with precisely identifying the target demographic (Taherdoost, 2016). The group of people that a study is intended to help is referred to as the target population (Godwin et al., 1998). A study needs to identify its target population to ensure the right cases are obtained to provide useful results.

This study targets the population who fall within the Middle 40% (M40) income group category in Malaysia. M40 refers to a household having a monthly income of RM4,850 to RM10,959 (Department of Statistics Malaysia [DOSM], 2019). In Malaysia, M40 households make up roughly 2.97 million of the total households (37.6% of the total 7.9 million households) (DOSM, 2023).

The main reason for choosing this target population is that individuals with higher income levels typically have more disposable income. They tend to have extra money to spare after paying for necessities like housing loans, food, and healthcare. Thus, their additional funds can be allocated towards investment, such as through robo-advisors. Therefore, it can be concluded that since those under the M40 income group are mostly working adults who tend to be more affordable to have extra funds to be put into an investment, such as robo-advisory services, they are suitable to be the target population or respondents of this study.

3.3.2 Sampling Frame and Sample Location

The sampling frame, also referred to as the operationalised representation of the target demographic, is the collection of units used to draw a sample from the population (Casteel & Bridier, 2021). Usually, a single person is a particular unit chosen as the study's participants. In this study, the sampling frame includes both younger and older adults who fall under the M40 income group from different areas in Malaysia. Besides, sampling location can be defined as a location where the data of the targeted respondents are collected. Thus, the questionnaires for this study will be distributed physically and digitally to the target population, especially in big cities.

3.3.3 Sampling Method

According to Casteel and Bridier (2021), the sampling method can be defined as the strategy used to collect the sample's constituents. There are two main sampling methods, and non-probability sampling is used. While populations are hidden from view and neither random nor probability sampling is an option, this sampling technique is more suitable (Casteel & Bridier, 2021).

A non-probability sampling method is used since this study is targeting a specific population, which is individuals from the M40 income group. Hence, not all members of the population can participate in the study. In terms of non-probability sampling, convenience sampling is utilised in this study. Based on Casteel and Bridier (2021), convenience sampling means recruiting from an appropriate sampling frame and choosing participants depending on their proximity to the researcher. Generally, it is highly accessible, economical, and practical for sample collecting, which has been chosen because of the sample size and the fact that time and resources are restricted. Since the M40 population in this study is large, the convenience sampling method is then helpful to rapidly gather a large number of questionnaires within a limited time frame.

3.3.4 Sampling Size

As mentioned by Andrade (2020), a larger than necessary sample is more representative of the population since it tends to produce a more accurate result. A smaller sample size can lead to Type II error, which means the researcher fails to reject a false null hypothesis due to lower statistical power (Andrade, 2020). Nevertheless, after a certain point, there is limited room to improve the accuracy and it is not worth the time and money spent on finding extra respondents. Hence, the appropriate sample size is crucial.

According to Business Today (2022), the category of M40 income group consists of 2.91 million households in Malaysia. If the size of the target population exceeding 1,000,000 is estimated at a 95% confidence level with a 5% margin of error, the required sample size for the study is 384 (Taherdoost, 2017), which is considered a desired amount of sample size to represent the target population. Therefore, this study aims to collect data from 400 respondents through the survey.

3.4 Research Instrument

A research instrument can be defined as a tool used by researchers to gather, assess, and analyse data from respondents relating to the research design (Wilkinson & Birmingham, 2003). Several tools can be used in a study; however, the questionnaire is utilised for further data collection and analysis in this study. Based on Krosnick and Presser (2009), the questionnaire is particularly important as the result of the survey depends significantly on the questionnaires distributed. Hence, questionnaire designs should adhere to the best practices to minimise answer errors.

3.4.1 Questionnaire Design

A questionnaire can be defined as a set of questions that are asked to persons to gather statistically meaningful information about a certain topic (Roopa & Rani, 2012). In this study, each questionnaire includes 66 questions in total, which can be categorised into Section A and Section B. Section A comprises the demographic information of the respondents, which is their details. It consists of 9 questions, including gender, age group, region, ethnicity, marital status, education level, income group, the respondent's experience investing with robo-advisory services, and their intention to use the robo-advisory services.

Additionally, there are 8 subsections in Section B, including both dependent and independent variables. The five-point Likert scale is applied to answer the questions on the intention to use the robo-advisory services in Malaysia, which is influenced by performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and trust. Respondents must select the best response from a five-point Likert scale. Scale 1 indicates that the respondent strongly disagrees with the statement, whereas scale 5 indicates that they firmly agree with the statement [1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree].

3.4.2 Pilot Test

A study with an appropriate experimental design is necessary to produce high-quality results. Hence, evaluating the study's viability before conducting the main study can be extremely helpful. A pilot study – typically a smaller-scale study that aids in planning and modifying the main study – is the initial step of a complete research methodology to assess the validity of the main trial (In, 2017). This is because performing a pilot test can provide early warning about potential failure areas for the main study, potential protocol violations, and whether suggested procedures or instruments are appropriate or overly complicated (Van Teijlingen & Hundley, 2001).

Therefore, a pilot questionnaire will be distributed and completed by 30 target respondents. After the collection, the data will be inserted into the designed software to run the analysis. A variety of results of outer loading, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted can be obtained. Hence, once the potential defeats of the survey are discovered, the designed questionnaire will be modified based on the answers collected.

3.5 Construct Measurements

The survey questionnaire is constructed to examine the 7 independent variables that affect Malaysians' intentions to use robo-advisory services, particularly those who fall under the M40 income group.

3.5.1 Scale of Measurement

Measurement refers to the allocation of numbers to things or events following rules (Stevens, 1946). Since numbers can be allocated according to various rules, there are numerous distinct forms of measurement and scales of measurement (Stevens, 1946). There are four specific groups of measurement scales – nominal, ordinal, interval, and ratio (Stevens, 1946). This study utilises three primary scales of measurement, except for the ratio scale during the questionnaire design to collect and analyse data.

3.5.1.1 Nominal Scale

As stated by Allanson and Notar (2020), nominal scales are the weakest type of measurement as they can only be used to label or categorise data. There is no numerical value or order to nominal scales. In other words, nominal data cannot be quantified or ranked. Hence, it is incapable of undergoing any mathematical operations. Furthermore, when numbers are allocated to a nominal category, there is no indication of ranking or order, they simply represent a unique label for that category. Thus, the nominal scale numbering indicates a qualitative difference rather than a quantitative difference. However, the researchers can use percentages or modes to measure the preference and popularity of each nominal category. For instance, gender, race, nationality, and marital status are some common nominal variables used to access the demographic profiles of respondents. Marateb et al. (2014) further added that survey questions with a yes or no option are nominal.

3.5.1.2 Ordinal Scale

The ordinal scale is the most frequent measurement scale applied in research studies (Stevens, 1946). According to Allanson and Notar (2020), both nominal and ordinal scales can be used to classify data into distinct categories. However, the main distinction between them is that there is a clear ranking or order for the ordinal categories. Although the ordinal data can be ranked, it is also incapable of undergoing any mathematical operations due to the unequal distance between rankings and the non-existence of a true zero value. For instance, education level, income level, and age group are some common ordinal variables.

3.5.1.3 Interval Scale

Interval scales are numeric scales with fixed and equal distances between each value on the scale but do not hold a true zero value (Marateb et al., 2014). In addition to classifying and ranking data, interval scales provide more sophisticated statistical analysis than nominal and ordinal scales as the computation of mode, median, mean, and standard deviation is allowed in interval scales (Allanson & Notar, 2020). For instance, a five-point Likert scale is an example of an interval scale with a fixed and equal distance between each rating score. It can be applied to gauge how much respondents agreed, were satisfied, or were likely to respond to certain statements outlined in the survey.

3.6 Data Processing

After data collection, the raw data of the respondents have to be transformed into usable or readable information for further comparisons and analysis. This procedure is known as data processing. It involves checking, editing, coding, and transcribing the data. In this study, 500 questionnaire sets are given out to gather responses from the intended participants. All the data collected is entered into SmartPLS 4.0 for data analysis.

3.6.1 Data Checking

Data checking involves filtering unnecessary or useless data after gathering the survey responses to ensure the validity of the data. The objective is to ensure that the right target respondents answer the entire set of the questionnaire correctly. Thus, researchers should exclude questionnaires with incomplete or incorrect survey responses. Besides, questionnaires that are completed by the wrong population should also be eliminated. This process is necessary for deriving reliable and accurate research results from the target population.

3.6.2 Data Editing

Editing the raw data comes first before analysis can begin. It is the process of finding flaws and omissions in the questionnaire returned by the respondents and making necessary corrections. The objective is to ensure the data collected is accurate and compatible with the research's objectives. Thus, the survey responses collected are dependable enough to reflect the viewpoint of the entire target population. Furthermore, data editing helps facilitate the coding and classification of data for further analysis.

3.6.3 Data Coding

Data coding is the process of allocating numbers or symbols to the survey responses to categorise them into a small number of groups. It eases the data entry in SmartPLS 4.0 for efficient analysis. For instance, male respondents are coded as 1 and female as 2 in Section A of the questionnaire. For Section B, the five-point Likert scale is used to measure the respondent's level of agreement with the statements provided. There are five levels of agreement, strongly disagree, disagree, neutral, agree, and strongly agree. They are coded as 1, 2, 3, 4, and 5 respectively.

3.6.4 Data Transcription

Data transcription is the process of transforming the data gathered from questionnaires into machine-readable form. In this study, the data gathered is converted into Excel format in advance to be directly inserted into SmartPLS 4.0 for data analysis.

