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FACTORS AFFECTING MALAYSIANS CONTINUANCE INTENTION TOWARDS FINANCIAL ROBO-ADVISORS

BY

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

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Degree Awarded : Bachelor of Marketing

Faculty : Faculty of Business and Finance (FBF)

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We hereby declare that:

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To us, for never giving up! Dream it, do it.

"Every finish line is the
beginning of a new race."

ABSTRACT

As the adoption of financial robo-advisors continues to increase in the Malaysian financial environment, there is a need to ensure that the significance of informing the continuance intention has become relevant. In this study, the intention of Malaysian working adults to use financial robo-advisors more will be analysed, and the impact of confirmation, perceived usefulness, and satisfaction on these issues will be assessed based on the Expectation Confirmation Model (ECM). The quantitative research approach was applied, and the results were collected by means of an online questionnaire of 200 participants. It was modelled using the partial least squares structural equation modelling (PLS-SEM). The results indicate that confirmation positively affects both perceived usefulness and satisfaction. The study describes the best practices that developers of fintech and financial service providers can adopt to retain more users using post-adoption experiences.

Keywords: Malaysian, Financial Robo-advisors, Expectation Confirmation Model, Continuance Intention, Structural Equation Modelling

Subject Area: HG4621 Stockbrokers. Security dealers. Investment advisers

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LIST OF ABBREVIATIONS

DIM	Digital Investment Management
AUM	Assets Under Management
AI	Artificial Intelligence
IS	Information System
IT	Information Technology
ECM	Expectation Confirmation Model
ECT	Expectation Confirmation Theory
IV	Independent Variable
DV	Dependent Variable
PLS-SEM	Partial Least Squares Structural Equation Modelling
CA	Cronbach’s Alpha
CR	Composite Reliability
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait Ratio
VIF	Variance Inflation Factor
CON	Confirmation
PU	Perceived Usefulness
SAT	Satisfaction
CI	Continuance Intention

LIST OF APPENDICES

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

The study focuses on the variables that determine the intention of Malaysians to keep using financial robo-advisors. In this section, the research context, problem and objective of the study will be discussed.

1.1 Research Background

The financial services and investment sectors are undergoing a significant transformation driven by big data, machine learning, and artificial intelligence (AI). One of the most significant developments in the industry is financial technology, or fintech, which is facilitated by the creation of online trading platforms (Todd & Seay, 2020; Cheong et al., 2023; Hassan et al., 2023). According to Jung et al. (2017), Ashrafi (2023) and Northey et al. (2022), financial robo-advisors are online platforms that provide automated, algorithm-driven financial planning and investment services. In general, financial robo-advisors gather information about users through online questionnaires, assessing their financial statuses and plans. Using this information, the system will create personalised suggestions and manage investments automatically on behalf of the user (Belanche et al., 2019; Shanmuganathan, 2020; Yeh et al., 2022; Nain & Rajan, 2023; Arenas-Parra et al., 2024).

Financial robo-advisors began to appear in the late 2000s, making investment advice more accessible to the public through technology. The 2008 financial crisis served as the driver of technology, and websites like Wealthfront and Betterment were created, providing algorithmic investment advice to individual investors (Fatima & Chakraborty, 2024; Zogning & Turcotte, 2024). With the growing popularity of digital technologies, the global financial field is expanding at a rapid pace. AI has further enhanced the viability of automated investing. Consequently, financial robo-advisors are replacing traditional financial managers in some aspects (Kumar, 2024). These platforms are also gaining popularity among retail investors due to their low costs and simplicity (Khanna & Jha, 2024). Furthermore, Zhang et al. (2021) note that the strategies employed by financial advisors are often speculative, despite these professionals being trained in trade management and portfolio construction.

According to Nguyen et al. (2023), the financial robo-advisory industry in Malaysia has been developing at a slower pace compared to Singapore and Hong Kong. To facilitate the digitalisation of the capital market in Malaysia, the Securities Commission Malaysia launched the Digital Investment Management (DIM) Framework in May 2017, which was the first of its kind in the region. This framework facilitated the entry of financial robo-advisors and digital investment managers (DIMs) into the local market, while also encouraging the development of innovative and more efficient approaches to delivering capital market services and products to investors (Floros, 2018). Malaysia's financial robo-advisory industry officially began in 2018 with the launch of its first platform. Shortly after, Singapore-based StashAway expanded into the Malaysian market, followed by the introduction of local players such as Mytheo and Wahed Invest in 2019. Since then, several other domestic financial robo-advisors have emerged, including Akru, BEST Invest by Bank Islam Malaysia, KDI Invest by Kenanga Investment Bank, and Raiz (Ruslan et al., 2022). As of January 2021, StashAway had assets under management (AUM) of more than US$1 billion (RM4.05 billion), representing the largest market share among robo-advisory platforms. MyTheo had an AUM of US$650 million, while Wahed had US$39 million (Nguyen et al., 2023).

Despite the current development of digital finance, financial robo-advisors in Malaysia remain poised for significant expansion. The combination of new opportunities, such as blockchain, AI or mobile banking, would additionally increase the effectiveness and efficiency of financial robo-advisory services (Yi et al., 2023). Moreover, government projects such as MyDigital ID and the Central Database Hub (PADU) contribute to the growth of the fintech industry by strengthening the security and enhancing the functionality of digital public services (Karnadi & Kurniawan, 2021). While financial robo-advisors are gaining traction in Malaysia, their long-term viability relies not only on expanding the market but also on retaining users and encouraging ongoing engagement. Gan et al. (2021) highlight that it is crucial to identify the determinants of Malaysians continued use of these platforms, especially as financial behaviours shift and digital technologies become increasingly integrated into daily routines. In addition, Malaysians adopt robo-advisory services for multiple reasons, such as enhanced financial literacy, confidence in technological solutions, and the influence of social networks (Cheng et al., 2019).

1.2 Research Problems

1.2.1 Practical Problem

Based on Bursa Malaysia (2023), 16.83% of Malaysian adults have been active investors in financial markets, reflecting relatively weak public participation. Despite this limited number of investors, the Malaysian financial robo-advisor business has witnessed explosive growth. According to Statista (2024), assets under management (AUM) have witnessed massive growth from USD 21.0 million in 2017 to USD 1.73 billion in 2023, which is bound to increase to USD 2.95 billion by 2029, as shown in Figure 1.1. This situation reflects that the Pareto Principle, also known as the 80/20 rule, states that a small percentage of participants usually contribute to most of the results (Abyad, 2020; Kharub et al., 2021; Sahu et al., 2024). In this case, it implies that a comparatively smaller percentage of financial robo-advisor users may produce the most value and market activity.

Figure 1.1. Assets Under Management in Malaysia's Robo-advisory Sector

Source: Statista. (2024)

Financial robo-advisors in Malaysia have evolved into standard digital advisory services offered by financial institutions as a solution for providing investment advice to clients (Lourenço et al., 2020). Even with the increasing sizes that the number of users takes, it is observed that a good number of financial institutions continue to suffer because of user retention rates, levels of customer satisfaction and chances of sustaining the same use even following the adoption phase (David & Viany, 2024; Cahyadi et al., 2025).

As Figure 1.2 shows that the Malaysian financial robo-advisor market has grown to include a wide range of competing platforms such as StashAway, Wahed Invest, MyTheo, and Akru, among others. Each platform adopts distinct investment methodologies and fee structures to attract different segments of investors. The increasing number of users in the market reflects the intensifying competition, as financial institutions strive to differentiate themselves by offering low fees, Shariah-compliant options, artificial intelligence capabilities, and user-personalised investment strategies (Figà-Talamanca et al., 2022; Xia et al., 2023).

Platform	Launched	Methodology	Annual fees
Akru	2020	Invest in a savvy portfolio of exchange-traded funds that are globally diversified and offer minimal costs.	0.2% to 0.7%
Best Invest	2020	Provides investment recommendations based on a broad portfolio of Shariah-compliant unit trust investments using artificial intelligence and big data technology.	0.5% to 1.8%
MyTheo	2019	Integrated risk-based investing and "smart beta" strategies are incorporated into the functional portfolios that are created using the company's proprietary algorithms.	0.5% - 1%
Raiz	2020	A portfolio of Amanah Saham Nasional Berhad (ASNBunit)'s trust funds will be constructed for investors based on the results of an algorithm that analyses the investor risk profile.	RM1.5 a month (under RM6,000) or 0.3% (RM6,000+)
StashAway	2018	Uses proprietary investment strategy that reacts to economic fundamentals	0.2% - 0.8%
Wahed Invest	2019	Using modern portfolio theory, optimises the investor's holdings to maximise profit while adhering to Shariah law	0.39% - 0.79%
KDI Invest	2022	Enables artificial intelligence-assisted investments in a variety of selected exchange-traded funds (ETFs) that are listed in the United States and that are in line with the preferences of the user.	0.3%-0.7% for investments above RM3000

Figure 1.2. List of Financial Robo-advisors Available in Malaysia

Source: Ruslan et al. (2022)

Furthermore, even though user satisfaction is one of the primary factors influencing loyalty and further usage, it is difficult to ensure due to the lack of sufficient understanding of users' evolving expectations (Puspitasari et al., 2022; Chung & Chung, 2023). Hence, financial institutions must investigate the primary factors driving customer continuance intention and enable investors to make decisions with greater confidence through self-assessment tools (Lourenço et al., 2020; Balakrishnan, 2024). Since financial robo-advisory services in Malaysia remain in a nascent stage, it is vitally important to identify the determinants of persistence to ensure user retention and the long-term sustainability of the platform.