3.7 Data Analysis

3.7.1 Descriptive Analysis

Descriptive analysis involves simplifying data in a meaningful manner to reveal patterns and enhance understanding (Loeb et al., 2017). It aids researchers in testing the hypotheses, determining the causal relationship, developing new metrics for their topic of interest, and explaining the demographic patterns of the population. The most common statistical tools that support descriptive analysis are measures of location and dispersion, which consist of mean, range, variance, and skewness (Loeb et al., 2017).

This study conducts descriptive analysis to evaluate the information obtained through the questionnaire. For instance, the demographic data in Section A is analysed through measures of location to identify and summarise respondents' characteristics. Besides, measures of variation are utilised to identify the standard deviation of datasets in Section B.

3.7.2 Partial Least Square-Structural Equation Modelling (PLS-SEM)

PLS-SEM is a statistical technique for estimating relationships between determinants, without requiring assumptions about the data distribution. It is particularly useful for complex models with several elements and paths, which involve a hybrid of multivariate and factor analysis. Estimating both observed and latent determinants allows improvement of knowledge of the structural links between determinants (Hair et al., 2012, as cited in Henseler et al., 2015). PLS-SEM is frequently used to prioritise prediction in modelling and to provide explanations for these connections.

3.7.2.1 Outer Loadings

The analysis of outer loadings refers to the process of obtaining the factor loading for each included indicator. When the outer loadings of items are high, it implies that the items share a common underlying variable that the construct measures. Different authors are arguing about the cut-off values in outer loadings. According to Yusuf Haji-Othman and Mohd Sholeh Sheh Yusuff (2022), all the outer loadings of the items must be statistically significant and attempt at least 0.7, showing that each item is a reliable indicator of the conceptual framework. Besides, Hair et al. (2014, as cited in Yusuf Haji-Othman & Mohd Sholeh Sheh Yusuff, 2022) also mentioned that if the outer loadings are less than 0.7, the effect of removing the item on composite reliability is evaluated. However, it is also stated by researchers (Chin, 1998; Hair et al., 2010, as cited in Memon & Rahman, 2014) that items with outer loading value less than 0.5 should be rejected.

3.7.3 Construct Reliability

Construct reliability measures how consistently the findings hold when they are obtained from different items and assessed under the identical construct. Also, it evaluates if the scores of the items examining the same conceptual framework are comparable, which can be determined by the strength of the correlations between the items.

3.7.3.1 Cronbach's Alpha (CA)

Cronbach's alpha measures the consistency or reliability of survey questionnaires (Nawi et al., 2019). It denotes the number of components in the scale as well as the degree of the inter-correlations. The value's alpha (α) is measured from the range 0 to 1, and it represents the proportion of shared variability among the factors. The formula that represents the concept of Cronbach's alpha is expressed as

$$\alpha = \frac{K * r}{[1 + (K - 1)\bar{r}]}$$

The formula for Cronbach's alpha involves the number of factors (represented by K) and the average correlation between them (represented by r) (Nawi et al., 2019).

According to Taber (2018), the benchmark value of 0.7 or higher is frequently used to indicate whether the items in the measure are consistent enough to be considered reliable. Also, Ursachi et al. (2015) mentioned that Cronbach's alpha value ranging from 0.6 to 0.7 indicates an acceptable level of reliability, while a value of 0.8 or higher signifies a higher degree of reliability. However, values greater than 0.95 do not necessarily indicate good reliability, as they can suggest redundancy in the measure (Ursachi et al., 2015). Therefore, it may be necessary to revise or remove the measure to improve its validity and usefulness.

3.7.3.2 Composite Reliability (CR)

Composite reliability addresses Cronbach's alpha drawbacks by considering the indicators may have different weights (Nils & Frederik, 2010). As stated by Hair et al. (2014, as cited in Yusuf Haji-Othman & Mohd Sholeh Sheh Yusuff, 2022), the aim of accessing CR is to investigate the scale construction's dependability and congruence. It considers the varying outer loadings of components within a construct (Yusuf Haji-Othman & Mohd Sholeh Sheh Yusuff, 2022). The formula that represents the concept of CR is expressed as

$$p_c = \frac{(\Sigma_{i=1}^{n} L_i)^2}{(\Sigma_{i=1}^{n} L_i)^2 + (\Sigma_{i=1}^{n} var\ (e_i))^2}$$

Similar to Cronbach's alpha, a CR value of 0.6 – 0.7 is appropriate for a formative study, whereas, for a more sophisticated study, a value that exceeds 0.7 is required (Hamid et al., 2017). However, values exceeding 0.9 are undesirable, thereby causing inflated correlations among the indicators' error terms (Hair et al., 2021a).

3.7.3.3 Average Variance Extracted (AVE)

The average variance extracted compares the variance owing to measurement error to the variance owing to the conceptual framework (Azwa & Wahab, 2016, as cited in Pervan et al., 2018). The primary use of AVE is to determine how well the dimensional determinants explain the average variance. A larger AVE shows a more adequate convergent validity. The formula that represents the concept of AVE is expressed as

$$AVE = \frac{\Sigma_{i=1}^{n} L_i^2}{n}$$

L_i indicates the standardised factor loading while i is the number of factors (Yusuf Haji-Othman & Mohd Sholeh Sheh Yusuff, 2022).

Following Hair et al. (2014, as cited in Yusuf Haji-Othman & Mohd Sholeh Sheh Yusuff, 2022), the lowest deemed satisfactory level of AVE is 0.5. They also stated that a value below 0.5 suggests that the conceptual framework explains less than 50% of the variance indicator. However, Fornell and Larcker (1981, as cited in Huang et al., 2013) claimed that a conceptual framework still fulfils the validity test when a CR value of 0.6 and above is obtained simultaneously with the AVE that falls below 0.5.

3.7.4 Discriminant Validity

Based on Carmines and Zeller (1979, as cited in Hill & Hughes, 2007), discriminant validity is applied to ensure that the measurements are uncorrelated. It tests whether the constructs that are expected to be independent of each other are independent, suggesting an insignificant relationship or uncorrelation between the determinants. This helps to ensure that the measures used in the study effectively capture distinct constructs and there is no issue of overlap or redundancy among the latent variables being measured (McKenny et al., 2013, as cited in Ronkko & Cho, 2020).

3.7.4.1 Heterotrait Monotrait Ratio of Correlations (HTMT)

Henseler et al. (2015, as cited in Roemer et al., 2021) proposed that HTMT is adopted to examine discriminant validity in Structural Equation Modelling (SEM). Besides, Henseler et al. (2015) also suggested that HTMT has higher specificity and sensitivity rates at around 97% to 99% relative to cross-loading criteria (0.00%) and Fornell-Lacker (20.82%).

Referring to Henseler et al. (2015), the evaluation of discriminant validity between the two constructs can be completed through HTMT via two means. Firstly, the HTMT ratio obtained has to be smaller than 1, indicating that the correlation between two constructs is lower than the average correlation between two constructs and highly not correlated with each other. However, if the HTMT value is nearly 1, it suggests an insufficient level of discriminant validity, meaning that the construct of the underlying concept is too similar and cannot be distinguished from each other, leading to the possibility of inaccurate and unreliable results.

Furthermore, HTMT can be utilised to determine the insufficiency of discriminant validity by using a predefined threshold as a criterion (Hamid et al., 2017). If the value exceeds the stated limit, there is an insufficient level of discriminant validity, leading to potential issues and the inaccuracy of the model. However, different researchers suggest different levels of thresholds for the HTMT method. Various past studies recommended a minimum value of 0.85 (Clark & Watson, 1995; Kline, 2011), while there are further recommendations for a minimum value of 0.9 (Gold et al., 2001; Teo et al., 2008, as cited in Hamid et al., 2017).

3.7.4.2 Fornell-Larcker Criterion

The Fornell-Larcker criterion is being widely used to test the discriminant validity measurement models. This suggests that the construct involves the square root of the average variance extracted (AVE), concerning the correlation among latent variables (Hamid et al., 2017). The AVE of a construct should represent more of its variance than that of other latent variables. Hence, the correlation has to be lower with other latent variables as compared to the square root of the AVE of each variable (Hamid et al., 2017). Although it has been developed for over three decades, there has been no systematic investigation into its usefulness in determining discriminant validity (Henseler et al., 2015). Few authors (Henseler et al., 2014; Ronkko & Evermann, 2013, as cited in Henseler et al., 2015) also recommended that Fornell-Larcker may not be reliable under some circumstances, questioning its effectiveness in assessing discriminant validity.

3.7.5 Evaluation of the Inner Model

The inner model, also known as the structural model, is determined using a path coefficient, indicating how strongly the determinants are connected (Purwanto et al., 2023). The direction of the path coefficient should align with the hypothesised theory and its significance can be determined through a t-test that is obtained from the bootstrapping method (Henseler et al., 2016).

Bootstrapping is a statistical technique that is a non-parametric procedure on specific assumptions about the data distribution and can be used to test the significance of various results obtained through Partial Least Squares (Streukens & Leroi-Werelds, 2016). However, since PLS-SEM does not imply normality, the absence of extreme values leads to the parametric significance tests being unable to evaluate the significance level of outer loadings and route coefficients (Mendez-Suarez, 2021). Therefore, adopting a non-parametric bootstrap helps assess the significance level of estimated coefficients.

3.7.5.1 Path Coefficient

While examining the structural model and hypothesis, the absolute magnitude and significance level of the path coefficients are utilised. It assists in the support and rejection of each hypothesis and also provides insight into the relationship between the latent variables. Mahmudul Hasan Khan et al. (2022) mentioned that if the path coefficient is statistically significant, a causal association is assumed between the dependent and explanatory factors.

The relevance of the path coefficient is generally expressed on a scale ranging from -1 to +1, where values nearer to -1 represent a significant negative association between explanatory variables and explained variables while values nearer to +1 represent a significant positive association (Hair et al., 2021b). Also, if the path coefficient in PLS-SEM exceeds the acceptable range of +1 or -1, it may indicate an issue of multicollinearity.