1.2.2 Theoretical Problem

Although the importance of continuance use in information systems (IS) and financial technologies (FinTech) success has been established, existing studies on financial robo-advisors have primarily focused on technological, legal, or adoption-related aspects, whereas the post-adoption behaviour of users, especially their continuance intention, has received comparatively limited exploration (Wu, 2013; Cheng, 2020a; Figà-Talamanca et al., 2022; Chou et al., 2023). Conversely, continuance intention has also been analysed extensively in other digital products, including mobile payment systems, mobile learning, food delivery services, and healthcare applications (Atmaji & Tjhin, 2022; Putra et al., 2022; Han & Zo, 2023; Hijazi et al., 2023; Mai et al., 2024; Singh & Suri, 2024). Nevertheless, the availability of forms of comprehensive models that can describe the post-adoption behaviour of financial robo-advisor users is not plentiful (Gan et al., 2021). Moreover, even though the adoption factors such as trust, perceived usefulness, threat and emotional factors have been addressed by available studies, the key determinants of continued use of financial robo-advisors by users are yet to be comprehensively explored (Bhatia et al., 2021; Chou et al., 2023; Ibrahim et al., 2023). Thus, by determining and analysing the antecedent factors affecting the continuance intention of the Malaysian users of financial robo-advisors, this research will fill this theoretical gap.

1.3 Research Objectives

1.3.1 General Objective

This research investigates the key factors influencing Malaysians' continuance intention towards financial robo-advisors.

1.3.2 Specific Objectives

I. To examine the relationship between confirmation and perceived usefulness of financial robo-advisors among Malaysians.

II. To examine the relationship between confirmation and satisfaction of financial robo-advisors among Malaysians.

III. To examine the relationship between perceived usefulness and satisfaction of financial robo-advisors among Malaysians.

IV. To examine the relationship between perceived usefulness and continuance intention of financial robo-advisors among Malaysians.

V. To examine the relationship between satisfaction and continuance intention of financial robo-advisors among Malaysians.

1.4 Research Questions

1.4.1 General Question

What are the factors that affect Malaysians' continuance intention toward financial robo-advisors?

1.4.2 Specific Questions

I. How does confirmation affect the perceived usefulness of financial robo-advisors among Malaysians?
II. How does confirmation affect the satisfaction of financial robo-advisors among Malaysians?
III. How does perceived usefulness affect the satisfaction of financial robo-advisors among Malaysians?
IV. How does perceived usefulness affect the continuance intention of financial robo-advisors among Malaysians?
V. How does satisfaction affect the continuance intention of financial robo-advisors among Malaysians?

1.5 Research Significances

1.5.1 Practical Significance

Policymakers, financial institutions, investors, and consumers all need to understand the factors that influence Malaysians' inclination to stick with financial robo-advisors. By identifying the primary factors that contribute to sustained use, the study can help develop more effective tactics for improving consumers' retention and long-term adoption of financial robo-advisory services. The study also provides a deeper understanding of investor behaviour in digital finance that will allow finance providers to compete in a competitive market. Furthermore, policymakers can utilise these insights in designing regulations that promote responsible and transparent financial robo-advisory services, while users can be empowered with more sound monetary choices, leading towards increased confidence in digital investing platforms. The study not only makes a research contribution but also a practitioner contribution towards improving business outcomes, designing finance regulations, as well as enhancing users' participation in Malaysia's financial robo-advisory marketplace.

1.5.2 Theoretical Significance

In this study, the Expectation Confirmation Model (ECM) is used to study users' intention to use a financial robo-advisor. While ECM has been heavily employed in anticipating post-adoption behaviour of information systems and digital technologies, its usage in the context of financial robo-advisors has been limited. Existing literature has primarily focused on financial robo-advisory service adoption with less attention to the post-adoption behaviour of users. Therefore, this study employs ECM as the theoretical framework to systematically examine the key determinants influencing Malaysian investors' intention to continue using financial robo-advisors, thereby contributing to the understanding of user behaviour and psychological processes in financial technology. Furthermore, by placing the model in Malaysia's unique fintech environment, this study contributes to the verification of ECM's relevance to emerging economies and financial service technologies. Thus, this study would be useful to future scholars and researchers who would like to determine the current intention of users in financial robo-advisors.

1.6 Conclusion

Chapter 1 has described an overview of this investigation. This introduction will assist in establishing the limitations of the overall research concerning the objectives of the study.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

In this section, we will discuss the involved theories, the Expectation Confirmation Model (ECM). Also, the correlation between independent variables (IV), confirmation, perceived usefulness, and satisfaction, and the dependent variable (DV), continuance intention towards financial robo-advisors is addressed. The conceptual framework will therefore demonstrate the different relationships between the independent and dependent variables.

2.1 Underlying Theory

The Expectation Confirmation Model (ECM), developed by Bhattacherjee (2001), aims to explain users' continued usage intentions of information systems (IS) by integrating concepts from the Expectation Confirmation Theory (ECT) proposed by Oliver (1980). The foundation of the ECM, ECT, has been frequently used in business to study post-purchase behaviour and customer satisfaction (Kim, 2010; Hsu et al., 2014; Xia & Chae, 2021). It suggests that consumers form certain expectations before making a purchase and determine their satisfaction by comparing the experience with those expectations. If the experience is at least satisfactory, the outcome is confirmed, which results in positive feelings. If not, negative confirmation leads to dissatisfaction. Accordingly, consumers' satisfaction directly impacts how willing they are to repurchase, as shown in Figure 2.1.

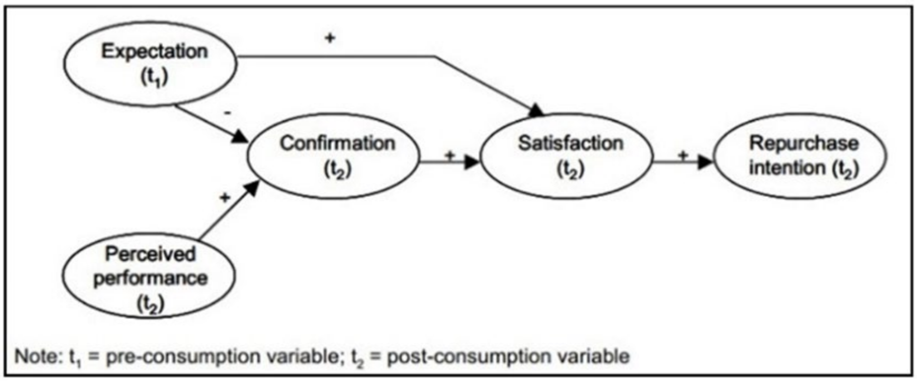

Figure 2.1. Research Model of Expectation Confirmation Theory (ECT)

Source: Bhattacherjee, A. (2001)

Based on the ECT, Bhattacherjee (2001) developed the ECM to explain the determinants of users' continuance intentions. While drawing from ECT, the ECM places greater emphasis on post-adoption cognitive variables, particularly confirmation, perceived usefulness and satisfaction. Bhattacherjee (2001) states that continuance intention is largely shaped by users' actual experiences with a system. When users' experiences meet or exceed their prior expectations, positive confirmation occurs, which enhances their satisfaction. Furthermore, users' perceptions of a system's usefulness significantly influence their intention to reuse it. When the system is perceived to effectively support users in achieving their goals, they are more likely to continue using it, as illustrated in Figure 2.2.