3.7.5.2 P-value

This study determines whether the determinants are statistically significant by using a predetermined significance level (α) of 5% as a benchmark. The null hypothesis of this study presupposes that there is an insignificant association between the variables. Rejection of the null hypothesis is made when the p-value falls below 5%, indicating that the variable is statistically significant.

3.8 Conclusion

Finally, chapter three has thoroughly discussed the research methods employed and offered some important information for future researchers. All the information regarding study designs, data collection techniques, sampling strategy, research tools, measurement scales, as well as the flows of processing and analysing data have been outlined. The following chapter will go through the relevant data and information gathered through questionnaires.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

Chapter four aims to analyse the questionnaire results. This chapter offers the respondents' demographic information as well as a descriptive analysis. The SmartPLS software program utilised for Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to facilitate the analysis of the data. This software allowed for the assessment of construct validity, discriminant validity, and path coefficient. The obtained results were elaborated upon in-depth, providing a more comprehensive understanding of the study.

4.1 Participation Rate

The summary of survey participants in this study is shown in Table 4.1. 500 surveys were distributed through different methods, such as social media, email, and physical distribution. There is a total of 87.6% response rate and 438 responses collected. However, only 400 responses fulfilled the requirement of the study’s objectives. The remaining 38 respondents are eliminated as it does not meet the requirement of representing the M40 population.

Table 4.1:

Frequency of Total Survey Collected

Items	Total surveys
Number of surveys distributed	500
Number of surveys collected	438
Response rate	87.6%
Number of surveys used	400
Number of surveys filtered out	38

4.2 Descriptive Analysis

Descriptive analysis aims to elaborate, illustrate and summarise the characteristics of the collected data. The collection of descriptive data allows a better understanding of the demographic profile of the respondents. It involves utilising visual aids such as charts, graphs, histograms, and so on to provide a concise summary and interpretation of the gathered data.

4.2.1 Respondents' Demographic Profile

<u>Gender</u>

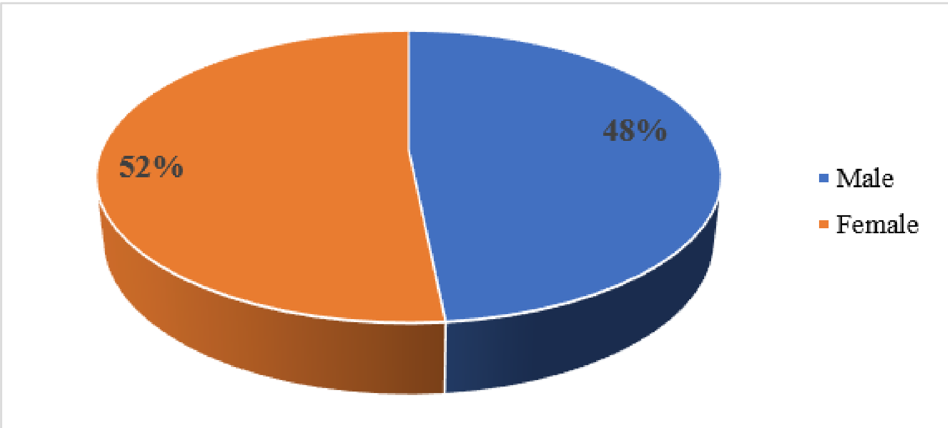

Figure 4.1. Gender. Adapted from the questionnaire for the study.

Figure 4.1 demonstrates the gender distribution of the survey respondents. According to the statistics, 208 (52%) of the respondents are female and 192 (48%) of the respondents are male. Interestingly, this survey achieved a relatively balanced participation rate between male and female respondents, as both groups occupy a similar proportion of the overall collected sample.

Age Group

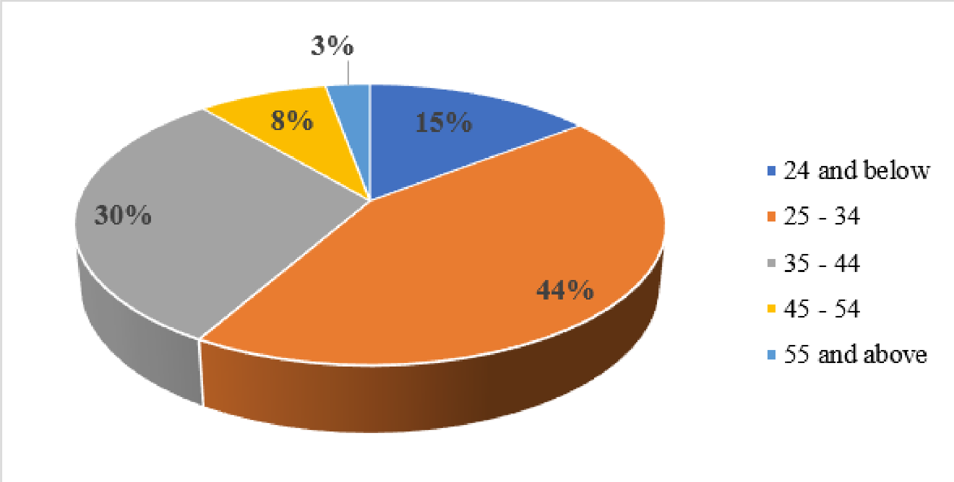

Figure 4.2. Age group. Adapted from the questionnaire for the study.

According to Figure 4.2, the age groups are classified into 5 categories for the demographic information in this study. Among the 400 data collected, it can be observed that the respondents aged 24 years old and below (Generation Z, who were born between 1997 and 2012) represent 15% of the total respondents. Followed by the age range of 25 to 34 years old and 35 to 44 years old, showing 176 respondents (44%) and 120 respondents (30%) respectively. Respondents in both age groups represent Generation Y, who were born between 1981 and 1996, making up a total of 74% of the respondents. Next, 32 respondents (8%) are between the ages of 45 and 54. In the meantime, 55 years old and above held the lowest rate of respondents in this study, which consists of only 12 respondents (3%), suggesting that a relatively small representative of this age group is targeted to participate in this study. The remaining age group represents Generation X, which was born between 1965 and 1980.

Region

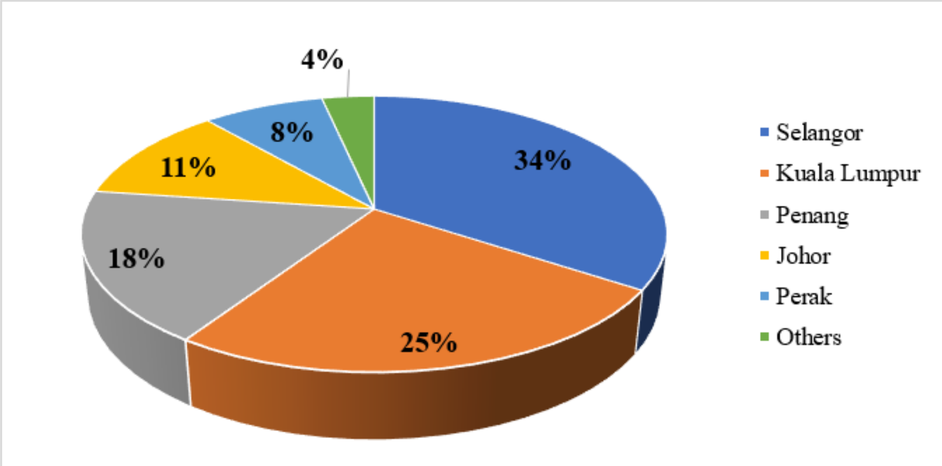

Figure 4.3. Region. Adapted from the questionnaire for the study.

Figure 4.3 describes the distribution of survey participants across different regions. According to the results collected, the population is mainly from urban cities. There are 34% (136 respondents) from Selangor, 25% (100 respondents) from Kuala Lumpur, and 18% (72 respondents) from Penang. Followed by Johor and Perak, which include 11% and 8% of respondents respectively. Lastly, the remaining 4% are from other regions, including Melaka and Pahang.

Ethnicity

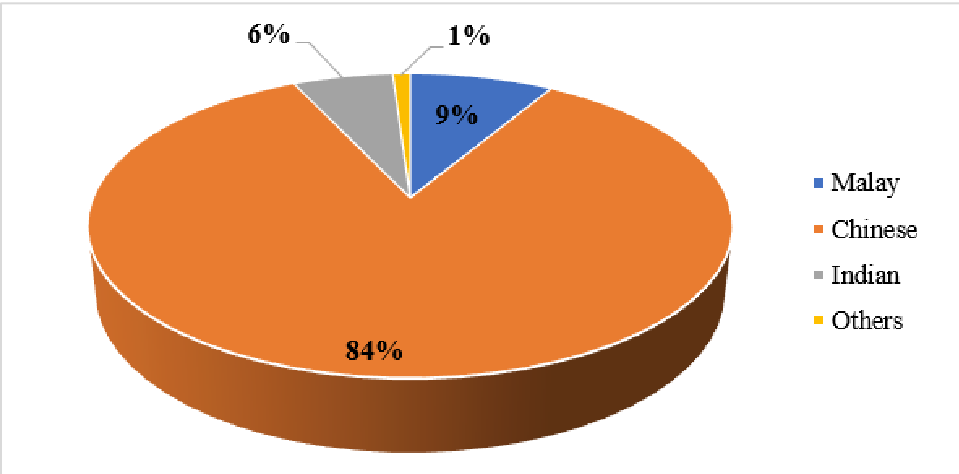

Figure 4.4. Ethnicity. Adapted from the questionnaire for the study.

Figure 4.4 demonstrates the distribution of survey participants across different ethnicities. Out of the 400 respondents, the Chinese achieved the highest rate of response (84%). Additionally, 36 respondents (9%) are Malay and 24 participants (6%) are Indian. The remaining 4 respondents fall into other ethnic categories, including Pakistani, Kadazan, Caucasian, and Iban.