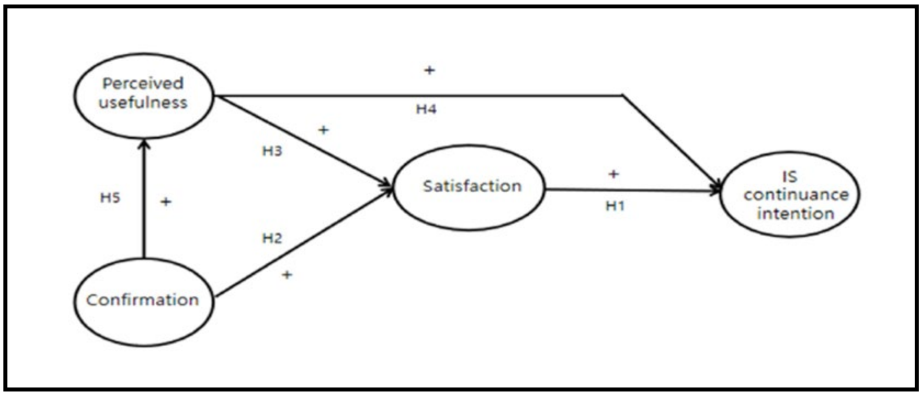

Figure 2.2. Research Model of Expectation Confirmation Model (ECM)

Source: Bhattacherjee, A. (2001)

On the other hand, the ECM has been extensively applied across various domains in previous studies, suggesting its usability in examining users' future usage intentions. For instance, Gunawan et al. (2022) employed the ECM to examine how radical and incremental innovations influence the continued use of leading e-commerce startups, focusing on the role of users' perceptions and satisfaction in sustaining long-term usage. Moreover, Cheng (2020a) examined medical doctors' continuance intention to adopt cloud-based e-learning systems in the context of medical education by integrating the ECM with flow theory, with particular emphasis on the influence of perceived usefulness and satisfaction. Similarly, Bhatnagr et al. (2024) applied the ECM to explore customers' long-term intention to engage with AI-powered digital banks, thereby demonstrating the model's applicability in the fintech sector. Overall, prior studies demonstrate the effective application of the ECM across various domains, including e-commerce, medical education, and financial technology. Nevertheless, little attention has been given to exploring the determinants of Malaysians continuance intention to use financial robo-advisors. This scarcity underscores the importance of examining how constructs such as confirmation, perceived usefulness, and satisfaction shape the long-term adoption of financial robo-advisors in Malaysia.

2.2 Review of Variables

2.2.1 Continuance Intention

Continuance intention refers to a user's intention to continue using an information system (IS) after initial adoption (Al-Emran et al., 2020; Cheng, 2020a). It highlights the behavioural tendency of users to sustain their usage of a system over time, rather than abandoning it after trial (Lee & Kwon, 2010). According to Franque et al. (2020), continuance intention reflects the long-term factors contributing to IS success, making it a crucial measure in post-adoption behaviour. Indrawati and Putri (2018) further define it as the extent to which an individual consistently plans a future behaviour, while Dayour et al. (2020) emphasise its correlation with one's behavioural intention. In essence, continuance intention represents a user's desire and decision to persist in using a familiar technology or service (Chen et al., 2009; Rahi & Ghani, 2019).

2.2.2 Confirmation

Confirmation refers to the extent to which users' initial expectations of a technology or information system (IS) are fulfilled during actual use (Bhattacherjee, 2001; Zhou, 2017). It arises when users perceive that the system's performance corresponds with the anticipated benefits (Lee & Kwon, 2010; Chiu et al., 2021). According to Tam et al. (2018), confirmation reflects the recognition of expected benefits derived from interacting with an information technology (IT) system. Similarly, Yu et al. (2024) describe it as the comparison between users' expectations and their actual experiences, while Rabaa'i and ALMaati (2021) define it as the degree to which these expectations are realised. Conceptually, confirmation is a cognitive construct that plays a crucial role in post-adoption behaviour by shaping satisfaction (Hariguna et al., 2023). Furthermore, the studies have consistently demonstrated that higher levels of confirmation enhance user satisfaction, which subsequently exerts a positive influence on continuance intention (Khan & Saleh, 2022).

2.2.3 Perceived Usefulness

Perceived usefulness reflects the subjective probability that a prospective user will adopt a specific application to enhance their business processes (Lu et al., 2003). Additionally, perceived usefulness refers to the belief that using a system will lead to satisfactory performance outcomes, thereby influencing users' post-acceptance effect, such as satisfaction (Halilovic & Cicic, 2011; Alshurideh et al., 2019). According to Davis (1989), users' perception that a specific technology will enhance their performance can also be seen as a mindset or belief system. Moreover, perceived usefulness is often reflected in the performance evaluation of a technology or application before it is used (Davis, 1989).

2.2.4 Satisfaction

Satisfaction is generally understood as a psychological or emotional reaction that emerges from a cognitive assessment of the gap between expected and actual performance (Bhattacherjee, 2001). Oliver (1997) defines it as "the consumer's fulfilment response," referring to the extent to which the fulfilment experience is perceived as pleasant or unpleasant. Similarly, Marinkovic and Kalinic (2017) and Gong et al. (2020) view satisfaction as an effective response that develops following the use of a product or service. When actual outcomes align with or surpass prior expectations, individuals are likely to experience positive emotions (Wang et al., 2019). Thus, satisfaction is shaped by users' evaluations that compare actual performance with expected outcomes (Kim et al., 2016). This emotional state plays a critical role in influencing a wide range of favourable post-purchase and post-adoption behaviours (Morgeson et al., 2015). Moreover, Kim et al. (2003) describe satisfaction as a cognitive mindset formed by mentally contrasting the quality of service received with what was initially anticipated. Overall, satisfaction can be characterised as a positive affective state derived from users' appraisal of their experiences (Loh et al., 2022).

2.3 Conceptual Framework

According to Figure 2.3, the Expectation Confirmation Model (ECM) proposed by Bhattacherjee (2001) describes issues that contribute to the continuance intention of users to adopt information systems (IS) and technology services. It has four main constructs, and the independent variables (IV) are confirmation, perceived usefulness and satisfaction, while the dependent variable (DV) is continuance intention. This model illustrates that IVs have an impact on DV.

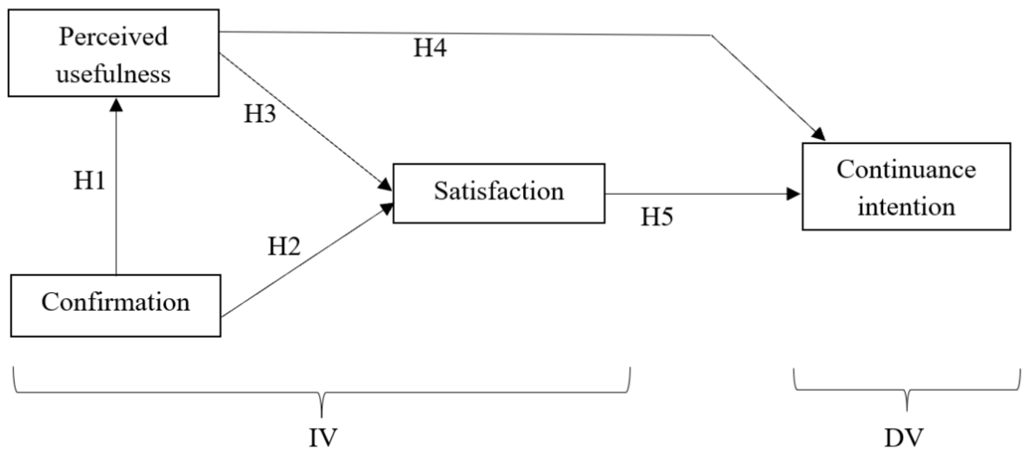

Figure 2.3. Conceptual Framework

Source: Developed from the research

2.4 Hypothesis Development

2.4.1 Confirmation and Perceived Usefulness

According to Bhattacherjee (2001), user confirmation plays an essential role in determining how long people will continue using online platforms. When users receive confirmation, it strengthens their technology adoption by enhancing their perceived ease of use and usefulness (Alshammari and Alshammari, 2024). The establishment of a connection between confirmation and user results serves as a fundamental principle in understanding the acceptance process as well as satisfaction levels across different domains.

The usefulness perception of financial robo-advisors is strongly influenced by confirmation of these platforms. Alalwan et al. (2017) suggest that when users' expectations are met during their journey, perceived usefulness increases, making them more likely to continue using the service. In addition, Singh and Kumar (2024) emphasise that user attitudes toward AI-integrated financial robo-advisory services are shaped by perceived usefulness and ease of use. Roh et al. (2023) demonstrated that user adoption of AI-enabled financial robo-advisors is strongly influenced by performance and effort expectancy. According to Alshammari and Alkhabra (2025), confirmation plays an integral role in both satisfaction and perceived usefulness. These factors are key to users' continued engagement with technology. The perceived effectiveness of financial robo-advisors depends heavily on user confirmation because it determines whether users will adopt them and keep using them for their investment needs. Thus, we propose the following:

H1: User confirmation has a significant positive relationship with user perceived usefulness in the context of financial robo-advisors.

2.4.2 Confirmation and Satisfaction

According to the Expectation Confirmation Model (ECM), customers' degree of satisfaction is indirectly influenced by how they perceive confirmation (Tian et al., 2024). Users adopt more positive attitudes and are more satisfied when they believe that their expectations have been fulfilled (Rahi et al., 2020). Satisfaction is a key factor in user retention, as it fosters continued technology usage. As users experience the confirmation of their expectations, their satisfaction levels tend to increase (Wandira et al., 2024). As AI-powered financial advising platforms, financial robo-advisors must continuously satisfy user demands for specific suggestions, ease of use, and investment success to maintain satisfaction with users (Roongruangsee & Patterson, 2023).

Satisfaction is achieved when the actual user experience meets or exceeds expectations (Loh et al., 2022). Moreover, Cheng (2022) further demonstrates that in the financial services sector, confirmation has a positive impact on user satisfaction with information systems and technology (IS/IT). This suggests that users will be more satisfied with the service if they discover that the financial robo-advisor meets or exceeds their expectations. Thus, we propose the following:

H2: User confirmation has a significant positive relationship with user satisfaction in the context of financial robo-advisors.