Marital Status

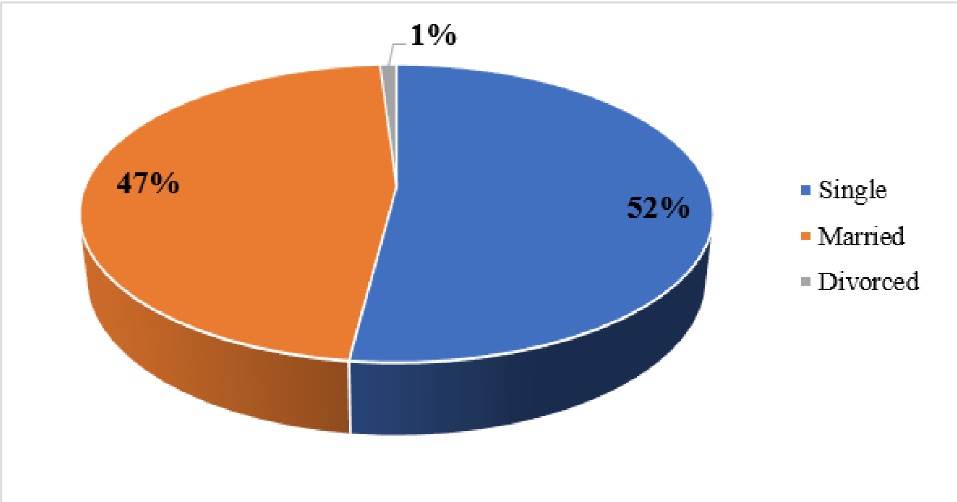

Figure 4.5. Marital Status. Adapted from the questionnaire for the study.

The distribution of respondents' marital status for a total sample size of 400 is shown in Figure 4.5. According to statistics, 208 respondents (52%) of the sample declared themselves to be single accounts. Next, married accounts are reported to be 47%, representing 188 respondents. Moreover, 4 respondents (1%) reported that they have been divorced.

Highest Academic Qualifications

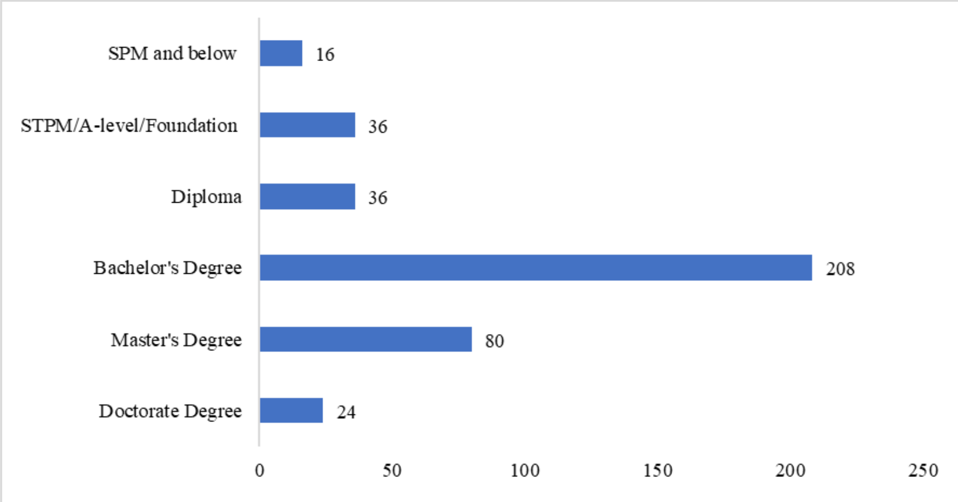

Figure 4.6. Highest academic qualifications. Adapted from the questionnaire for the study.

The educational attainment level of respondents is presented in Figure 4.6, which is categorised into six levels. Among these categories, bachelor's degrees have the highest participation rate, with 208 respondents accounting for 52% of the total. The second-highest contributor is the master's degree category, which comprises 80 respondents, representing 20% of the total respondents. Additionally, Diploma holders and STPM/ A-level/ Foundation qualification, with both consisting of 36 respondents (9%). Followed by the Doctorate holders, which includes 24 respondents, covering 6% of the response rate. Finally, the SPM and below qualifications represent 4% of the total respondents, with 16 respondents falling into this group.

Do you have any experience investing in robo-advisory services?

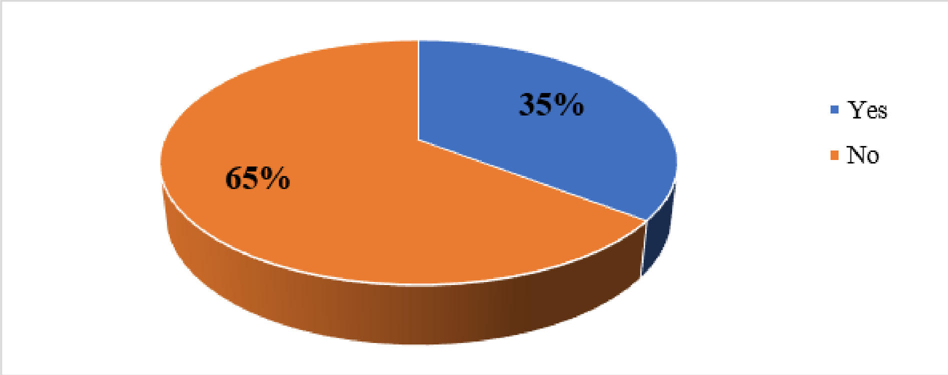

Figure 4.7. Do you have any experience investing in robo-advisory services? Adapted from the questionnaire for the study.

Figure 4.7 describes the respondents' experiences investing with robo-advisory services. There are 260 respondents (65%) who have indicated they do not have any experience with robo-advisory services, while 140 respondents (35%) revealed that they do have experience in adopting the services.

Do you have the intention to use the robo-advisory services in Malaysia?

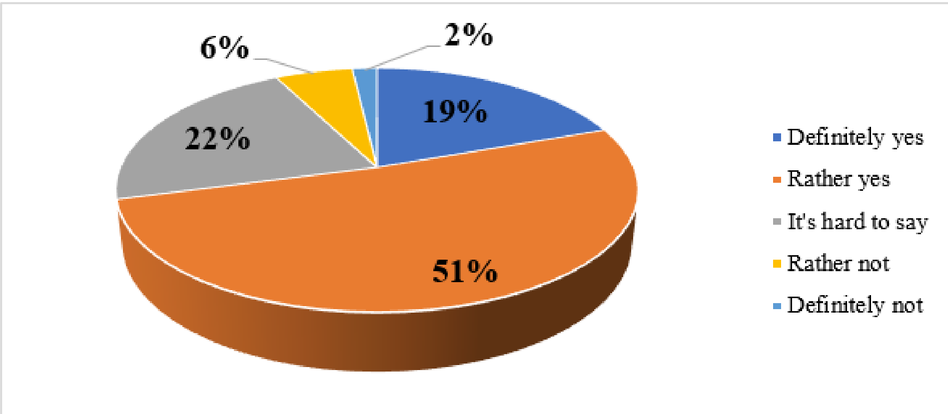

Figure 4.8. Do you have the intention to use the robo-advisory services in Malaysia? Adapted from the questionnaire for the study.

Figure 4.8 demonstrates whether respondents have the intention to use robo-advisory services in Malaysia. The findings indicate that the largest proportion of respondents, accounting for 51% (204 respondents), chose "Rather yes", showing a positive attitude towards using robo-advisory services. Besides, 76 respondents (19%) chose "Definitely yes", expressing a strong intention to use robo-advisory services in Malaysia. An adequate percentage of respondents (22%) found it challenging to determine their intentions. Conversely, a lower proportion of respondents reported "Rather not" and "Definitely not", representing 24 respondents (6%) and 8 respondents (2%) respectively. Throughout the data collected, the results revealed that more than 50% of the respondents demonstrate a strong interest in robo-advisory services.

4.3 Measurement and Structural Model (PLS-SEM)

4.3.1 Outer Loadings

Table 4.2:

Outer Loadings

	BI	PE	EE	SI	FC	HM	PV	TT
BI1	0.827							
BI2	0.708							
BI3	0.860							
BI4	0.825							
BI5	0.866							
BI6	0.879							
PE1		0.792						
PE2		0.825						
PE3		0.752						
PE4		0.781						
PE5		0.718						
EE1			0.766					

EE2	0.810					
EE3	0.796					
EE4	0.851					
EE5	0.729					
SI1		0.730				
SI2		0.779				
SI3		0.736				
SI4		0.739				
SI5		0.721				
FC1			0.725			
FC2			0.778			
FC3			0.790			
FC4			0.788			
FC5			0.731			
HM1				0.799		
HM2				0.796		
HM3				0.818		
HM4				0.818		
HM5				0.700		
PV1					0.708	
PV2					0.752	
PV3					0.812	
PV4					0.837	
PV5					0.789	
TT1						0.823
TT2						0.751
TT3						0.788
TT4						0.779
TT5						0.776

According to the result above, all variables exhibit values that lie within 0.70 and 0.90, which indicates a high level of satisfaction with the outcome of the outer loadings. In addition, the variable that is being discussed, the behavioural intention towards using robo-advisory services in Malaysia, displays its outcome that demonstrates great internal consistency. No items would be removed from this model since none of the variables in the table have values lower than 0.70. Hence, in this model, the discriminant validity is valid.

4.3.2 Cronbach's Alpha, Composite Reliability, Average Variance Extracted

Table 4.3:

Cronbach's Alpha, Composite Reliability, Average Variance Extracted

Constructs	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
BI	0.908	0.929	0.688
PE	0.833	0.882	0.600
EE	0.850	0.893	0.626
SI	0.799	0.859	0.550
FC	0.820	0.874	0.582
HM	0.846	0.890	0.620
PV	0.839	0.886	0.610
TT	0.843	0.888	0.614

According to Table 4.3, all variables exhibiting Cronbach's alpha are greater than 0.7, showing the value computed is satisfactory. The variable of behavioural intention to use robo-advisory services displays the highest Cronbach's alpha of 0.908, indicating it is the most reliable variable among all the variables. Aside from the variable of social influence, the other variables are regarded as having "good" internal consistency reliability since they lie within the range of 0.80 and 0.90. The social influence value of 0.799 is nearly reaching the range too. As a result, the finding suggests that the variables demonstrate high dependability and strong internal consistency.

In addition, Hair et al. (2012) and Bagozzi and Yi (1988) have proposed “Composite Reliability” as a substitute (Wong, 2013). Similar to Cronbach’s alpha, the dependent variable shows the greatest value of composite reliability (0.929). Apart from that, all other variables showed a value greater than 0.8, implying their exceptionally reliable and consistent contribution in explaining the internal consistency of these findings.

Average Variance Extracted (AVE) is employed to evaluate convergent validity by comparing the variance values derived from each construct to the variance values arising from measurement error. AVE must have a minimum value of 0.5 to pass the reliability test. Any value that is less than 0.5 denotes a measurement mistake in the variance. According to the table mentioned above, all variables have values exceeding 0.5, meaning that more than 50% of the variation has been reflected by the latent variable. Therefore, the convergent validity is proven.

4.3.3 Heterotrait-Monotrait Ratio of Correlations (HTMT)

Table 4.4:

Heterotrait-Monotrait Ratio of Correlations (HTMT)

	BI	EE	FC	HM	PE	PV	SI	TT
BI								
EE	**0.661**							
FC	0.657	**0.740**						
HM	0.773	0.755	**0.795**					
PE	0.700	0.634	0.609	**0.671**				
PV	0.742	0.695	0.674	0.769	**0.694**			
SI	0.617	0.552	0.541	0.571	0.591	**0.563**		
TT	0.841	0.655	0.742	0.818	0.761	0.816	**0.593**	

According to the outcomes in Table 4.4, the HTMT ratio of correlations shows that all values are less than 1, with the highest value being 0.841 for the relationship between BI and TT. These results suggest that there are distinct relationships between each pair of constructs in this study with little correlation between them. Additionally, the results derived via HTMT should not exceed the pre-established criteria as an alternate method of determining discriminant validity. Based on the results, no construct combination exceeds the lower criterion of 0.85. As a result, the results of the HTMT ratio of correlations indicate that there are no problems with discriminant validity in this study.

4.3.4 Fornell-Larcker Criterion

Table 4.5:

Fornell-Larcker Criterion

	BI	EE	FC	HM	PE	PV	SI	TT
BI	**0.829**							
EE	0.583	**0.791**						
FC	0.575	0.621	**0.763**					
HM	0.688	0.644	0.667	**0.787**				
PE	0.619	0.543	0.508	0.577	**0.775**			
PV	0.655	0.587	0.561	0.653	0.591	**0.781**		
SI	0.547	0.472	0.453	0.485	0.504	0.475	**0.741**	
TT	0.740	0.554	0.620	0.699	0.644	0.691	0.500	**0.784**

The Fornell-Larcker Criterion theory stipulates that the square roots of AVE for each variable combination must exceed that of other latent variables. According to the table above, the square root of the AVE for each variable combination is shown in each column's top value. The values are each displayed as having the highest value in relation to other latent variables in the same column. As a result, this demonstrates the discriminant validity of the variables in this study.

4.3.5 Path Coefficient

Results of Bootstrapping

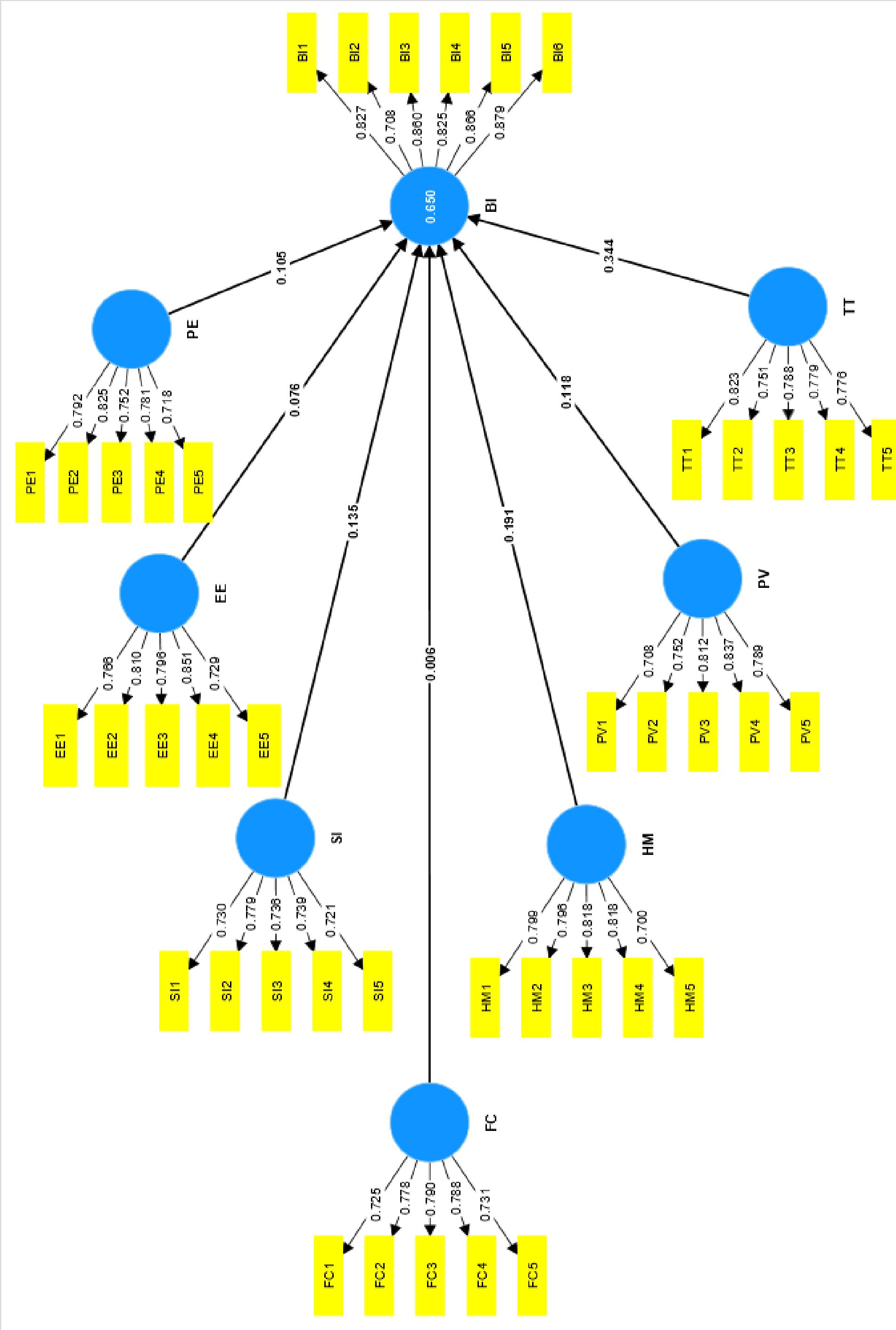

Figure 4.9. Results of Bootstrapping. Adapted from results of SmartPLS.

Table 4.6:

Summary of Structural Model

Constructs	Sample Mean	Standard Deviation	T-stat	P-value	Result
H1: PE -> BI	0.103	0.043	2.434	0.015***	Supported
H2: EE -> BI	0.077	0.047	1.625	0.104	Unsupported
H3: SI -> BI	0.136	0.039	3.425	0.001***	Supported
H4: FC -> BI	0.009	0.049	0.125	0.900	Unsupported
H5: HM -> BI	0.188	0.063	3.039	0.002***	Supported
H6: PV -> BI	0.120	0.057	2.094	0.036***	Supported
H7: TT -> BI	0.345	0.059	5.795	0.000***	Supported

Note: P-value less than or equal to 0.05 (5%) is considered significant***.

Table 4.6 summarises the structural model. It shows that all variables are statistically significant to explain the behavioural intention towards using robo-advisory services in Malaysia, except for effort expectancy and facilitating conditions. The results indicate that performance expectancy and social influence significantly influence the intention to use robo-advisors. One rationale is that individuals are more likely to use it if they believe robo-advisors can improve financial decisions and performance, as well as important people like their family and friends, who use or recommend robo-advisors. The results agree with the earlier research by Gan et al. (2021) and Nourallah (2023) for both variables. In terms of performance expectancy, investors are more willing to adopt this technology when they believe that robo-advisors can enhance their investment returns and performance, making their investment process more efficient (Gan et al., 2021). In terms of social influence, investors would rely on others' opinions that are openly spoken in public when they are unfamiliar with and have never used robo-advisors (Bhattacherjee, 2001).

This study also indicates that hedonic motivation and price value significantly affect Malaysians' intention to use robo-advisory services. According to Hohenberger et al. (2019), a higher degree of joy and pleasure will lead to a stronger willingness towards utilising robo-advisors. Thus, hedonic motivation will improve people's good feelings about robo-advisory services, which may increase their faith in using the services (Gillath et al., 2021; Glikson & Woolley, 2020, as cited in Nourallah, 2023). Besides, in terms of price value, when individuals find that robo-advisors are valuable and worth the costs, they are more likely to use robo-advisory services, and conversely (Bhatia et al., 2020). Thus, the results have shown a significant association between the price value and intention to use. Moreover, trust is also found to affect the intention towards adopting robo-advisors significantly, indicating a positive attitude towards using robo-advisors if individuals believe that these services are reliable and trusted. The result is verified by Gan et al. (2021), Chong et al. (2010) and Kaabachi et al. (2017).