2.4.3 Perceived Usefulness and Satisfaction

Bhattacherjee (2001) defines perceived usefulness as consumers' assessment of the advantages gained from using technology. In addition, Pozón-López et al. (2020) identified a link between satisfaction and perceived usefulness in the context of information technology usage. Likewise, Wilson et al. (2021) show that perceived usefulness positively influenced both customer satisfaction and their intention to repurchase or continue using services from the same provider or organisation.

Han and Sa (2021) found that the perceived usefulness of a customised tourist platform positively influences customer satisfaction. Consistent with this, prior post-adoption studies have also confirmed the link between perceived usefulness and satisfaction (Al-Sharafi et al., 2022). In the context of financial robo-advisors, perceived usefulness refers to the degree to which users view these platforms as beneficial for wealth management, investment decision-making, and financial planning (Xia et al., 2023). When users perceive robo-advisors as effective tools for managing complex financial tasks, they are more likely to experience higher satisfaction and maintain continued usage (Cheng, 2020b). Thus, we propose the following:

H3: User perceived usefulness has a significant positive relationship with user satisfaction in the context of financial robo-advisors.

2.4.4 Perceived Usefulness and Continuance Intention

The central construct, perceived usefulness, shows consistent influence on users' continuance intention in every digital service, including financial platforms (Davis, 1989). According to Venkatesh and Davis (2000), individuals who perceive financial systems or applications as useful for decision-making and task performance are more likely to continue using them over the long term. Similarly, Bhattacherjee (2001) demonstrated that users who recognise the value of information systems are inclined to sustain their use across platforms such as banking and investment tools. Fintech users demonstrate repeat usage of platforms like digital wallets and mobile banking because they find such services useful (Tam et al., 2018).

Financial robo-advisors benefit significantly from perceived usefulness in influencing user continuance intention (Gan et al., 2021). Moreover, Jung et al. (2017) stated that financial robo-advisors foster user retention by demonstrating their ability to manage investments, enhance financial planning, and reduce the decision-making workload. Users continue using financial robo-advisors in digital financial management due to their perceived usefulness (Yi et al., 2023). Thus, we propose the following:

H4: User perceived usefulness has a significant positive relationship with user continuance intention in the context of financial robo-advisors.

2.4.5 Satisfaction and Continuance Intention

Satisfaction is a crucial determinant of post-adoption behaviour, particularly in the competitive market of free financial robo-advisor applications, where it influences whether users continue engaging with such services (Oghuma et al., 2015). A higher level of satisfaction with information technology (IT) has been shown to positively affect users' intention to persist in its use. Thong et al. (2006) note that the Expectation Confirmation Model (ECM) draws a conceptual parallel between consumers' repurchasing goods or services and the continued usage of IT products and services. Similarly, Susanto et al. (2016) emphasised that, within information systems (IS), continuance intention is strongly shaped by user satisfaction. In the context of financial robo-advisors, satisfaction is a decisive factor influencing whether individuals choose to adopt and continue using these automated investment tools. Prior research on smart products and services has further demonstrated a strong association between satisfaction and continuance intention, a relationship that is equally relevant to financial robo-advisors (Park, 2019). Consistent with this, our study suggests that users are more likely to sustain their use of financial robo-advisors when they are satisfied with their performance. Thus, we propose the following:

H5: User satisfaction has a significant positive relationship with continuance intention in the context of financial robo-advisors.

2.5 Conclusion

In short, Chapter 2 has entailed the thorough discussion of the theoretical framework, an extensive review of the variables, and elaboration on the hypotheses. Furthermore, the literature also emphasises the connection between confirmation, perceived usefulness and satisfaction in forming continuance intention with financial robo-advisors.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter presents a detailed discussion of the research methodology, outlining its purpose, design, and implementation.

3.1 Research Design

This study adopts a quantitative research design to investigate the determinants of Malaysians continuance intention toward financial robo-advisors. Quantitative methods enable the structured collection and analysis of numerical data, allowing hypotheses to be tested statistically (Kandel, 2020). Through this approach, the study ensures both objectivity and the generalizability of its results.

This research adopts a cross-sectional design, in which data are gathered at a single point in time to capture a snapshot of the variables being studied without accounting for temporal changes (Vega et al., 2021). Such a design is well-suited for examining current trends, particularly the factors that influence Malaysian users' acceptance of and continuance intention toward financial robo-advisors. Considering the rapid evolution of financial technology, employing a cross-sectional approach offers valuable insights into the elements shaping users' decision-making processes.

For data collection, the study employs a questionnaire survey of employed adults in Malaysia. The survey is conducted through a self-administered Google Form, which is distributed to respondents. The questionnaire consists of two general sections. Demographic information such as age, gender, level of education, employment status, and income is addressed in the first section. The second section includes survey questions measuring the most significant variables, that is, confirmation, perceived usefulness, satisfaction, and continuance intention to use financial robo-advisors.

3.2 Sampling Design

3.2.1 Target Population and Sampling Frame

The population targeted in this study is Malaysian working adults with experience using financial robo-advisors. As of 31 July 2024, the estimated number of people living in Malaysia is 34.1 million (Department of Statistics Malaysia, 2024). By 2025, there will be approximately 54,335 robo-advisor users in Malaysia (Statista, 2024). In terms of employment, as of February 2025, Malaysia recorded approximately 16.73 million employed persons, with a labour force participation rate of 70.7% (Department of Statistics Malaysia, 2025). The target of this study is people within the working age group, since they tend to be more active users of financial technology services, including financial robo-advisors. By confining the population to current users, the study aims to more comprehensively understand the determinants of continuance intention to use financial robo-advisory services. Although data for the general population exists, the lack of an obvious sampling frame for financial robo-advisor users is an issue (Vafaei-Zadeh et al., 2022). In addition, protection legislation and data privacy legislation further limit the usage of fine-grained user information, hence keeping researchers out of directly knowing and sampling the intended user set.

3.2.2 Sampling Techniques

According to Chung and Al-Khaled (2021), non-probability sampling techniques provide alternative means of selecting samples through subjective opinions. A non-probability sampling technique is suitable for this study due to its specific interest in Malaysian working adults and the inability to obtain a representative sampling frame. Judgmental sampling is utilised since it allows the researcher to select the most suitable people for the study voluntarily. According to Nanjundeswaraswamy and Divakar

(2021), judgmental sampling ensures that respondents most capable of providing the required information are selected. The quality of the findings depends on the researcher's judgment in determining the appropriate sample. This study specifically targets Malaysian working adults with experience in using financial robo-advisors. In conducting judgmental sampling, filtering questions will be applied to identify suitable respondents.

The questionnaire will be distributed via online investment platforms and financial forums to reach individuals who meet the eligibility criteria for the study. The filtering questions are: (1) "Are you working in Malaysia?" (to guarantee that the respondent is an employed adult) and (2) "Have you ever used a financial robo-advisor?" (Should a respondent say "Yes," our survey will be sent to them). Only such respondents meeting these requirements will be part of the study.

Through this method, the participants will be ensured to represent the target population and generate meaningful information regarding how they view and plan to continue with financial robo-advisors.

3.2.3 Sample Size

The sample for the current study is computed based on the item-to-respondent ratio, which advises a minimum of 10 respondents per survey item (Naqvi et al., 2020). Since the current study has 16 measurement items for four variables (confirmation, perceived usefulness, satisfaction, and continuance intention), the minimum sample size would be $16 \times 10 = 160$ respondents. However, to ensure statistical validity and reliability for data analysis, the study aims to collect approximately 200 responses to account for the possibility of receiving invalid or incomplete responses.

3.3 Data Collection Methods

3.3.1 Primary Data

For a particular purpose, data collection from first-hand sources, such as questionnaires, interviews, and observations, is known as primary data (Ajayi, 2017). Primary data collection methods are directly associated with the identification stage, as researchers must obtain original information from primary sources. The analysis and interpretation phases, in contrast, emphasise synthesising and drawing conclusions from data that are mainly derived from secondary sources (Atici et al., 2012). To collect primary data from the target respondents without necessitating direct interaction with the researcher, Google Forms will be employed as the main platform for administering the questionnaires. Specifically, the primary data collection method will involve distributing questionnaires to 200 participants.

3.3.2 Questionnaire Design

Google Forms will be used to distribute the English-language survey via Facebook, Instagram, WhatsApp, and Rednotes. The questionnaire commences with a cover page that includes the researchers' names and contact information, along with a personal data protection disclaimer to enhance transparency and encourage participation. Following this introduction, the instrument is organised into two principal sections, Section A and Section B, each structured to capture the demographic details and core research constructs necessary for this study (see Appendix 3.1). The targeted participants' gender, age, ethnicity, greatest level of education, occupation, and monthly personal income are among the crucial demographic information gathered in Section A. The purpose of Section B is to collect respondents' opinions on the confirmation, perceived usefulness, satisfaction, and continuance intention of this study. There are 16 questions in all in this section. The seven-point Likert scale, which goes from 1 (strongly disagree) to 7 (strongly agree), was used to create the questions in Section B.