Regarding effort expectancy and facilitating conditions, their relationship to the utilisation of robo-advisors in Malaysia appears to be insignificant. Based on the findings, the intention of Malaysians towards adopting robo-advisors is not directly impacted by both ease of use and technical support. The finding aligns with the journals of Zhou et al. (2010), Fadzil (2017) and Gan et al. (2021). This means that the difficulty in using fintech due to its specifications will not directly affect the consumers' perception (Fadzil, 2017). According to Wang et al. (2014), since modern consumers typically have significant computing knowledge, ease of use (effort expectancy) is no longer an obstacle in adopting technology, resulting in an insignificant result. Besides, there is a statement claiming that in the initial stages of technology adoption, effort expectancy shows an insignificant influence on intention (Davis, 1989, as cited in Hu et al., 2019), implying Malaysia is still in the early stages of robo-advisory development.

In addition, the insignificance of facilitating conditions is evidenced by the studies of Fadzil (2017), Kurniasari et al. (2022) and Nourallah (2023). It is not statistically significant to the behavioural intention to use robo-advisors. Facilitating conditions do not change the intention since individuals have the necessary knowledge and capacity to utilise the technology without extra technical support (Sebastian et al., 2022). Some respondents believed that implementing some practical solutions would increase the behavioural intention to use robo-advisors, but the majority believed that other variables included in this study are more crucial (Jahanbakhsh et al., 2018). Besides, it is possible to be relatively the same among respondents in terms of the facilitating conditions, such as having access to a reliable internet connection, getting help from someone, etc (Zuiderwijk, 2015).

4.4 Conclusion

This chapter covers descriptive analysis and shows all the results obtained through SmartPLS 4.0 software. The obtained data are subjected to descriptive information analysis, reliability testing, discriminant validity testing, and bootstrapping, to examine the relationships and differences between independent and dependent variables as well as the demographic profile of Malaysia's M40 population.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

This chapter includes an overview of the statistical data and a discussion of the key conclusions. Additionally, it discusses the results' implications and the suggestions made to enhance the quality of subsequent studies.

5.1 Discussion of Major Findings

5.1.1 Performance Expectancy

Performance expectancy means the degree to which the robo-advisory services will enhance the investors' wealth management performance. This study shows a positively significant relationship between performance expectancy and the intention to use robo-advisory services in Malaysia. If the robo-advisors can enhance investors' portfolios and are efficient in generating higher returns, investors are more likely to use them with the understanding of benefits and usefulness. The result is consistent with prior studies, such as Oliva et al. (2019), Gan et al. (2021) and Yeh et al. (2022), which found that performance expectancy significantly affects the intention to adopt fintech services. Users may hold robo-advisors to a higher standard of performance than portfolio managers because the automated robo-advisory process does not involve human interaction (Gan et al., 2021). Thus, users will only utilise the services if they believe that robo-advisors can solve their problems (Alkhwaldi et al., 2022). Their behavioural intention towards using robo-advisors will be motivated by the services' advantages and benefits (Rabaa'i, 2021). Therefore, this study rejects H_0

and robo-advisory services providers should develop and improve applications that enhance investors' portfolio performance and efficiency.

5.1.2 Effort Expectancy

Effort expectancy indicates easiness in using robo-advisory services. This study shows that effort expectancy is insignificant in explaining the intention to use robo-advisory services in Malaysia, implying that their user-friendliness does not directly affect the intention. This result is inconsistent with studies by Belanche et al. (2019) and Seiler and Fanenbruck (2021), whereas supported by Gan et al. (2021) and Pan and Gao (2021). Chong (2013) and Venkatesh et al. (2012), as cited in Fadzil (2017), also stated that the user-friendliness of the services will not directly influence the consumers' opinion of them. According to Davis (1989, as cited in Hu et al., 2019), some researchers claimed that since consumers are unfamiliar with the technology or have no opportunity to use it, its ease of use is usually not substantial to intention in the preliminary stages of the adoption. This reflects that robo-advisors are still new in Malaysia and that many investors have not used them (Hu et al., 2019). Moreover, modern consumers frequently possess extensive technical and computing knowledge, yet effort expectancy is no longer a barrier to their adoption of technology (Wang et. al., 2014). In this study, most respondents are Generation Y (born between 1981 and 1997) and Z (born between 1997 to 2012), which are 74% and 15% respectively. Hence, they are deemed to be tech-savvy, more adaptable and flexible, as well as the primary drivers of fintech (Lipton et al., 2016; Hu et al., 2019). To sustain favourable behavioural intention among investors, the robo-advisory services providers should aim to design more user-friendly and easy programs.

5.1.3 Social Influence

Social influence implies others' opinions that affect investors' intention towards utilising the technology. Social influence is significant in this study to explain the intention of using robo-advisory services in Malaysia, indicating that investors would consider friends and family's viewpoints regarding adoption. The finding conforms with Milani (2019), Gan et al. (2021), Xie et al. (2021) and Nourallah (2023). According to Bursa Malaysia (2022), local retail participation increased from 34.3% in 2020 to 35.2% in 2021, reaching a new high. The pandemic which has impacted investors' income streams would have emphasised the significance of financial planning (Gan et al., 2021). Investors or newbies looking to invest may begin seeking low-cost financial consulting services and the usage of robo-advisors by those around them may influence their intention (Gan et al., 2021). The study of Gerlach and Lutz (2021) also found that the adoption of fintech services will rise if consumers see others utilising it in their personal and professional environment. They further added that financial institutions should consider clients' social networks to eventually benefit from network effects.

5.1.4 Facilitating Conditions

Facilitating conditions implies sufficient assistance available in supporting the use of robo-advisors. Facilitating conditions are insignificant in this study to explain the intention towards using robo-advisory services in Malaysia, indicating that technical support available for difficulties encountered by investors when using robo-advisory services is not important to explain the intention. The studies of Fadzil (2017) and Gan et al. (2021) showed the same result, while it contradicts the findings of Bajunaied et al. (2023) and Rahim (2023). The majority of investors already have the necessary tools and expertise to use robo-advisors; hence, it is not the primary reason to persuade them to use the services (Utomo et al., 2021).

They tend to have a specific degree of digital literacy and the capacity to use robo-advisors in the digitalised era. Besides, according to Sebastian et al. (2022), people have the essential competence and capacity to use the technology without additional technical assistance. Moreover, Venkatesh et al. (2003) suggested that facilitating conditions tend to be insignificant when the study uses effort expectancy and performance expectancy as variables. Thus, their inclusion in this study may also cause the result of insignificance.

5.1.5 Hedonic Motivation

Hedonic motivation implies the perceived enjoyment experienced while embracing new technology (Chen et al., 2016; Chuang et al., 2016). Hedonic motivation is significant in this study to explain the intention towards using robo-advisory services in Malaysia, indicating that respondents would be motivated to embrace robo-advisory services if they could perceive fun and pleasantness from the usage. The results are consistent with the studies of Gerlach and Lutz (2021) and Chung et al. (2023). Based on Gerlach and Lutz (2021), hedonic motivation affects the perceived benefits of robo-advisors, driving future usage intention. They further added that gamification elements embedded in robo-advisory applications would encourage customer engagement with robo-advisors by creating fun and pleasant experiences. Besides, Chung et al. (2023) discovered that the biggest contribution of the intention towards using robo-advisors is hedonic motivation as it tends to enhance customer experience and satisfaction. They suggested that emotional traits are key in determining the acceptance of robo-advisors. Hence, interesting features in robo-advisors would make the system more enjoyable to use, thus encouraging the adoption of robo-advisors.

5.1.6 Price Value

Price value means how consumers evaluate the equilibrium between perceived benefits and related financial costs of adopting new technology (Shaw & Sergueeva, 2019). In this study, the respondents perceive that the potential benefits provided by robo-advisors would be greater than the monetary costs of investing through robo-advisors. Since the respondents perceive that robo-advisors would provide good value for money, they would adopt robo-advisory services more presumably. Thus, results show that price value is significant to the intention towards using robo-advisory services, which is in line with that of Ashrafi and Kabir (2023), indicating that perceived value motivates consumers' intention towards adopting robo-advisors. Furthermore, Gerlach and Lutz (2021) claimed that the cost-performance ratio of the services is vital to examining the usage intention. They further suggested that financial institutions should provide a compelling pricing model by regularly tracking competitors' costs and performance. Financial institutions should also introduce additional features to the robo-advisory application to enhance product differentiation and its perceived value for the consumers if the pricing model provided is not as attractive as the competitor's (Gerlach & Lutz, 2021).

5.1.7 Trust

Trust in new technology is the belief that it will fulfil its commitments to meet users' requirements (Eren, 2023). The findings of this study demonstrate a significant positive relationship between trust and the intention to use robo-advisory services, showing that respondents of this study perceive robo-advisory services to be secure and reliable; thus, increasing the probability of adoption. The results are supported by the recent findings of Ashrafi and Kabir (2023), Eren (2023), Roh et al. (2023), and Cho (2019), which stated that a higher level of trust would increase the likelihood of adoption in robo-advisory services. This is because trust has the power to reduce perceived risks and uncertainty in the application of such advanced technology (Faqih, 2022). According to Roh et al. (2023), perceived security and perceived privacy positively influence users' trust in adopting robo-advisory services. Users are assumed to perceive little risks while conducting transactions on a robo-advisory platform if they believe it is secure and trustworthy (Ashrafi & Kabir, 2023). Besides, users would have trust in the robo-advisory services if their personal and financial information is stored and handled properly, protecting them from any losses or fraud (Roh et al., 2023). Thus, users are more likely to adopt robo-advisory services if they find it safe to trust the investment and portfolio rearrangement advice provided (Lee & Kim, 2020; Senyo & Osabutey, 2020).