3.3.3 Pre-test

In survey research, pre-testing involves administering the questionnaire to a small subset of the target population to assess the instrument's validity and reliability before full distribution (Hu, 2023). For this study, two lecturers reviewed the questionnaire and provided feedback to identify possible errors or weaknesses. Their suggestions were incorporated, and minor adjustments were made to improve clarity and consistency.

3.3.4 Pilot Study

According to Lowe (2019), a pilot study is a brief feasibility study intended to evaluate multiple aspects of the approaches intended for a more extensive, exacting, or confirmatory inquiry. Pilot studies can be carried out with mixed methods, quantitative, and qualitative research (Shakir & Rahman, 2022). The primary goal of a pilot study is to determine whether a method that will eventually be applied in a larger-scale investigation is feasible (Leon et al., 2010).

Hertzog (2008) suggests collecting approximately 10 people, or 10% of the research's overall size; the decision will ultimately be influenced by the population's size and variability, as well as financial and scheduling limitations. A pilot sample size of 20 respondents is considered appropriate for this study, given the target of collecting approximately 200 responses in the main survey. According to Johanson and Brooks (2009), a pilot study generally requires between 10 and 30 participants, depending on the study design and variability. Hence, selecting 20 participants not only aligns with this guideline but is also sufficient to identify potential issues before the full-scale data collection, while considering practical constraints.

3.3.5 Pilot Study Result

As discussed in the above section, a reliability test was carried out on a pilot sample consisting of 20 survey responses to determine the consistency of all measurement variables. According to the reliability analysis of PLS-SEM, the findings showed that all 20 sets of responses had acceptable reliability to be further analysed.

Table 3.1:

Reliability Analysis for Pilot Test

Construct	Cronbach's Alpha	Composite Reliability	Number of Items
CI	0.774	0.790	4
CON	0.922	0.957	4
PU	0.750	0.749	4
SAT	0.840	0.891	4

Source: Developed for pilot study

Note: CI = Continuance Intention, CON = Confirmation, PU = Perceived Usefulness, SAT = Satisfaction

The reliability test was conducted on 20 pilot survey questionnaires, as presented in Table 3.1. The results indicated that both Cronbach's Alpha and Composite Reliability values for all variables exceeded the threshold of 0.70.

3.4 Data Analysis Tools

3.4.1 Descriptive and Inferential Analysis

Descriptive analysis provides statistically reliable and objective information for identifying sensory characteristics, thus providing a scientific basis for sensory evaluation (Kemp et al., 2018). Following this, inferential statistical methods are often applied to test differences between treatment groups and to extend conclusions from the study sample to the larger population (Kuhar, 2010). Consistent with these practices, the present study employed both descriptive and inferential analyses to explore the main constructs and to assess the proposed hypotheses.

3.4.2 SmartPLS Software

Partial least squares (PLS) path modelling is implemented through the SmartPLS software, which is widely used for structural equation modelling (SEM). SmartPLS provides a user-friendly interface that allows researchers to manage both reflective and formative latent variables while simplifying the estimation of complex models (Wong, 2013). Its adaptable design makes it especially valuable for studies involving small sample sizes or non-normally distributed data (Hair et al., 2021b). Because of these advantages, SmartPLS has become a prominent analytical tool across disciplines such as business, social sciences, and engineering, where it is frequently applied to evaluate measurement and structural models (Sarstedt & Cheah, 2019). In addition, the software supports theory building and interpretation by offering diverse statistical techniques, including confirmatory factor analysis, multigroup analysis, and mediation and moderation testing (Hair et al., 2019).

3.4.3 Outer Measurement Model

In SmartPLS, the assessment of the measurement model is a prerequisite for structural model analysis, as researchers must first verify the reliability and validity of the constructs under study. Reliability is typically evaluated using Cronbach's Alpha (CA) and Composite Reliability (CR). A measurement model is considered to have strong internal consistency when these values exceed 0.7 (Henseler et al., 2009; Hair et al., 2021a). Compared to CA, CR is recommended in PLS-SEM because it accounts for differences in indicator factor loadings. Prior studies have established that a construct demonstrates reliability when its CR value surpasses 0.7, indicating stable measurement across items (Chin, 1998).

According to Fornell and Larcker (1981) and Hair et al. (2019), a construct achieves valid measurement when it can account for the variance observed in its measurement items. The Average Variance Extracted (AVE) is the primary indicator used to evaluate this aspect. Convergent validity is established when the AVE value is 0.5 or above, meaning the construct explains at least 50% of the variance in its indicators. Through this process, the construct is shown to adequately represent the underlying measurement concept.

Discriminant validity indicates the degree to which each construct in a model is distinct from the others. A common method for assessing this is the Fornell-Larcker Criterion, which compares the square root of a construct's AVE with its correlations to other constructs. In this study, discriminant validity was established because each construct showed stronger relationships with its own indicators than with those of different constructs (Henseler et al., 2014; Franke & Sarstedt, 2019). Beyond the Fornell-Larcker approach, the Heterotrait-Monotrait Ratio (HTMT) is also widely used to test discriminant validity by analysing correlations between constructs. Following prior guidelines, the HTMT results in this study were all below the recommended threshold of 0.90, thereby offering additional support for discriminant validity (Voorhees et al., 2015).

The validity of indicators in SmartPLS is evaluated through its outer loadings. A successful measurement requires all items to obtain outer loadings higher than 0.7 (Chin, 1998; Haji-Othman & Yusuff, 2022). The removal of measurement items with low loadings is usually appropriate except when solid theoretical evidence exists for keeping them. The assessment of measurement items in SmartPLS is achieved through outer loadings to check their strong correlation with constructs, which guarantees model validity.

3.4.4 Inner Structural Model

Following the assessment of the measurement model, the next step is to evaluate the structural model in order to examine the relationships among latent variables and test the proposed hypotheses. As part of this process, collinearity is assessed using the Variance Inflation Factor (VIF). According to Hair et al. (2021b), VIF values greater than 5 indicate severe collinearity problems, whereas values between 3 and 5 are considered acceptable with minimal bias. Becker et al. (2018) note that structural model testing primarily relies on path coefficients, supported by statistical measures such as p-values, t-values, and the coefficient of determination (R^2). The predictive strength of the model is interpreted through R^2, where values above 0.70 reflect strong explanatory power, values near 0.50 suggest moderate accuracy, and those around 0.25 indicate weak predictive ability (Humida et al., 2021). In addition to R^2, effect size (f^2) is used to determine the relative contribution of predictor constructs, with thresholds of 0.02, 0.15, and 0.35 representing small, medium, and large effects, respectively (Cohen, 2013). Furthermore, predictive relevance can be assessed using Q^2 values, where values greater than zero demonstrate the model's capability to predict (Shmueli et al., 2019). Together, these evaluation criteria provide meaningful insights into the theoretical relationships within the structural model.

3.5 Conclusion

This chapter outlines the sampling methods and analytical techniques within a structured framework, providing a clear and comprehensive explanation of the data collection methodology.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

The chapter first presents a descriptive analysis of respondents' demographic profiles, followed by the evaluation of the measurement model using PLS-SEM.

4.1 Demographics of Targeted Respondents

The demographic profile of the respondents includes variables such as gender, age, ethnicity, educational attainment, occupation, monthly personal income, and prior use of at least one financial robo-advisor. In total, 210 survey responses were obtained, of which 10 were excluded because the participants had no experience with financial robo-advisors. The final demographic distribution, along with the percentage for each category, is summarised in the table below.

Table 4.1:

Demographic Summary Table

Demographic Profile	Categories	Frequency	Percentage (%)
I am currently using at least one mobile robo-advisor (e.g., Stashaway)	Yes	200	95.7
Gender	Male	85	42.5
	Female	115	57.5
Age	21-25	89	44.5
	26-30	49	24.5
	31-35	21	10.5
	36-40	11	5.5
	41-45	14	7
	46-50	5	2.5
	51-55	6	3
	56-60	5	2.5
	Above 60	0	0
Ethnicity	Chinese	98	49
	Malay	57	28.5
	Indian	45	22.5
Highest Education Level	Primary or Secondary School	16	8
	Pre-U or Diploma or Advanced Diploma	21	10.5
	Bachelor or Professional Qualification	149	74.5
	Master or PhD	14	7

Occupation	Full-Time Employee	150	75
	Part-Time Employee	29	14.5
	Self-Employed	21	10.5
Monthly Personal Income	RM1,500-RM2,999	56	28
	RM3,000-RM4,499	40	20
	RM4,500-RM5,999	43	21.5
	RM 6,000-RM7,499	39	19.5
	RM7,500-RM8,999	13	6.5
	Above RM9,000	9	4.5

Table 4.1 presents the demographic characteristics and financial robo-advisor usage of the 200 valid respondents. The majority of participants in this study are Chinese females aged between 21 and 25, with a monthly income ranging from RM1,500 to RM2,999. The growing adoption of financial robo-advisors is largely driven by their automation, affordability, and ease of access, making them particularly attractive to Generation Z and Millennials, who often prefer self-directed approaches to digital financial planning (Cao et al., 2025a). As digital literacy increases, individuals are more inclined to adopt AI-powered platforms that deliver investment recommendations without requiring human advisors (Al-Afeef & Alsmadi, 2025). Previous studies also highlight that factors such as system trust, user-friendly design, and personalised services significantly contribute to the acceptance and continued use of these technologies (Hildebrand & Bergner, 2020).

Financial robo-advisors satisfy the psychological needs of autonomy and competence in a mobile context (Schütz et al., 2023). Financial robo-advisors are expected to continue expanding and transforming the personal investment sector, driven by the increasing demand for financial independence. Within this survey, most respondents are female, and most participants reported attaining at least a Bachelor’s degree or a Professional Qualification.

4.2 Measurement Model Assessment

4.2.1 Reliability Analysis

Table 4.2 presents the reliability analysis test results, which were collected from 200 sets of usable data. As shown in the table, all constructs achieved values above the recommended threshold of 0.70 for both Cronbach’s Alpha (CA) and Composite Reliability (CR). CA is a widely used statistic to evaluate internal consistency by measuring the intercorrelation among items that are intended to assess the same construct, with values above 0.70 considered acceptable (Kamis et al., 2020; Yusoff et al., 2020; Musa et al., 2021; Cheung et al., 2023). Similarly, CR reflects the overall reliability of a latent construct, and values between 0.60 and 0.70 may be considered acceptable for exploratory research, while values above 0.70 are generally preferred for confirmatory studies (Shrestha, 2021; Wu et al., 2023). Thus, as all CR values exceeded the 0.70 benchmark in this study, the constructs demonstrate adequate internal consistency and reliability in the measurement model.

Table 4.2:

Reliability Analysis Data

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Number of Items
PU	0.889	0.890	0.923	4
CON	0.923	0.924	0.946	4
SAT	0.936	0.936	0.954	4
CI	0.951	0.951	0.964	4

Source: Developed for the research

Note: PU = Perceived Usefulness, CON = Confirmation, SAT = Satisfaction, CI = Continuance Intention

4.2.2 Validity Analysis

4.2.2.1 Convergent Validity

Convergent validity describes the degree to which a construct is well represented by its indicators, as reflected in the proportion of variance explained through the Average Variance Extracted (AVE) (Ismail et al., 2020). According to the guideline proposed by Fornell and Larcker (1981), an AVE value of 0.50 or greater is regarded as acceptable, since it demonstrates that the construct is capable of capturing at least 50% of the variance in its measurement items (Purwanto & Sudargini, 2021; Suleiman & Abdulkadir, 2022). In this study, the results displayed in Table 4.3 confirm that all constructs successfully achieve convergent validity, as their AVE values exceed the recommended minimum threshold of 0.50, thereby ensuring that the constructs are adequately measured by their indicators.

Table 4.3:

Average Variance Extracted (AVE)

Construct	Average Variance Extracted (AVE)
PU	0.750
CON	0.813
SAT	0.838
CI	0.871

Source: Developed for the research

Note: PU = Perceived Usefulness, CON = Confirmation, SAT = Satisfaction, CI = Continuance Intention

4.2.2.2 Discriminant Validity

Hair et al. (2019) define discriminant validity as the extent to which a construct can be distinguished empirically from other constructs in a model. In order to evaluate this requirement within the structural model, the present study employed two common approaches: the Fornell-Larcker criterion and the cross-loading assessment (Fornell & Larcker, 1981; Chin, 1998).

The cross-loading approach is used as an initial step to evaluate discriminant validity, which is confirmed when each indicator exhibits a higher loading on its own construct than on any other construct (Ameen et al., 2020; Sukendro et al., 2020). As shown in Table 4.4, all bolded outer loading values for the constructs surpass the respective cross-loadings on other constructs, thereby validating discriminant validity through the cross-loading method.

Table 4.4:

Cross-Loading

	CI	CON	PU	SAT
CI1	**0.932**	0.763	0.676	0.792
CI2	**0.921**	0.773	0.702	0.768
CI3	**0.943**	0.796	0.687	0.788
CI4	**0.938**	0.772	0.708	0.806
CON1	0.729	**0.889**	0.674	0.723
CON2	0.767	**0.899**	0.631	0.718
CON3	0.756	**0.898**	0.639	0.714
CON4	0.748	**0.920**	0.686	0.739
PU1	0.630	0.616	**0.839**	0.585
PU2	0.643	0.613	**0.899**	0.628
PU3	0.619	0.616	**0.891**	0.594
PU4	0.674	0.677	**0.834**	0.701
SAT1	0.755	0.739	0.657	**0.897**
SAT2	0.759	0.736	0.662	**0.926**
SAT3	0.791	0.743	0.679	**0.926**
SAT4	0.789	0.720	0.664	**0.913**

Source: Developed for the research

Note: CI = Continuance Intention, CON = Confirmation, PU = Perceived Usefulness, SAT = Satisfaction

The Fornell-Larcker criterion posits that discriminant validity is achieved when the square root of a construct's Average Variance Extracted (AVE) exceeds its correlations with all other constructs in the model (Afthanorhan et al., 2021; Rasoolimanesh, 2022). As indicated in Table 4.5, the square root of the AVE for each construct in this study is higher than its respective inter-construct correlations, confirming that discriminant validity has been successfully established.

Table 4.5:

Fornell-Lacker

	CI	CON	PU	SAT
CI	**0.933**			
CON	0.831	**0.902**		
PU	0.743	0.730	**0.866**	
SAT	0.845	0.802	0.727	**0.915**

Source: Developed for the research

Note: CI = Continuance Intention, CON = Confirmation, PU = Perceived Usefulness, SAT = Satisfaction

4.3 Structural Model Assessment

4.3.1 Path Coefficient

Table 4.6 displays the results of the structural model assessment, including path coefficients, T-statistics, and P-values, which were generated through bootstrapping procedures (Qazi et al., 2020). The results indicate that confirmation significantly and positively influences perceived usefulness (β = 0.730, T = 19.279, P = 0.000) and satisfaction (β = 0.582, T = 8.283, P = 0.000). Perceived usefulness also shows a significant positive effect on continuance intention (β = 0.273, T = 4.047, P = 0.000) and satisfaction (β = 0.302, T = 4.324, P = 0.000). Furthermore, satisfaction has a strong positive impact on continuance intention (β = 0.647, T = 9.463, P = 0.000). Since all path coefficients are statistically significant at the 0.001 level (P < 0.05), the corresponding hypotheses developed in Chapter 2 are supported (Cheah et al., 2020; Rachmad, 2022).

Table 4.6:

Path Coefficient

Path	Original sample (O) / Path coefficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Significance
CON→ PU	0.730	0.731	0.038	19.279	0.000	**Yes**
CON→ SAT	0.582	0.580	0.070	8.283	0.000	**Yes**
PU → CI	0.273	0.275	0.067	4.047	0.000	**Yes**
PU→ SAT	0.302	0.303	0.070	4.324	0.000	**Yes**
SAT → CI	0.647	0.645	0.068	9.463	0.000	**Yes**

Source: Developed for the research

Note: CON = Confirmation, PU = Perceived Usefulness, SAT = Satisfaction, CI = Continuance Intention

4.3.2 R^2 and Construct Cross-Validated Redundancy

The coefficient of determination (R^2) evaluates a model's predictive capability by indicating the proportion of variance in the dependent variable that can be explained by the independent variables (Wherry, 1931; Rigdon, 2012; Ramayah et al., 2018; Hair & Alamer, 2022; Gupta et al., 2024). As presented in Table 4.7, all constructs exhibit R^2 values above the 0.50 benchmark, reflecting strong predictive accuracy. Among them, Continuance Intention (CI) demonstrates the highest R^2 of 0.749, meaning that 74.9% of its variance is accounted for by its predictors. Satisfaction (SAT) follows with an R^2 of 0.687, while Perceived Usefulness (PU) shows an R^2 of 0.533.

Table 4.7:

R-Square Results

Construct	R-square
CI	0.749
PU	0.533
SAT	0.687

Source: Developed for the research

Note: CI = Continuance Intention, PU = Perceived Usefulness, SAT = Satisfaction

The Q^2 statistic assesses the predictive relevance of a model by determining its capacity to forecast data that were not included in the model estimation, with values above zero indicating meaningful predictive capability (Hair et al., 2014; Hew et al., 2020). As shown in Table 4.8, all Q^2 values exceed zero, confirming the model's predictive relevance. Specifically, Continuance Intention (CI) has a Q^2 of 0.676, Satisfaction (SAT) registers 0.639, and Perceived Usefulness (PU) reaches 0.527, all surpassing the recommended threshold of 0. This demonstrates that the model is capable of reliably predicting data beyond the estimation sample.