5.2 Implications of the Study

Robo-advisory services have gained popularity globally and become increasingly recognized by investors nowadays. Hence, portfolio managers are aware of the rise of these services which change the dynamic of the industry. As investors increasingly show their interest in robo-advisors and are attracted by automated and cost-effective investment solutions, traditional portfolio managers find themselves facing heightened competition for customer acquisition and retention. For portfolio managers to remain competitive in this industry, they have to be proactive in adapting the business model and offering, incorporating technology to enhance its services. For instance, performance, convenience, cost, and trust are significant in shaping users' intentions regarding robo-advisory. Portfolio managers may use these insights to gauge the level of effort needed to enhance their abilities and services or consider integrating robo-advisory into their asset management strategies if there is a high intention to use robo-advisory among consumers.

Moreover, this study can also bring significant benefits to robo-advisory firms. The firms will be able to determine the pertinent factors influencing the usage intention of robo-advisory services, which may enhance their offerings and potentially increase adoption. The findings can provide corporations with a deeper understanding of potential users' needs and preferences, allowing them to tailor their services to better meet investors' expectations and make their services more attractive and user-friendly. The results computed in Chapter 4 showed that people presumably use robo-advisors more if these services can enhance their financial decisions and performance as well as if their family and friends are recommending or using them. Armed with this knowledge, robo-advisory firms can strategically position themselves to thrive in the highly competitive wealth management industry and meet the changing demands of investors effectively. It then can ultimately improve the overall financial services experience. Thus, robo-advisory firms can leverage their insights from this study to better understand the investors' preferences and intentions, positioning themselves to thrive in the evolving landscape of robo-advisory services.

As a developing country, Malaysia may need to enhance its services and cater to the needs of investors to provide a more developed and user-friendly platform to users. Thus, the government may need to invest in advanced technological infrastructure and algorithms that enhance the platform's capabilities to provide more accurate and personalised investment advice. For instance, utilising advanced big data analytics can help process and analyse vast amounts of financial data, identifying trends and assessing risk factors for better investment decisions. Thus, the government is important in encouraging the incorporation of new features and services to attract and retain more potential users.

Additionally, the survey of this study revealed that the majority of Malaysians have never tried and are not familiar with robo-advisory services. This indicates a low current adoption rate of robo-advisors in Malaysia. However, it is promising that the survey showed a majority of Malaysians are interested in trying robo-advisors in the future, with growing curiosity and openness among the population. Besides that, the results would offer the academic community and upcoming researchers the research methodology and valuable knowledge about using robo-advisors in Malaysia. With the additional factor included in the UTAUT2 model, these findings provide significant insights regarding Malaysians' willingness to adopt robo-advisory services. The relationship and significance between the selected variables in the study comprehensively explain the factors that influence the robo-advisor's adoption among Malaysians. Therefore, future researchers may use the study as a guiding reference, enabling a deeper investigation into the topics and potentially contributing further solutions or ideas that support the future development of robo-advisors in Malaysia.

5.3 Limitations of the Study

First and foremost, although the research model is computed using the UTAUT2 model, it has not included the potential moderating effects such as age, gender and experience that consider personality or characteristics towards the intention of the study. This is because the moderating effects are not part of the research objectives of this study. Since it did not explore the moderating effect such as investment experience, age and gender in the UTAUT2 model, it may not account for the potential impact of individual differences on these factors. Hence, addressing these individual differences would provide a deeper comprehension of all contributing aspects.

Furthermore, this study was conducted in certain urban cities in Malaysia, specifically Selangor, Penang, and Johor. The population in these big cities are deemed to have a higher disposable income than other areas, making them potential users of the robo-advisors. However, investors in other areas still exhibit unique cultural landscapes in terms of financial planning and investments. They could have different viewpoints regarding the robo-advisory services available in Malaysia. Consequently, these characteristics could influence the result of the usage intention regarding robo-advisors.

Lastly, this study solely uses the quantitative data collection method, the survey method to collect data. While answering survey questions, respondents must perform a self-assessment to indicate their levels of agreement or satisfaction with certain statements provided in the questionnaire. Since only close-ended inquiries were applied in this study, the underlying motivations behind the respondents' behaviour are unknown. Due to time constraints, qualitative data collection methods, such as interviews, could not be conducted to allow the respondents to elaborate on their answers. Thus, deeper insights regarding the thoughts and experiences of the respondents cannot be uncovered.

5.4 Recommendations for Future Research

There are several recommendations and solutions proposed to address the limitations. Firstly, it is recommended that future researchers should consider including potential moderating variables in the research objectives to enhance the model's comprehensiveness and accuracy. For example, the researchers may include investment experience, age and gender to further explore the variables in shaping the user's intentions. Besides, it is believed that comparative studies can provide insights into how consumers' intentions to use AI-enabled technologies differ across moderating variables such as gender and among various industrial sectors. To identify possible differences, future studies can discover valuable details and create focused strategies to address the specific needs and preferences of various user groups.

In addition, individuals with different backgrounds will have varied impressions and attitudes towards new technology, such as robo-advisors. Hence, to increase the reliability of the data analysis, further studies could focus on other states across the entire Malaysia instead of focusing on limited areas. To get a more thorough knowledge of investors' views on robo-advisors, upcoming researchers are encouraged to distribute the questionnaires in small- and medium-sized cities or non-urban areas of Malaysia. Since a larger geographical scope could provide different perceptions, attitudes and behaviours, such comparisons could also be explored by the following researchers.

Lastly, future scholars are urged to adopt mixed research techniques that combine quantitative and qualitative methodologies while investigating similar topics. For instance, the researchers may adopt the survey method as a quantitative approach and, subsequently, conduct a qualitative interview. The study is still primarily quantitative, but a series of qualitative interviews may be carried out among a portion of respondents who filled in the questionnaires. It is believed that this mixed methods approach would help disclose the facts behind the response data. Hence, the quantitative findings can be better explained by the qualitative data derived from the interviews. An in-depth analysis may be provided, thus enhancing the study's quality.

5.5 Conclusion

To sum up, this study discusses the usage intention towards robo-advisory services in Malaysia. 400 responses collected from the M40 income group were run by SmartPLS and the study has concluded that all determinants are significant to the behavioural intention towards using robo-advisory services, except for effort expectancy and facilitating conditions. Together with limitations and recommendations for future researchers, the key results and ramifications are also presented. It can be concluded that the objective of this study has been satisfied by determining the factors affecting the behavioural intention towards using robo-advisory services in Malaysia.

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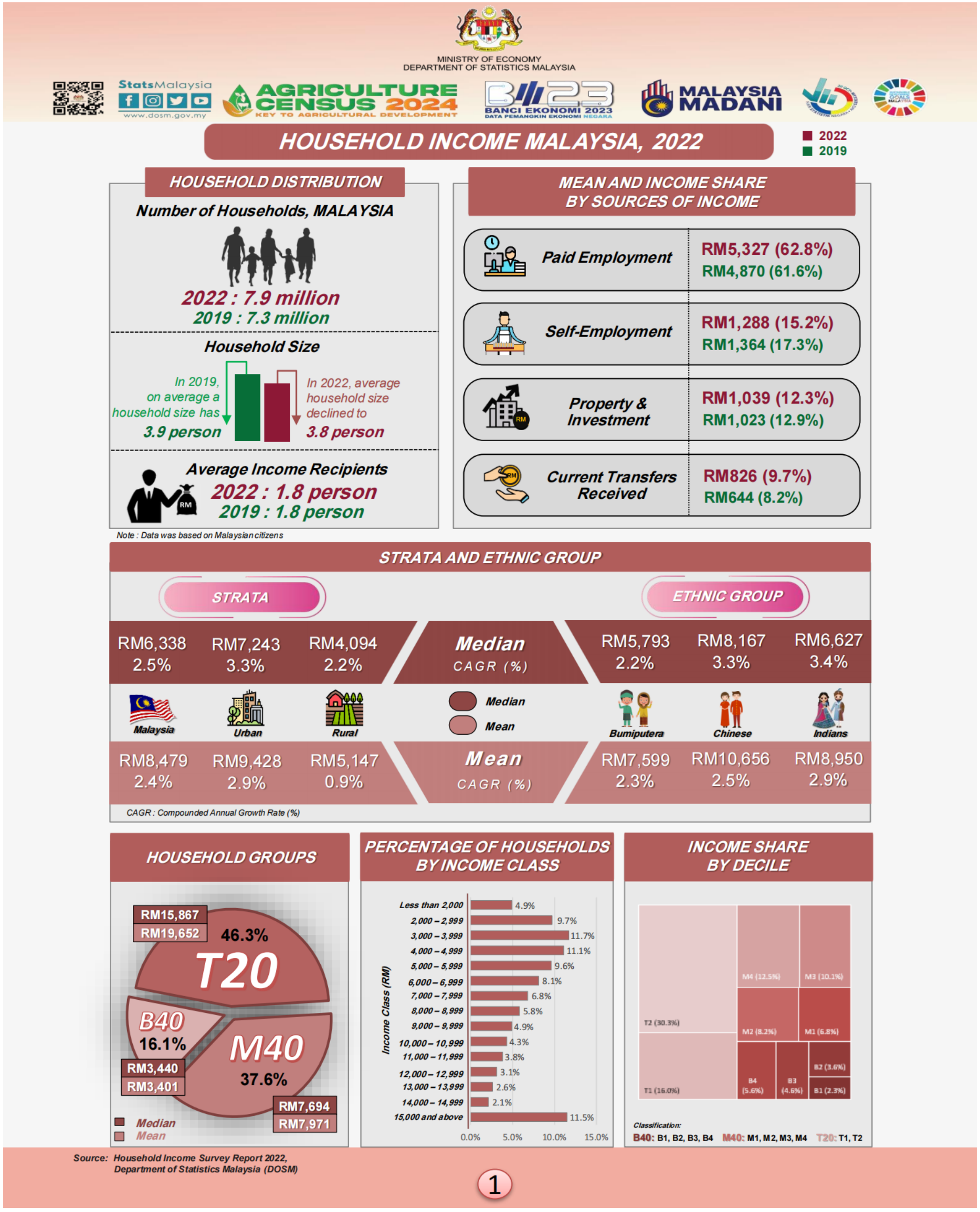
APPENDICES

Appendix 3.1: Population of Each Income Group in Malaysia



Appendix 3.2: Survey Questionnaire Permission Letter

UNIVERSITI TUNKU ABDUL RAHMAN *DU012(A)*

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

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

3rd July 2023

To Whom It May Concern

Dear Sir/Madam,

Permission to Conduct Survey

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

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

The student are as follows:

Name of Student	**Student ID**
Chow Chi Ving	19ABB06515
Genevieve Tan Xin Yii	19ABB05714
Tan Min Xin	19ABB06309

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

Thank you.