Table 4.8:

Construct Cross-Validated Redundancy Results

Construct	Q^2 predict	RMSE	MAE
CI	0.676	0.574	0.424
PU	0.527	0.695	0.545
SAT	0.639	0.605	0.425

Source: Developed for the research

Note: CI = Continuance Intention, PU = Perceived Usefulness, SAT = Satisfaction

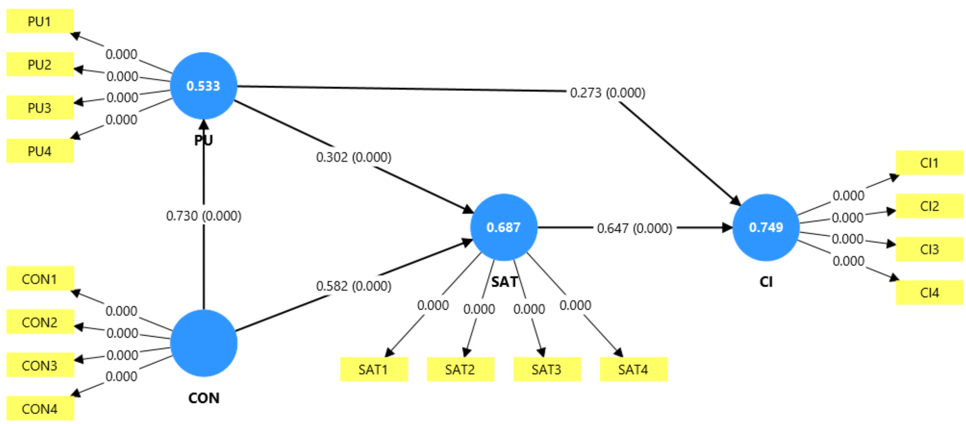

Figure 4.1. SMART-PLS 4 Model

Source: Developed for the research

4.4 Conclusion

The main metrics used for analysis encompassed path coefficients, convergent validity, discriminant validity, and reliability measures. All hypotheses proposed in this study were confirmed, with the results summarised in the accompanying tables.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

This chapter presents the main findings of the study and integrates the results of the statistical analyses. It also discusses the theoretical and practical implications, highlights the study's limitations, and provides recommendations to inform future research directions.

5.1 Summary of Statistical Analysis

The results of all hypothesis tests (H1–H5) have been compiled and are displayed in Table 5.1.

Table 5.1:

Results of Hypothesis Testing

	Hypothesis	Result
H1	User confirmation has a significant positive relationship with user perceived usefulness in the context of financial robo-advisor.	Supported
H2	User confirmation has a significant positive relationship with user satisfaction in the context of financial robo-advisors.	Supported

H3	User perceived usefulness has a significant positive relationship with user satisfaction in the context of financial robo-advisors.	Supported
H4	User perceived usefulness has a significant positive relationship with user continuance intention in the context of financial robo-advisors.	Supported
H5	User satisfaction has a significant positive relationship with continuance intention in the context of financial robo-advisors.	Supported

Source: Developed from the research

5.2 Discussions of Major Findings

5.2.1 The Relationship Between Confirmation and Perceived Usefulness

The result supports the prediction of H1, which implies that there is a significant positive relationship between confirmation and perceived usefulness among Malaysian users of financial robo-advisors. According to Alshammari and Alshammari (2024), confirmation improves the perception of systems as useful to the users. In the analysed case, Malaysian users perceive the platform as beneficial primarily when it meets their expectations, particularly with respect to ease of use, efficiency, and personalisation. According to Singh and Kumar (2024), perceived usefulness is among the most significant incentives of user satisfaction and engagement in AI-based services in the future. In that way, confirmation can be regarded as the foundation of the perceived growth of the benefits of financial robo-advisors.

5.2.2 The Relationship Between Confirmation and Satisfaction

The results support H2, showing a significant positive relationship between confirmation and satisfaction among Malaysian users. This finding aligns with the Expectation Confirmation Model (ECM), which suggests that meeting or exceeding user expectations enhances satisfaction levels (Habib et al., 2025). As financial robo-advisors increasingly provide personalised investment recommendations, younger Malaysian users, in particular, are more likely to perceive these services as satisfying, as they address individual preferences and needs effectively (Rahi et al., 2019; Wandira et al., 2024). In addition, confirmation helps reinforce users' trust in the platform's reliability, further contributing to higher satisfaction and greater loyalty.

5.2.3 The Relationship Between Perceived Usefulness and Satisfaction

The analysis confirms H3, indicating a strong positive relationship between perceived usefulness and satisfaction among Malaysian users. As Xia et al. (2023) note, financial robo-advisors provide greater value when designed to support personal wealth and investment management. In the post-adoption phase of smart technologies, perceived usefulness significantly influences user satisfaction (Al-Sharafi et al., 2022). In this study, respondents reported higher satisfaction when the platform offered convenient, easily understandable, and results-oriented financial guidance, highlighting how practical utility enhances the overall user experience.

5.2.4 The Relationship Between Perceived Usefulness and Continuance Intention

The results support H4, indicating that perceived usefulness positively influences the continuance intention of Malaysian users. According to Yi et al. (2023), perceived usefulness is a key factor in extending the long-term adoption of fintech platforms, particularly robo-advisors. In addition, Gan et al. (2021) found that higher perceptions of usefulness enhance trust and encourage continued engagement with AI-based financial applications. In this study, Malaysian users reported that the service was valuable for saving time, managing their investment portfolios, and facilitating straightforward financial transactions. Consequently, these perceived benefits provide strong motivation for users to continue using the platform.

5.2.5 The Relationship Between Satisfaction and Continuance Intention

The analysis supports H5, demonstrating a significant positive relationship between satisfaction and continuance intention among Malaysian users. This finding aligns with previous research, which emphasizes the importance of satisfaction in fostering long-term engagement with smart technologies (Park, 2019; Roongruangsee & Patterson, 2023). In the context of financial robo-advisors, user satisfaction is largely influenced by service quality, the perceived reliability of the platform, and trust in AI-generated financial decisions. The results indicate that higher satisfaction levels among Malaysian users are linked to an increased likelihood of continued use of financial robo-advisors for managing their financial planning.

5.3 Implications of the Study

5.3.1 Practical Implications

The findings of this study carry significant implications for policymakers, financial institutions, investors and consumers (Nourallah et al., 2022). Specifically, confirmation, perceived usefulness and satisfaction were found to have positive and significant effects on users' intention to continue using such platforms. The platform providers should work to enhance confirmation by minimising the differences between what users expect and what they receive. Providers can achieve this by providing clear onboarding instructions and realistic projections, together with regular updates about investment progress. Additionally, when the platform fails to meet expectations, quick recovery actions such as explanations, recalibrated projections, or compensation in the form of service credits can assist in restoring user confidence.

Secondly, users tend to maintain long-term dependence on financial robo-advisors when the service demonstrates genuine advantages for their financial planning needs. The platform providers need to showcase the concrete outcomes from their platform through portfolio optimisation, together with automated goal-based recommendations and intelligent rebalancing features. Users need visual displays of value in the form of goal dashboards and investment summary snapshots, and performance comparisons to understand how the service assists their decision-making and cost and time savings.

Thirdly, users who have positive experiences with their platform interactions usually become loyal customers who establish regular usage patterns. Platform providers need to deliver seamless interactions across all customer contact points, starting with an intuitive interface and fast support responses to achieve maximum satisfaction. Organisations need to use brief in-app surveys and post-action pop-ups to acquire continuous feedback, which must be promptly addressed. Moreover, organisations can develop stronger satisfaction levels among their loyal users by offering them loyalty badges together with insights reports and intermittent rewards.

5.3.2 Theoretical Implications

Firstly, this research contributes to the theoretical pursuit of how the Expectation Confirmation Model (ECM) can be applied to the new financial sector of financial robo-advisors in the case of Malaysia. Although the Expectation Confirmation Model (ECM) has been successfully applied in subsequent studies in areas such as e-commerce, online banking, and e-learning, its application within the fintech context is limited, particularly in financial robo-advisory services that operate autonomously without human intervention (Chiu et al., 2021). Therefore, this research helps the community extend the ECM to the new and ever-growing technology market by analysing some of the main issues and terms, such as confirmation, perceived usefulness, and satisfaction with the topic of financial robo-advisors.

Secondly, the results empirically validate the robustness of the ECM in explaining user continuance intention in the fintech context. The findings are in support of the fundamental relationships proposed in the model, as confirmation has a positive effect on the two relationships with perceived usefulness and satisfaction, which exhibit a significant influence on user continuance intention. This once again confirms the predictive capacity and theoretical quality of the model, even in the context in which decision-making is based on algorithms with little interaction between the human and computer in making the decision. Thus, the ECM continues to be a well-established and current construct of the post-adoption behaviour of digital financial services.

5.4 Limitations of the Study

Firstly, this study did not incorporate any moderator variables, such as age, income, or financial literacy, into the research framework, which restricts our understanding of how these factors might influence Malaysians' continuance intention toward financial robo-advisors. In the absence of moderator variables, it is not possible to examine whether specific demographic or socio-economic groups respond differently to the relationships among confirmation, perceived usefulness, satisfaction, and continuance intention, thereby limiting the depth and explanatory power of the findings.