Yours sincerely,

…………………………………

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

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

Appendix 3.3: Survey Questionnaire Sample

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

UNIVERSITI TUNKU ABDUL RAHMAN

Faculty of Business and Finance

Survey Questionnaire

Dear respondents,

We are final-year undergraduate students of Bachelor of Finance (HONS) from Universiti Tunku Abdul Rahman (UTAR) and currently conducting a survey on **A Study of the Intention to Use Robo-advisory Services in Malaysia** for our Final Year Project (FYP).

Your cooperation in answering this questionnaire is highly important to us as it will greatly assist us in the completion of our study and the achievement of its objectives. All of the information obtained regarding this study will be kept **STRICTLY CONFIDENTIAL**. Your response will be solely used for academic purposes and not be identified in any data or report.

This questionnaire will roughly take 10 - 15 minutes to complete. We truly appreciate your participation and cooperation in answering the questions. If you have any inquiries, please feel free to contact any one of our group members.

Yours sincerely,
Chow Chi Ving, chiving51@1utar.my, 016-2175086
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Please be informed that in accordance with Personal Data Protection Act 2010 ("PDPA") which came into force on 15 November 2013, Universiti Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal information.

Acknowledgement of Notice

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

…………………………
Date:

Section A: Demographic Information

The following questions refer to the demographic profile of the respondents. Please provide the appropriate information by placing a (√) in the bracket provided to represent your answer.

Note*: Robo-advisory services are served as automated investment solutions that offer automated portfolio rebalancing using trading algorithms based on passive investment and diversification strategies, to guide them through a self-assessment process and shape their investment behaviour based on investors' expectations.*

Local companies*: StashAway, MyTHEO, Wahed Invest, Akru Now, BEST Invest, Raiz, Kenanga Digital Investing, and Versa.*

1. Income group
   - ☐ B40 (RM 4,849 and below) **Thank you for your participation*
   - ☐ M40 (RM 4,850 - 10,959)
   - ☐ T20 (RM 10,960 and above) **Thank you for your participation*

2. Gender
   - ☐ Male
   - ☐ Female

3. Age group
   - ☐ 24 and below
   - ☐ 25 - 34
   - ☐ 35 - 44
   - ☐ 45 - 54
   - ☐ 55 and above

4. Region
   - ☐ Selangor
   - ☐ Kuala Lumpur
   - ☐ Penang
   - ☐ Johor
   - ☐ Perak
   - ☐ Other: ______________________

5. Ethnicity
   - ☐ Malay
   - ☐ Chinese
   - ☐ Indian
   - ☐ Other: ______________________

6. Marital status
   - ☐ Single
   - ☐ Married
   - ☐ Divorced

7. Highest academic qualifications
   - ☐ SPM and below
   - ☐ STPM/ A-Level/ Foundation
   - ☐ Diploma
   - ☐ Bachelor's degree
   - ☐ Master's degree
   - ☐ Doctorate degree

8. Do you have any experience investing in robo-advisory services?
   - ☐ Yes
   - ☐ No

9. Do you have the intention to use the robo-advisory services in Malaysia?
   - ☐ Definitely yes
   - ☐ Rather yes
   - ☐ It's hard to say
   - ☐ Rather not
   - ☐ Definitely not

Section B: Factors Affecting the Intention to Use Robo-advisory Services in Malaysia

Note: Scale 1 indicates that you strongly disagree with the statement and 5 indicates you strongly agree with the statement.

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

Sub-section 1: Performance Expectancy

It means an individual's belief that adopting robo-advisory services will improve performance.

		1	2	3	4	5
1	I find robo-advisory services useful in making financial decisions.	☐	☐	☐	☐	☐
2	Using robo-advisory services would help me to accomplish my financial goals more quickly.	☐	☐	☐	☐	☐
3	Using robo-advisory services would enable me to access services 24/7.	☐	☐	☐	☐	☐
4	Using robo-advisory services would help me to gain greater control over my finances.	☐	☐	☐	☐	☐
5	Robo-advisory services could manage and allocate my funds more efficiently.	☐	☐	☐	☐	☐

Sub-section 2: Effort Expectancy

It means the ease associated with using robo-advisory services.

		1	2	3	4	5
1	I find robo-advisory services easy to use.	☐	☐	☐	☐	☐
2	I find robo-advisory services flexible to changes (e.g., automated rebalancing and asset allocation).	☐	☐	☐	☐	☐
3	My interaction with the robo-advisory services would be clear.	☐	☐	☐	☐	☐
4	My interaction with the robo-advisory services would be understandable.	☐	☐	☐	☐	☐
5	Using robo-advisory services would require minimal effort in monitoring my investments.	☐	☐	☐	☐	☐

Sub-section 3: Social Influence

It means that individuals are more likely to adopt robo-advisory if someone agrees they should do so.

		1	2	3	4	5
1	I would use robo-advisory services when my family and friends think I should.	☐	☐	☐	☐	☐
2	When I see my family and friends using robo-advisory services that inspire me, I would use them too.	☐	☐	☐	☐	☐
3	My family and friends who use robo-advisory services would have higher respect and impression.	☐	☐	☐	☐	☐
4	I would like to try robo-advisory services due to their technology trend.	☐	☐	☐	☐	☐
5	I would use robo-advisory services if doing so makes me feel accepted by others.	☐	☐	☐	☐	☐

Sub-section 4: Facilitating Conditions

It means the availability of adequate resources and support for individuals to use robo-advisory services.

		1	2	3	4	5
1	I have the knowledge necessary to use robo-advisory services.	☐	☐	☐	☐	☐
2	I could always get assistance quickly when I have difficulties in using robo-advisory services.	☐	☐	☐	☐	☐
3	The platform of robo-advisory services is always up to date.	☐	☐	☐	☐	☐
4	I find the technical support of robo-advisory services effectively resolves my problems.	☐	☐	☐	☐	☐
5	Robo-advisory services can work and function without disruption at all times.	☐	☐	☐	☐	☐

Sub-section 5: Hedonic Motivation

It means the enjoyment or pleasure an individual derives from utilising robo-advisory services.

		1	2	3	4	5
1	I would have fun when using robo-advisory services.	☐	☐	☐	☐	☐
2	I feel the motivation to explore more about robo-advisory services.	☐	☐	☐	☐	☐
3	I find that it would be interesting to use robo-advisory services.	☐	☐	☐	☐	☐
4	The robo-advisory services are comfortable and convenient to use.	☐	☐	☐	☐	☐
5	I would feel confident in the financial decisions made using robo-advisory services.	☐	☐	☐	☐	☐

Sub-section 6: Price Value

It means the monetary cost of utilising robo-advisory services.

Note: Most robo-advisory platforms would charge investors an annual management fee of approximately 1% or less for portfolio management.

		1	2	3	4	5
1	I believe that the fees of robo-advisory services would be reasonable.	☐	☐	☐	☐	☐
2	I believe that the benefits I get from robo-advisory services would create value for the money.	☐	☐	☐	☐	☐
3	I believe that robo-advisory services would be worth more than their costs (fees).	☐	☐	☐	☐	☐
4	Compared to the effort I need to put in, I believe that robo-advisory services are beneficial for me.	☐	☐	☐	☐	☐
5	I respond quickly to the cost change between services offered by human financial advisors and robo-advisors.	☐	☐	☐	☐	☐

Sub-section 7: Trust

It means the belief or confidence that an individual has the reliability to use robo-advisory services.

		1	2	3	4	5
1	I believe that robo-advisors would provide secure and reliable services.	☐	☐	☐	☐	☐
2	I believe that the robo-advisory services' performance would be close to my expectations.	☐	☐	☐	☐	☐
3	I believe that robo-advisory services would provide detailed information about their terms and conditions.	☐	☐	☐	☐	☐
4	I believe that the terms of use are strictly followed while investing via robo-advisory services.	☐	☐	☐	☐	☐
5	I believe that robo-advisory service providers keep customers' interests in mind.	☐	☐	☐	☐	☐

Sub-section 8: Behavioural Intention

It means the individual's willingness to adopt the robo-advisory services for managing financial investments.

		1	2	3	4	5
1	I intend to use robo-advisory services in the future.	☐	☐	☐	☐	☐
2	I intend to use robo-advisory services in my daily life.	☐	☐	☐	☐	☐
3	I intend to use robo-advisory services for quick and easy access to my investment information.	☐	☐	☐	☐	☐
4	I intend to change from using financial advisory services to a robo-advisory services platform.	☐	☐	☐	☐	☐
5	I intend to use robo-advisory services to obtain recommendations in investment portfolios.	☐	☐	☐	☐	☐
6	I would love to use robo-advisory services for financial decision-making.	☐	☐	☐	☐	☐

Thank you for your participation

We highly appreciate your cooperation in our Final Year Project

Wish you all the best in the future!