Secondly, although Malaysia is a multi-ethnic country, the composition of respondents in this study was skewed, with 49% Chinese, 28% Malay, and 23% Indian. Since the proportion of Chinese respondents is higher than their actual representation in the general population, the results may not fully reflect the perspectives of other ethnic groups, particularly Malays and Indians. This imbalance limits the generalizability of the findings across all Malaysian users.

Thirdly, a prominent shortcoming of this paper is the theoretical scope of the study, as it only used the Expectation Confirmation Model (ECM) to analyse the continuation intention of financial robo-advisors among Malaysians. Although the ECM is considered to have a solid foundation in explaining user satisfaction and post-adoption behaviour, it fails to describe other psychological, technological, and situational factors that may affect user choice. Therefore, the findings may not fully reflect the continuation intention in the financial robo-advisory context.

5.5 Recommendations for Future Research

Firstly, future studies should consider incorporating moderator variables, such as age, income level, or financial literacy, into the research framework (Lau et al., 2021; Loh et al., 2021). Including moderators would allow researchers to examine whether different demographic or socio-economic groups respond differently to the relationships among confirmation, perceived usefulness, satisfaction, and continuance intention. This approach could enhance the explanatory power of the ECM model and provide more nuanced insights into factors influencing Malaysians' continuance intention toward financial robo-advisors. According to Venkatesh et al. (2003), demographic and socio-economic factors may moderate users' perceptions and continuance intentions in information systems adoption.

Secondly, using an unbalanced or non-representative sample can restrict the generalizability of the study's findings (Milanzi et al., 2015; Cao et al., 2025b). Therefore, future studies should strive to include a more representative sample that reflects the diverse, multi-ethnic composition of Malaysia's population. Efforts should be made to balance the participation of Chinese, Malay, Indian, and other minority respondents better to reflect the actual ethnic composition of the country. A more proportionate sample would improve the generalizability of findings and ensure that the results more accurately capture the perspectives of all Malaysian users.

Thirdly, regarding the research model, this study primarily draws upon the Expectation Confirmation Model (ECM), while other potentially relevant constructs, such as trust or users' investment orientation, were not incorporated as additional indicators of interest. Therefore, future studies are expected to expand the existing model to consider more variables to more accurately describe the multifaceted relationship between financial robo-advisors and the intention to use the application again (Gu et al., 2021; Tew et al., 2021; Loh et al., 2023a; Loh et al., 2023b).

5.6 Conclusion

In summary, this study validates the key findings across all tested hypotheses. Furthermore, the chapter discusses the research limitations and offers a series of recommendations to guide and enhance future studies.

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Appendices

Appendix 3.1 Research Instrument

Variables	Measurement Items	Sources
Confirmation	CON1: My experience of using mobile robo-advisor was better than what I had expected.	Putra et al. (2022)
	CON2: The service of mobile robo-advisor was better than what I had expected.	
	CON3: The expectations that I had about using mobile robo-advisor were correct.	
	CON4: Overall, my expectations on using mobile robo-advisor were confirmed.	
Perceived Usefulness	PU1: I believe that using mobile robo-advisor is convenient.	Loh et al. (2022)
	PU2: I believe that using mobile robo-advisor enhances my productivity.	
	PU3: I believe that using mobile robo-advisor improves my efficiency.	
	PU4: I believe that using mobile robo-advisor is useful for my current situation.	
Satisfaction	SAT1: Mobile robo-advisor fulfilled my expectations.	Loh et al. (2023c)
	SAT2: I am satisfied with the experiences I had with using mobile robo-advisor.	
	SAT3: My decision to use mobile robo-advisor was a wise one.	
	SAT4: Overall, I am satisfied with my use of mobile robo-advisor.	

Continuance Intention	CI1: I intend to continue using mobile robo-advisor in the future.	Cheng (2020b)
	CI2: I will keep using mobile robo-advisor as regularly as I do now.	
	CI3: I will always try to use mobile robo-advisor.	
	CI4: I intend to increase my use of mobile robo-advisor in the future.	

Appendix 3.2 Questionnaire for Main Study

UNIVERSITI TUNKU ABDUL RAHMAN
FACULTY OF BUSINESS AND FINANCE
BACHELOR OF MARKETING (HONS)
UNDERGRADUATE FINAL YEAR PROJECT [FYP]

Title of Topic: Factors Affecting Malaysians Continuance Intention Towards Financial Robo-advisors

Questionnaire

Dear respondent,

We are students currently pursuing Bachelor of Marketing (Honours) in Universiti Tunku Abdul Rahman (UTAR). We are conducting research on the topic of **"Factors Affecting Malaysians Continuance Intention Towards Financial Robo-advisors".**

Participation in this survey is voluntary. The completion of this survey will take you approximately 5 to 10 minutes.

Your response will be kept **PRIVATE** and **CONFIDENTIAL** and will be used solely for academic purposes. Your participation would be appreciated and by submitting your responses, you are hereby consent to the researcher to utilise your data for this study.

If you have any enquiries, please do not hesitate to contact us at email **lihun0228@1utar.my** or **pennyloo2004@1utar.my**.

Thank you for your time and cooperation to answer the questionnaire.

Yours sincerely,

Ng Li Hun

Loo Pui Nee

PERSONAL DATA PROTECTION NOTICE

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.

1. Personal data refers to any information which may directly or indirectly identify a person which could include sensitive personal data and expression of opinion. Among others it includes: Name, identity card, place of birth, address, education history, employment history, medical history, blood type, race, religion, photo, personal information and associated research data.

2. The purposes for which your personal data may be used are inclusive but not limited to:
   a) For assessment of any application to UTAR
   b) For processing any benefits and services
   c) For communication purposes
   d) For advertorial and news
   e) For general administration and record purposes
   f) For enhancing the value of education
   g) For educational and related purposes consequential to UTAR
   h) For replying any responds to complaints and enquiries
   i) For the purpose of our corporate governance
   j) For the purposes of conducting research/ collaboration

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

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

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

Consent:

1. By submitting or providing your personal data to UTAR, you had consented and agreed for your personal data to be used in accordance to the terms and conditions in the Notice and our relevant policy.

2. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

3. You may access and update your personal data by writing to us at
    - Ng Li Hun (lihun0228@1utar.my)
    - Loo Pui Nee (pennyloo2004@1utar.my)

Acknowledgment of Notice

[   ] I have been notified and that I hereby understood, consented and agreed per UTAR above notice.

[   ] I disagree, my personal data will not be processed.

Screening Question

I am currently using at least one mobile robo-advisor (e.g., Stashaway)

- Yes
- No (Note: If selected, the form will end immediately.)

Section A: Demographic Question

We would like you to fill in some of your details in this section.

Please tick your answer, and your answers will be kept strictly confidential.

1. Gender
   - Male
   - Female

2. Age
   - 21-25
   - 26-30
   - 31-35
   - 36-40
   - 41-45
   - 46-50
   - 51-55
   - 56-60
   - Above 60

3. Ethnicity
   - Chinese
   - Malay
   - Indian

4. Highest Education Level
    - Primary or Secondary School
    - Pre-U or Diploma or Advanced Diploma
    - Bachelor or Professional Qualification
    - Master or PhD

5. Occupation
    - Full-Time Employee
    - Part-Time Employee
    - Self-Employed

6. Monthly Personal Income
    - RM1,500-RM2,999
    - RM3,000-RM4,499
    - RM4,500-RM5,999
    - RM6,000- RM7,499
    - RM7,500 to RM8,999
    - Above RM9,000

Section B: Research Variables

This section is seeking your opinion regarding the factors that influence continuance intention.

Respondents are asked to indicate the extent to which they agreed or disagreed with each statement using 7-point likert scale 【(1) = strongly disagree; (2) = disagree; (3) = slightly disagree; (4) = neutral; (5) = slightly agree; (6) = agree and (7) strongly agree】response framework.

Please select one number per line to indicate how much you agree or disagree with the following statements.

Confirmation

1. My experience of using mobile robo-advisor was better than what I had expected.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

2. The service of mobile robo-advisor was better than what I had expected.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

3. The expectations that I had about using mobile robo-advisor were correct

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

4. Overall, my expectations on using mobile robo-advisor were confirmed.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Perceived Usefulness

1. I believe that using mobile robo-advisor is convenient.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

2. I believe that using mobile robo-advisor enhances my productivity.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

3. I believe that using mobile robo-advisor improves my efficiency.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

4. I believe that using mobile robo-advisor is useful for my current situation.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Satisfaction

1. Mobile robo-advisor fulfilled my expectations.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

2. I am satisfied with the experiences I had with using mobile robo-advisor.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

3. My decision to use mobile robo-advisor was a wise one.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

4. Overall, I am satisfied with my use of mobile robo-advisor.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Continuance Intention

1. I intend to continue using mobile robo-advisor in the future.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

2. I will keep using mobile robo-advisor as regularly as I do now.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

3. I will always try to use mobile robo-advisor.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

4. I intend to increase my use of mobile robo-advisor in the future.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree