

## ORIGINAL ARTICLE

# Understanding consumer's adoption of financial robo-advisors at the outbreak of the COVID-19 crisis in Malaysia

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**Abstract**

The COVID-19 crisis that resulted in diminished close contact interaction and increased financial volatility could influence consumer's perception toward online automated financial robo-advisor, in order to manage their financial planning. Based on the data collected (i.e., between February [9 reported cases] and March [36 reported cases] 2020) within the developed urban cities in Malaysia just before the nationwide lockdown, the present study examines the antecedents of financial robo-advisor's adoption during the COVID-19 crisis. A variance based analysis shows that consumers with higher financial knowledge and having a greater tendency to rely on robo-advisor tend to adopt financial robo-advisor in times of crisis. In line with the unified theory of acceptance and use of technology model, performance expectancy, social influence, and trust in robo-advisor, in particular during the pandemic, drive consumer's intention to subscribe online financial robo-advisor. The findings imply how consumers, robo-advisory service providers, and regulators could respond to unprecedented crisis such as novel corona virus-19.

**KEYWORDS**

COVID-19, financial advice, financial robo-advisor, Malaysia, UTAUT

**JEL CLASSIFICATION**

D14; D18; G11; O33

## 1 | INTRODUCTION

Financial robo-advisors refer to digital platforms that provide automated web-based portfolio management services with no or minimal human intervention (Ponnaiya & Ryan, 2017). The concept of financial robo-advisors has gained significant attention from the financial industry and academia in recent years due to the high market demand for inexpensive automated portfolio management approaches. Despite the growing literature on the antecedents of adopting financial robo-advisors (e.g., Belanche et al., 2019; Hohenberger et al., 2019; Lourenco et al., 2020; Ruhr et al.,

2019), there have been few studies detailing the adoption of financial robo-advisors during an economic crisis. Therefore, this study aims to investigate the antecedents driving the adoption of financial robo-advisory platforms during the COVID-19 pandemic.

In response to the COVID-19 pandemic, the World Health Organization (WHO) had recommended preventive measures to reduce close contact human interaction and public gatherings. Consequently, the pandemic forced financial advisors to conduct virtual meetings instead of physical meetings with clients while creating challenges in securing new clients due to higher advisory fees and

existing biases. This development has accelerated the adoption of digital technology, including robo-advisory platforms that preclude human intervention within the automated processes. In addition, the COVID-19 crisis has led to financial volatility, prompting investors to adopt robo-advisory services for wealth and investment management. Annual robo-advisory fees in Malaysia range from 0.2% to 1% based on the portfolio size (Lim, 2020); whereas, human advisors charge professional fees and commissions depending on the services offered to the clients (Zeng, 2020). Despite the benefits, robo-advisors have certain disadvantages given the lack of human interaction and personalized advice.

The global COVID-19 crisis has negatively impacted the Malaysian economy and job market, resulting in reduced income (Shah et al., 2020). The Financial Education Network (FEN) in 2019 reported that only 24% of Malaysians could survive for at least 3 months or more if they lost their primary income source; whereas, merely 10% of Malaysians could sustain for more than 6 months during critical times. Moreover, 41% of Malaysians have only the employee provident funds as their primary savings for retirement (FEN, 2019). The 2020 RinggitPlus Malaysian Financial Literacy Survey revealed that Malaysians generally have poor financial habits, which has led to a lack of emergency funds and inadequate retirement planning. Such practices have changed little since November 2019 and were particularly evident during the pandemic, which raises concerns about the need for personal financial planning among Malaysians (Suriya, 2020). Considering this circumstance, robo-advisors can ideally support financial planning, wealth management, and investment at lower fees during the COVID-19 crisis. Unfortunately, research on robo-advisors in Malaysia is scant, and there is a lack of awareness and understanding among Malaysian consumers regarding robo-advisors. This study aims to contribute toward the utilization of robo-advisors by providing a thorough understanding of the antecedents of adopting financial robo-advisors among Malaysians.

The motivation for this research is also predicated by the increasing number of robo-advisory service providers in Malaysia (Lim, 2020). The Securities Commission of Malaysia recently introduced the digital investment management (DIM) framework that supports regulatory and licensing functions for robo-advisory services. Under the DIM framework, the Securities Commission of Malaysia awarded its first Capital Market Services License to StashAway, an online investment management company headquartered in Singapore; thereby, establishing it as the first authorized robo-advisory service provider in the Malaysian market (Pikri, 2018). Shortly after, MyTHEO—a joint venture between Japanese and Malaysian fintech

companies, Wahed Invest—a Malaysian fintech company that provides online Halal investment platform, BEST Invest—a Shariah-compliant unit trust funds, and Raiz Invest—a Malaysian company that provides services to invest locally in Amanah Saham Nasional funds, were granted Capital Market Services Licenses; and thereafter, were authorized to provide robo-advisory services in Malaysia (Lim, 2020). This recent development highlights a trend toward the implementation of robo-advisors within the Malaysian fintech landscape. Against this backdrop, the findings of this study will give robo-advisory service providers insights into establishing effective policies and regulations to stimulate the engagement of robo-advisory services in Malaysia.

Our study collected data from the most developed urban cities in Malaysia with a relatively comprehensive internet coverage (i.e., George Town, Ipoh, Kuala Lumpur, and Johor Bahru) during the initial stages of the COVID-19 pandemic. As such, this study was framed within the context of a period that saw unique factors stemming from the crisis. Firstly, individuals faced difficulties in seeking financial advice from human advisors as close contact interactions were prohibited by law, and typically, licensed financial planners do not have a robust online presence (Gomes, 2021). Robo-advisors, on the other hand, could offer automated services online without human intervention. Secondly, from a theoretical perspective, the study contributes to the literature on financial robo-advisors by demonstrating the roles of performance expectancy, social influence, and trust in robo-advisors, perceived financial knowledge, and tendency to rely on robo-advisors in predicting the adoption of financial robo-advisors in Malaysia. Arguably, not only would these findings be relevant to similar pandemics or financial crises in the future, but they would also have post-pandemic implications, given that the COVID-19 crisis has created a “new normal” in which digital technology has been more ubiquitously adopted. Thirdly, our study extends the unified theory of acceptance and use of technology (UTAUT) model by incorporating three additional variables, namely trust in robo-advisors, perceived financial knowledge, and tendency to rely on robo-advisors, in examining the adoption of financial robo-advisors, which hinges upon recent studies underscoring the importance of these variables in adopting financial robo-advisors (Alwi et al., 2019; Lewis, 2018; Stewart & Jürjens, 2018). Fourthly, framed within the context of Malaysia, the findings of this study will enrich the literature on the adoption of robo-advisors in emerging markets or developing countries. The adoption of robo-advisors is not well understood in Malaysia despite the high growth potential, and thus, this study fills a critical gap in understanding the antecedents driving the adoption of robo-advisors in Malaysia.

## 2 | LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

### 2.1 | Financial robo-advisory services

Financial robo-advisors are systems powered by artificial intelligence (AI) algorithms that provide automated portfolio management services (Jung et al., 2018). Robo-advisors offer zero to minimal human intervention or personal contact within the advisory process (Bruckes et al., 2019). Robo-advisors employ a set of standardized online questionnaires to capture consumers' risk profiles (Coombs & Redman, 2018), which contrasts with traditional human advisors who identify the risk profiles of consumers through human-to-human conversations (Ruhr et al., 2019). Robo-advisors can simulate the behavior of conventional human advisors in providing financial services to develop and execute investment strategies, albeit without emotional biases (Milani, 2019). Rebalancing is made autonomously when a significant market movement is sensed to maintain the target asset allocations (Kaya, 2017).

Financial robo-advisors benefit both service providers and consumers (Ponnaiya & Ryan, 2017). Service providers could employ robo-advisors to deal with relatively less sophisticated investors with disintermediation and enhanced efficiency. The disintermediation helps service providers to cut costs and thus charge consumers a lower management fee (around 0.2% to 1% per annum). As a result, financial robo-advisory services are more affordable than the more expensive traditional human advisors whose price points may be beyond the reach of lower net worth individuals. Moreover, the automation of robo-advisors offers highly accessible services through mobile applications or over the web, anytime, anywhere.

The financial robo-advisory services industry is expected to grow, given its contributions to a win-win situation for service providers and consumers. In Malaysia, the benefits of financial robo-advisors have been more visible against the backdrop of the COVID-19 crisis, which has consequently led to a higher interest in robo-advisors. For instance, Tan (2020) stated that the COVID-19 pandemic had stimulated an increasing number of Malaysian retail investors. Further, Gomez (2020) reported that financial robo-advisors had seen more interest and investments during the COVID-19 crisis as they are regarded as an option for consumers to engage in investment management services. The enhanced interest and utilization of financial robo-advisory services can also be attributed to the sound performance of robo-advisors in dealing with the market volatility caused by the pandemic (Martinsville, 2020).

### 2.2 | Related studies on the acceptance of robo-advisors

Jung et al. (2018) conducted an experimental study to assess the design requirements of a robo-advisor from the consumer perspective and found that the dimension of trustworthiness was a key factor affecting the attitude toward robo-advisors among consumers with no experience, and a low budget, and a low level of risk tolerance. Ruhr et al. (2019) conducted a study in which 171 university students in Germany were given a scenario of having 5000 euros and four options of investment management services to engage with: hybrid robo-advisor, fully automated robo-advisor, human advisor, and delegated human advisor. They found that performance expectancy and perceived risk had significant roles in predicting behavioral intention; the use of algorithms in robo-advisory services caused a high-performance expectancy that led to a high behavioral intention. In a later study with 148 participants from a German University, Ruhr (2020) found that the impact of automation on the intention to use robo-advisors was inversely U-shaped pointing toward the benefits of hybrid automation, which indicated that the participants strongly valued the advanced hybrid automation compared with the low or full automation of robo-advisory services.

Milani (2019) examined the adoption of robo-advisors in Italy through the lens of the UTAUT. The data collected from 635 Italian employees of PricewaterhouseCoopers indicated that participants with high levels of education, investing experience, and understanding of robo-advisors tended to have a higher intention of adopting robo-advisors. Moreover, the study showed that perceived relative advantage, effort expectancy, social influence, and trust had a positive impact on behavioral intention via attitude. Belanche et al. (2019) conducted a similar study grounded on the extended technology acceptance model (TAM) with additional variables including subjective norm and familiarity. Based on 765 respondents from the US, Portugal, and the UK, it was demonstrated that perceived usefulness and perceived ease of use were predictors of attitude, and attitude, in turn, predicted behavioral intention to adopt financial robo-advisors. Sa et al. (2018) conducted a study with respondents consisting of fund managers, corporation fund managers, and fintech employees, and found that perceived ease of use and perceived usefulness predicted the intention to use financial robo-advisors.

Hohenberger et al. (2019) examined the acceptance of robo-advisors in the US using a sample of 630 adults categorized into three generations, namely baby boomers, generation X, and millennials. They found that white participants, married, or lived with a partner, and have postgraduate work, were more willing to use

robo-advisors. Moreover, the study revealed that perceived anxiety had a negative impact on the willingness to use financial robo-advisors, whereas perceived joy positively impacted the willingness to use financial robo-advisors. Lourenco et al. (2020) investigated the acceptance of robo-advisors that focused on different advisory firms. Employing survey data collected from 1649 respondents who watched an explanatory video on robo-advisors, the study found that trust and expertise predicted the acceptance of automated financial advice. Moreover, they found that the impact of firm types on acceptance of automated financial advice was mediated by trust and expertise.

Bruckes et al. (2019) investigated the determinants of and barriers to adopting robo-advisory services. The participants in their study were asked to provide information such as facts and explanations about the basic functionality of robo-advisors to increase the accuracy of the responses. These authors found that trust in robo-advisors was positively influenced by structural assurance; whereas, risk was negatively impacted by structural assurance. Moreover, it was shown that trust in banks predicted trust in robo-advisors, which led to a high intention of using robo-advisors. Based on data collected from users in Taiwan who had experience using robo-advisors, Cheng (2020) found that perceived usefulness, satisfaction, and flow experience were antecedents of continued intention to use robo-advisors. Brenner and Meyll (2020) examined the impact of robo-advisors on traditional human advisors using the National Financial Capability Investor Survey data from 2000 investors in the US who sought advice from both human and automated advisors in 2015. They found that the users of robo-advisors tended to be millennials, and investors who had low portfolio values and a low level of financial literacy were more likely to use robo-advisors. Musto (2020) reviewed the relation between robo-advisors and the growth of index funds to infer relevant trends and implications for public corporations.

The mixed findings from the robo-advisor literature demonstrate an inconclusive collective inference concerning the antecedents driving the adoption of robo-advisors. Moreover, Belanche et al. (2019) argued that while technical and legal issues have been the primary focus in many studies (Glaser et al., 2019; Ji, 2017), further robo-advisor research should focus on the customer perspective to extend robo-advisor services to a greater number of customers. The scant research on robo-advisor designs has highlighted a need to increase the usability of these systems to facilitate users' interaction with them (Jung et al., 2018). It is also notable that most of the studies were conducted in the US and European countries such as Italy, Portugal, United Kingdom, and Germany. In this regard, the limited literature on adopting

financial robo-advisors in Asian countries, particularly in Malaysia, suggests a critical research gap.

### 2.3 | Theoretical framework and hypothesis

We chose the UTAUT model as the baseline theory to explain the behavioral intention of consumers to adopt robo-advisors. Developed by Venkatesh et al. (2003), the UTAUT model is an integrative theory that has reviewed, analyzed, and integrated eight different models to understand consumers' behavioral intention. The four most influential predictors, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, were incorporated into the framework of the UTAUT model. While previous studies have applied the UTAUT framework, they were unable to reach a consensus on the role of each predictor in affecting behavioral intention. Hence, our study proposes a conceptual framework that extends the UTAUT model in examining the factors affecting the intention of consumers to adopt robo-advisors. Accordingly, based on relevant studies, we incorporated three additional variables, including trust in robo-advisors, perceived financial knowledge, and tendency to rely on robo-advisors, into the proposed framework.

The UTAUT model proposes that performance expectancy, effort expectancy, and social influence could significantly affect consumers' behavioral intention. Hence, these three variables were hypothesized to predict the intention of using robo-advisors. Performance expectancy is defined as the extent to which the consumer believes their performance would be improved with the use of the application (Venkatesh et al., 2003). In this research, we expected that the willingness of the consumer to adopt robo-advisors depends on the belief that robo-advisors can facilitate financial and investment management. Consumers could not have physical meetings with human advisors through traditional financial advisory processes during the COVID-19 crisis; thus, they might have regarded the use of robo-advisors as an alternative approach to manage their finances and investment at the onset and during the COVID-19 crisis.

Effort expectancy encompasses the belief that using a specific application requires little or no effort (Venkatesh et al., 2003). The behavioral intention of consumers to adopt robo-advisors may depend on the extent to which they perceive the use of robo-advisors to be easy, effortless, and comfortable. Consumers only need to fill a set of standardized online surveys regarding their financial goals and risk appetites, making the robo-advisors effortless to adopt. The robo-advisors then employ computer algorithms to develop, execute, and monitor investment

strategies autonomously. The ease of using robo-advisors could help consumers, especially those who have just started financial wealth and investment management during the COVID-19 crisis, to deal with their finances without spending much time and effort.

Social influence refers to consumers' reliance on third-party opinions when considering whether to utilize an application (Venkatesh et al., 2003). Social influence becomes crucial when the consumer is concerned about the views of friends and family when deciding to adopt robo-advisors. The COVID-19 pandemic that has generally affected the income sources of consumers would have underscored the importance of financial planning. The consumers might have started seeking low-cost financial advisory services when the people around them, such as friends and family members, are also doing so.

By adapting the well-established relationships in UTAUT into the robo-advisory context, we expected that performance expectancy, effort expectancy, and social influence would drive the adoption of financial robo-advisors in Malaysia during the initial surge of COVID-19 cases. Therefore, we hypothesized that:

**H1.** *Performance expectancy is positively related to the intention to adopt financial robo-advisors in Malaysia during the initial surge of the COVID-19 crisis.*

**H2.** *Effort expectancy is positively related to the intention to adopt financial robo-advisors in Malaysia during the initial surge of the COVID-19 crisis.*

**H3.** *Social influence is positively related to the intention to adopt financial robo-advisors in Malaysia during the initial surge of the COVID-19 crisis.*

Facilitating conditions are defined as perceived enablers or barriers in the environment that influence a person's perception of ease or difficulty of performing a task. Although the UTAUT model only proposes a correlation between facilitating conditions and usage behavior, some studies found that facilitating conditions significantly impact behavioral intention. For instance, Rahman et al. (2020) found a direct impact of facilitating conditions on both behavioral intention and actual behavior to adopt mobile financial services. Similarly, studies demonstrated that consumers' behavioral intentions to adopt electronic wallets and digital payments increased with the level of facilitating conditions (Soodan & Rana, 2020; Widodo et al., 2019).

Preventive measures that inhibited personal and close contact interactions could form barriers to engaging in traditional financial advisory services during COVID-19. By the same token, robo-advisors feature services without human contact or intervention, thereby generating facilitating conditions that can encourage consumers to adopt the platforms. Moreover, connected computing devices such as mobile phones and personal computers permeate people's lives, enabling and facilitating users to set up and utilize the robo-advisors efficiently during the initial stages of the COVID-19 pandemic. It was therefore hypothesized that:

**H4.** *Facilitating condition is positively related to the intention to adopt financial robo-advisors in Malaysia during the initial surge of the COVID-19 crisis.*

In general, it has been shown that trust drives the intention of consumers to use contemporary technologies such as new payment systems (Bui & Bui, 2018; Indrawati & Putri, 2018; Singh & Sinha, 2020; Widodo et al., 2019), online recommendation systems (Nilashi et al., 2016), and fintech products and services (Alwi et al., 2019; Stewart & Jürjens, 2018). Bui and Bui (2018) extended the UTAUT model to include trust when examining mobile payment acceptance in Vietnam. Their findings indicated a substantial correlation between trust and behavioral intention of consumers to accept mobile payment. A consistent statement has also been found by a set of studies showing trust as a significant antecedent of digital wallet adoption (Singh & Sinha, 2020; Widodo et al., 2019). In another context, trust was found to affect behavioral intention to purchase through online recommendation agents (Nilashi et al., 2016). Stewart and Jürjens (2018) found a significant correlation between trust and behavioral intention of consumers to adopt fintech services. Alwi et al. (2019), who conducted similar research, found a similar result in the context of fintech. Collectively, these findings affirm that trust plays a predicting role in the behavioral intention of contemporary technologies; and by extension, trust should also affect the intention to use robo-advisory platforms. Moreover, the automated portfolio functions that allow robo-advisors to execute investment strategies without emotional biases could have increased consumers' trust levels, especially given the market volatility caused by the COVID-19 crisis. Hence, we expected that trust, specifically in financial robo-advisors, would positively impact its adoption. Therefore, we hypothesized that:

**H5.** *Trust in robo-advisors is positively related to the intention to adopt financial robo-advisors in Malaysia during the initial surge of the COVID-19 crisis.*

Our study proposes financial knowledge as one of the determinants beyond the main components of the UTAUT model to better explain the intention to adopt robo-advisors. This notion hinges upon the existing literature, which indicates the relationship between financial knowledge and the adoption of robo-advisors. Financial knowledge is referred to as the consumer's self-assessed and perceived financial knowledge (Lusardi & Mitchell, 2017). Barber and Odean (2001) and Konana and Balasubramanian (2005) argued that when individuals were exposed to new information from different sources (e.g., the internet), they accumulated more knowledge, and the phenomenon of the illusion of knowledge was unearthed. In other words, individuals' perceived belief about the accuracy, depth, and breadth of their knowledge can become unequally higher than their objective levels of knowledge. Some studies have shown the impacts of perceived financial knowledge on various financial behaviors. Perceived financial knowledge was found to have a more substantial impact on investment behaviors (e.g., spending, saving) than objective knowledge (Allgood & Walstad, 2016; Henager & Cude, 2016). In the case of robo-advisors, Brenner and Meyll (2020) found that objective financial literacy levels are lower for the users of robo-advisors. Similarly, Todd and Seay (2020) demonstrated that those who scored high in objective investment knowledge were less likely to use robo-advisors; inversely, those with higher subjective financial knowledge showed a higher willingness to use robo-advisors. Perceived financial knowledge was a positive contributor to the adoption of robo-advisor platforms (Fan & Chatterjee, 2020). Hence, a positive relationship is expected between subjective financial knowledge and the intention to adopt robo-advisors considering the COVID-19 pandemic.

Financially literate individuals understand the financial market well and might observe financial planning more closely during the COVID-19 crisis, leading to a significant market movement. In the middle of a crisis, individuals who perceive themselves to be financially knowledgeable would be more likely to delegate their financial planning to robo-advisors that offer low-cost, bias-free, and automated advisory services. Further, financially knowledgeable individuals might not prefer to take uncertain risks under such a volatile market environment. Therefore, we expected those with high-perceived financial knowledge to choose to get advice from non-human entities, that is, robo-advisors, during the initial stage of the COVID-19 crisis. Thus, we proposed the following hypothesis:

**H6.** *Perceived financial knowledge is positively related to the intention to adopt financial robo-advisors in Malaysia during the initial surge of the COVID-19 crisis.*

Apart from the above factors, consumer's tendency to rely on robo-advisors compared with human advisors may be a significant predictor of the adoption of robo-advisors. Tendency to rely on robo-advisors could be interpreted as the willingness of consumers to rely on robo-advisors for their financial services. Mumuni et al. (2019) examined the reliance on online product reviews in the United States and found that consumers' attitude strongly predicted their tendency to rely on online product reviews. Moreover, Thoumrunroje (2014) found reliance on electronic word-of-mouth to have a strong impact on the behavior of individuals to consume conspicuous products.

In the context of robo-advisors, we expected consumers to be more likely to adopt financial robo-advisors when they are more willing to rely on the platforms rather than the traditional financial advisory services. During the COVID-19 crisis, conventional financial advisory services that involve a high degree of personal and close contact interaction would be confronted with challenges in managing workflow and communicating with co-workers and clients. The precautions to curb the coronavirus spread might drive consumers' tendency to rely on robo-advisory platforms as an alternative to traditional financial advisory services. Thus, it was hypothesized that:

**H7.** *Tendency to rely on robo-advisors is positively related to the intention to adopt financial robo-advisors in Malaysia during the initial surge of the COVID-19 crisis.*

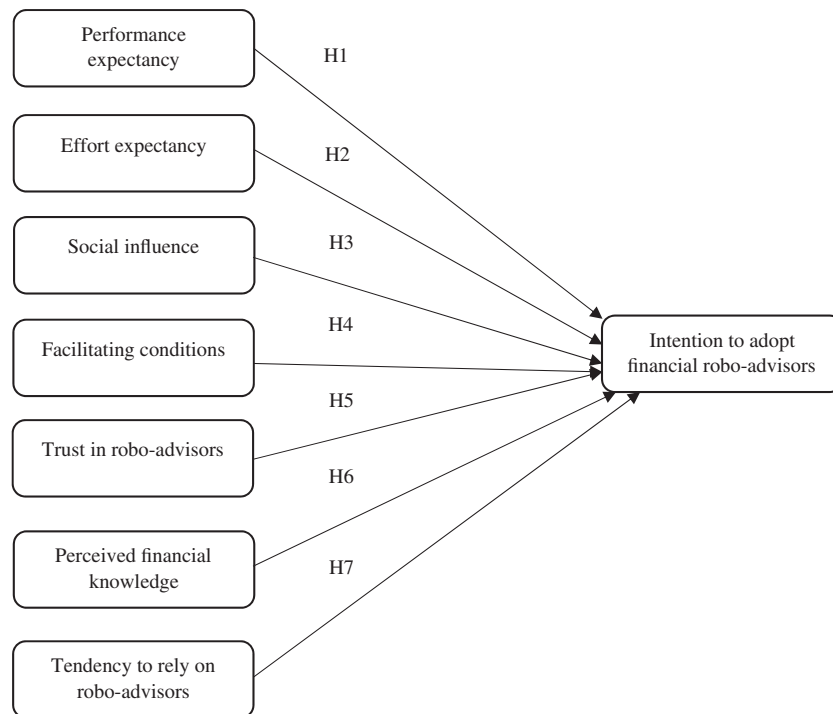
The proposed framework is denoted in Figure 1.

### 3 | METHODOLOGY

#### 3.1 | Data collection

The survey data were collected from Malaysia's most developed urban cities, as indicated in the IQI Global report (2017). These cities, including George Town (Penang), Ipoh (Perak), Kuala Lumpur (Selangor), and Johor Bahru (Johor), are known to have comprehensive and robust internet coverage, which is an essential precondition for robo-advisors. The data collection was conducted between February 3, 2020 and March 2 2020, during the initial surge of the COVID-19 cases in Malaysia. The duration of the survey collection was crucial as right after the end of data collection, the number of reported COVID-19 infected cases rose exponentially in Malaysia, which then led to the first nationwide movement control order that lasted for 83 days (from March 18, 2020 to June 9, 2020).

FIGURE 1 Proposed framework



The questionnaires were distributed following the non-probability purposive sampling method based on the following reasons: (1) the potential respondents were judged based on their ages with the criterion of age being above 18 years, and (2) respondents must have possessed an investment portfolio and have online banking experience, as the investment with financial robo-advisors involves online transactions and investable assets. We expected respondents who had online banking experience and investment portfolios to have a higher likelihood of adopting robo-advisors than others. A purposive sampling strategy is more appropriate when there is a deliberate selection of respondents based on their specific characteristics (Etikan et al., 2016). Potential respondents were approached at different locations in each of the four cities (e.g., investment banks, shopping malls) and briefed about the purpose and expected activity of the data collection. After getting their oral consent, respondents were then shown a 3-min video on a tablet explaining the interface and functionality of a robo-advisor's application platform.<sup>1</sup> Keeping in line with industry practice, the simulated robo-advisor application in the video was designed to mimic the interface of the StashAway application—which is the first robo-advisory platform in Malaysia. The video had been subjected to a review by a portfolio manager associated with a Malaysian robo-advisory service provider (i.e., MyTheo); and was deemed valid and satisfactory in quality.

After watching the video, respondents were then asked to answer the questionnaire measuring the variables. One hundred questionnaires were distributed in each of the

four selected Malaysian cities; hence, the total questionnaires distributed for this research were 400 questionnaires. A total of 285 usable responses was obtained after filtering out the incomplete responses. This represents a response rate of 71.2%. This sample size satisfied the minimum sample size based on G\*Power, which was 153. Moreover, the number of responses was comparable with the sample size of other similar studies with similar numbers of responses (Ruhr et al., 2019; Stewart & Jürjens, 2018).

### 3.2 | Measurement of variables

To measure the explanatory variables, four items were designed to measure performance expectancy; five items for effort expectancy, four items for social influence, and four items for facilitating conditions. Three items for the behavioral intention to adopt financial robo-advisors were designed to measure the dependent variable. All the items from the UTAUT variables were adapted from previous research (Moore & Benbasat, 1991; Venkatesh et al., 2003; Venkatesh et al., 2012). For the additional variables, three items were adapted from Zhou et al. (2019) for trust in robo-advisors, four items for perceived financial knowledge (Park et al., 2010; Robb et al., 2012), and four items for tendency to rely on robo-advisors (Bachmann & Hens, 2015; Safari et al., 2016). All the items were adapted to fit well into the context of robo-advisors, and the five-points Likert scale was utilized as the measurement scale. The final version of the questionnaire was established after

TABLE 1 Frequency distribution of respondents' demography

	Frequency	Percentage (%)
<b>Gender</b>		
Male	118	41.4
Female	167	58.6
<b>Age</b>		
<18	-	-
18–25	122	42.8
26–35	105	36.8
36–45	32	11.2
46–55	14	4.9
56 and above	12	4.2
<b>Ethnicity</b>		
Malay	101	35.4
Chinese	149	52.3
Indian	33	11.6
Others	2	0.7
<b>Education</b>		
STPM level and below	62	21.8
Diploma	78	27.3
Bachelor's degree	129	45.3
Postgraduate	16	5.6
<b>Marital status</b>		
Single	181	63.5
Married	104	36.5
<b>Awareness of robo-advisor</b>		
Yes	59	20.7
No	226	79.3

minor amendments were made following the review sessions by three academic experts and one industry practitioner and a pilot test with 30 respondents. The details of the items are shown in the Appendix, Table A1.

### 3.3 | Empirical estimation

Our study employed partial least square-structural equation modeling (PLS-SEM) for data analysis, aligning with the proposed framework's theory exploration. After conducting the normality test, the data were assumed to be normally distributed based on the range of the skewness and kurtosis. Although non-normal distribution is one of the criteria to employ PLS-SEM, the variance-based PLS-SEM was used in this research due to low restriction on sample size and bootstrapping technique, besides the exploratory nature of the proposed framework (Hair et al., 2017). The composite reliability analysis that

determines the level of data consistency was assessed as this has a direct relationship with the outcome of the research (Hair et al., 2014). Convergent and discriminant validity were then assessed to evaluate the measurement model, while path coefficients and coefficient of determination ( $R^2$ ) were assessed to evaluate the structural model.

## 4 | RESULTS

### 4.1 | Demographic information

SPSS was used to analyze the demographic information of the respondents. Table 1 reports the frequency distribution of the demographic data. Of the 285 respondents, 118 respondents were male, and the remaining 167 were female. The majority of the respondents fell in the age group of 18 to 25 years old (42.8%), followed by 26 to 35 (36.8%). Based on the data regarding the age group, it can be inferred that most of the respondents were categorized as Gen Z and Millennials. Concerning ethnicity, the majority of the respondents belonged to the Chinese ethnic group (52.3%), and the second majority was represented by the Malay ethnic group (35.4%). Most of the respondents have completed their bachelor's degree (45.3%), while only 5.6% have completed their postgraduate studies. When it comes to marital status, it is observed that more than 50% of the respondents were single, and the remaining 36.5% were married. The data indicates that only about 20% of the respondents have heard about robo-advisors.

### 4.2 | Convergent validity and composite reliability

The composite reliability was assessed to ensure a high level of internal consistency reliability. Outer loadings and average variance extracted (AVE) were also assessed to establish the convergent validity, which shows the degree of positive correlation between each questionnaire item of a certain variable. As shown in the composite reliability in Table 2, all variables satisfied the threshold suggested by Hair et al. (2014), which is 0.70. According to Hair et al. (2014), only the items with outer loadings higher than 0.70 could be retained directly, while the items with outer loadings of between the range of 0.40 to 0.70 would be deleted if the elimination could improve the result of the AVE and composite reliability. Only the outer loadings of FC\_4 (Facilitating Condition\_4) (0.536) were below the threshold. However, FC\_4 was not eliminated because its AVE (0.536) and composite reliability (0.813) achieved the corresponding threshold of 0.50 and 0.70, respectively. It



TABLE 2 Convergent validity and composite reliability

Variables	Items	Loadings	AVE	Composite reliability	Cronbach's alpha
Performance expectancy	PE_1	0.815	0.731	0.916	0.877
	PE_2	0.850			
	PE_3	0.876			
	PE_4	0.876			
Effort expectancy	EE_1	0.818	0.708	0.924	0.899
	EE_2	0.868			
	EE_3	0.878			
	EE_4	0.842			
	EE_5	0.796			
Social influence	SI_1	0.892	0.759	0.926	0.892
	SI_2	0.927			
	SI_3	0.909			
	SI_4	0.746			
Facilitating conditions	FC_1	0.734	0.526	0.813	0.690
	FC_2	0.792			
	FC_3	0.808			
	FC_4	0.536			
Trust in robo-advisors	T_1	0.857	0.782	0.915	0.860
	T_2	0.903			
	T_3	0.892			
Perceived financial knowledge	PFK_1	0.831	0.781	0.934	0.907
	PFK_2	0.903			
	PFK_3	0.900			
	PFK_4	0.900			
Tendency to rely on robo-advisors	R_1	0.905	0.828	0.951	0.931
	R_2	0.934			
	R_3	0.904			
	R_4	0.895			
Intention to adopt financial robo-advisors	INT_1	0.933	0.892	0.961	0.939
	INT_2	0.950			
	INT_3	0.949			

Abbreviations: EE, effort expectancy; FC, facilitating conditions; INT, intention to adopt financial robo-advisors; PE, performance expectancy; PFK, perceived financial knowledge; R, tendency to rely on robo-advisors; SI, social influence; T, trust in robo-advisors.

means that the elimination of FC\_4 will not have any consequences in improving its AVE and composite reliability to achieve their minimum acceptable value. Hence, FC\_4 was retained in the model.

### 4.3 | Discriminant validity

Discriminant validity was assessed to ensure the variables in the proposed model are distinct from each other. Cross loadings and Fornell-Larcker criterion were used to

measure the discriminant validity. The rule of thumb for Fornell-Larcker is that the square root of AVE ought to be greater than its the largest correlation with any other variables proposed in the framework. Table 3 shows that the square root of AVE for all variables were higher than the correlation values. Heterotrait-monotrait (HTMT) measurement model was also assessed to measure the discriminant validity. Table 4 shows that the HTMT values of all variables were below 0.90. According to Henseler et al. (2015), the discriminant validity is established when HTMT value is below 0.90.

TABLE 3 Fornell-Larcker criterion

	PE	EE	SI	FC	T	PFK	R	INT
PE	<b>0.855</b>							
EE	0.545	<b>0.841</b>						
SI	0.465	0.465	<b>0.871</b>					
FC	0.433	0.535	0.364	<b>0.726</b>				
T	0.589	0.47	0.442	0.425	<b>0.884</b>			
PFK	0.137	0.206	0.205	0.267	0.261	<b>0.884</b>		
R	0.509	0.371	0.457	0.293	0.574	0.215	<b>0.91</b>	
INT	0.482	0.414	0.429	0.396	0.56	0.322	0.537	<b>0.944</b>

Abbreviations: EE, effort expectancy; FC, facilitating conditions; INT, intention to adopt financial robo-advisors; PE, performance expectancy; PFK, perceived financial knowledge; R, tendency to rely on robo-advisors; SI, social influence; T, trust in robo-advisors.

TABLE 4 HTMT criterion

	PE	EE	SI	FC	T	PFK	R	INT
PE								
EE	0.61 CI.90 (0.513, 0.692)							
SI	0.525 CI.90 (0.425, 0.613)	0.516 CI.90 (0.414, 0.609)						
FC	0.581 CI.90 (0.464, 0.683)	0.699 CI.90 (0.595, 0.784)	0.476 CI.90 (0.356, 0.588)					
T	0.678 CI.90 (0.597, 0.751)	0.524 CI.90 (0.415, 0.619)	0.504 CI.90 (0.394, 0.606)	0.576 CI.90 (0.469, 0.666)				
PFK	0.154 CI.90 (0.065, 0.267)	0.224 CI.90 (0.113, 0.341)	0.231 CI.90 (0.130, 0.338)	0.331 CI.90 (0.200, 0.454)	0.296 CI.90 (0.166, 0.412)			
R	0.564 CI.90 (0.461, 0.657)	0.392 CI.90 (0.279, 0.493)	0.501 CI.90 (0.399, 0.594)	0.378 CI.90 (0.247, 0.494)	0.64 CI.90 (0.538, 0.724)	0.227 CI.90 (0.122, 0.332)		
INT	0.531 CI.90 (0.430, 0.619)	0.431 CI.90 (0.310, 0.540)	0.47 CI.90 (0.365, 0.565)	0.492 CI.90 (0.349, 0.614)	0.622 CI.90 (0.538, 0.697)	0.342 CI.90 (0.224, 0.455)	0.572 CI.90 (0.466, 0.667)	

Abbreviations: EE, effort expectancy; FC, facilitating conditions; INT, intention to adopt financial robo-advisors; PE, performance expectancy; PFK, perceived financial knowledge; R, tendency to rely on robo-advisors; SI, social influence; T, trust in robo-advisors.

### 4.4 | Hypotheses testing

The proposed hypotheses were assessed by significant levels of the path coefficients. The result is reported in Table 5. It shows that performance expectancy is positive and significantly related to the behavioral intention to adopt financial robo-advisors. Similarly, a positive and statistically significant relationship is observed between

social influence and the intention to adopt financial robo-advisors. Consumer's trust toward robo-advisors is related to the adoption of financial robo-advisors. This relationship is statistically highly significant. A stronger relationship is also observed between perceived financial knowledge and the adoption propensity of financial robo-advisors. Consumers who perceive themselves to be financially knowledgeable prefer to seek advice from

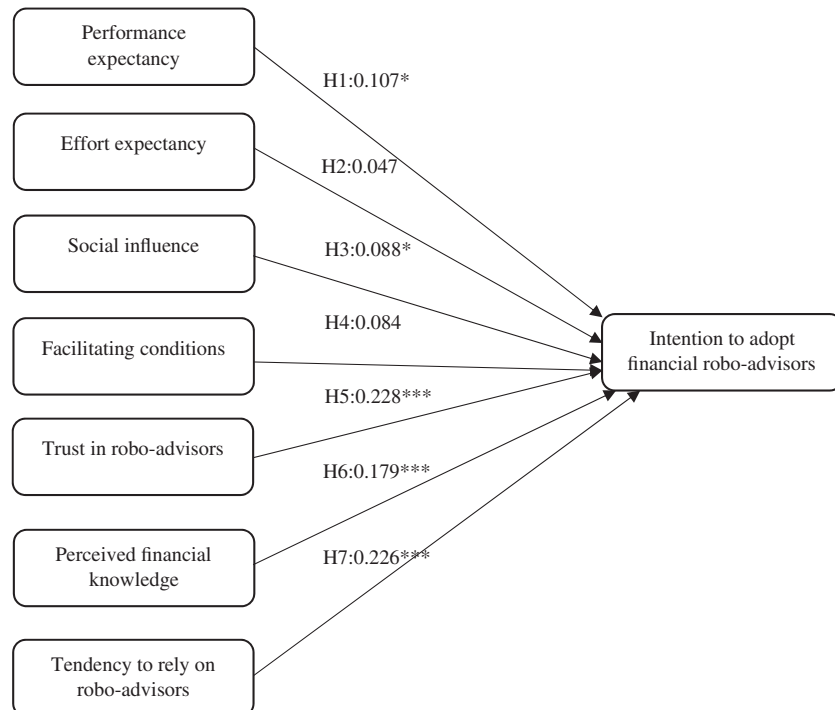
TABLE 5 Hypothesis testing result

	Relationship	Coefficients ( <i>p</i> -value)	t-value	Decision
H1	PE→INT	0.107(0.067)*	1.499	Supported
H2	EE→INT	0.047(0.307)	0.505	Not supported
H3	SI→INT	0.088(0.072)*	1.459	Supported
H4	FC→INT	0.084(0.117)	1.191	Not supported
H5	T→INT	0.228(0.001)***	3.178	Supported
H6	PFK→INT	0.179(0.006)***	2.513	Supported
H7	R→INT	0.226(0.001)***	3.043	Supported

Abbreviations: EE, effort expectancy; FC, facilitating conditions; INT, intention to adopt financial robo-advisors; PE, performance expectancy; PFK, perceived financial knowledge; R, tendency to rely on robo-advisors; SI, social influence; T, trust in robo-advisors.

\* $p < 0.10$ , \*\*\* $p < 0.01$ .

FIGURE 2 Empirical framework



robo-advisors by adopting this advisory service. Further, the results show that the higher the tendency to rely on robo-advisors, the greater the behavioral intention to adopt financial robo-advisors. Effort expectancy and facilitating conditions are found to be insignificant in predicting the adoption of financial robo-advisors. In short, performance expectancy, social influence, trust in robo-advisors, perceived financial knowledge, and tendency to rely on robo-advisors have a positive and significant impact on the consumer's behavioral intention to adopt financial robo-advisors during the initial surge of COVID-19; thus, H<sub>1</sub>, H<sub>3</sub>, H<sub>5</sub>, H<sub>6</sub>, and H<sub>7</sub> are affirmed. On the other hand, the impacts of effort expectancy and

facilitating conditions on the intention to adopt financial robo-advisors were not significant; thus, H<sub>2</sub> and H<sub>4</sub> are rejected. Figure 2 exhibits the empirical model with the path coefficients and significance level. Figure A1 in the appendix shows the PLS-SEM diagram.

#### 4.5 | Coefficient of determination

The predictive accuracy of the model was evaluated by assessing the coefficient of determination ( $R^2$ ). Based on  $R^2$  value, the set of predictors (performance expectancy, social influence, trust in robo-advisors, perceived

financial knowledge, tendency to rely on robo-advisors) accounted for 44.4% of the variance in the behavioral intention to adopt the financial robo-advisors, which represents a weak to moderate extent of predictive accuracy.

## 5 | DISCUSSION

The results of this study demonstrated that consumer's robo-advisor adoption during the initial stages of the COVID-19 pandemic in Malaysia was related to performance expectancy, social influence, trust in robo-advisors, perceived financial knowledge, and tendency to rely on robo-advisors. Consistent with the UTAUT model, performance expectancy was found to have a significant and positive influence on the adoption of robo-advisors. Given that the automated robo-advisory process does not require human intervention, consumers might have a higher performance expectation for robo-advisors than for traditional financial advisors during the pandemic that prohibited close contact meetings. From a theoretical perspective, this finding aligns with the results of prior studies on fintech, specifically by Arias-Oliva et al. (2019), who found that performance expectancy was the strongest predictor of behavioral intention to adopt fintech; whereas, Widodo et al. (2019) claimed that performance expectancy was the second strongest predictor of behavioral intention to adopt fintech. This finding is also in line with Ruhr et al. (2019), who found a strong positive impact of performance expectancy on the acceptance of the decision support system that had a high level of automation.

As another component of the UTAUT model, social influence positively impacted the adoption of robo-advisors. The COVID-19 crisis has stimulated an increasing number of Malaysian retail investors in the stock market (Tan, 2020). These investors who were new to the financial market might have looked for a low-cost investment management approach. In addition, the use of automated financial services by people around them might have driven their intentions to adopt robo-advisors. This conforms with the findings of Gerlach and Lutz (2019), which demonstrated that social influence was a determinant of behavioral intention to adopt fintech and digital finance solutions in Germany. A supporting argument was stated by Soodan and Rana (2020), whose findings revealed that behavioral intentions of Indian consumers to adopt electronic wallets increased with the level of social influence. Thus, it could be argued that consumers would be more willing to adopt robo-advisors when the people around them, such as family and friends, have a favorable opinion toward their decision to adopt them.

The data from this study also indicated that trust in robo-advisors had a positive impact on the adoption

intention of financial robo-advisors in Malaysia during the initial surge of the COVID-19 cases. Arguably, the trust level toward automated online advisors might have been enhanced against the backdrop of the pandemic. Specifically, the prohibited or restricted close contact situation during the COVID-19 pandemic might have prompted individuals to be more willing to trust robo-advisors as an alternative to traditional human advisors for financial and wealth management. The augmented trust then led to a stronger intention to adopt financial robo-advisors among Malaysians. From a theoretical perspective, this finding aligns with prior results indicating that consumers' trust could positively drive their behavioral intention to accept automated financial advice (Lourenco et al., 2020). Moreover, this finding converges with an argument put forth by Bruckes et al. (2019) that consumers who have a high level of trust in robo-advisors are more likely to adopt it for financial advisory services.

This study also demonstrated that perceived financial knowledge predicted the intention to adopt financial robo-advisors in Malaysia when the COVID-19 cases started to spike. This finding may shed some light on the relationship between financial knowledge and human financial advice. A positive relationship was observed between perceived financial knowledge and the adoption of financial robo-advisors. This finding parallels those from prior studies (Fan & Chatterjee, 2020; Todd & Seay, 2020), which indicated a similar positive association; albeit, the contexts of critical situations such as the COVID-19 pandemic were not considered in those studies. In the context of this study, we argue that consumers with high financial knowledge might have more awareness about how robo-advisory processes are conducted through unbiased AI algorithm operations; and this, in turn, elevated their intention to adopt financial robo-advisors. In particular, financially literate consumers might have been more aware of the market volatility stemming from the COVID-19 crisis and thus regarded financial and investment management to be more crucial during the pandemic.

Lastly, this study showed that the tendency to rely on robo-advisors predicted the adoption intention of financial robo-advisors. This finding coheres with Thourungrroje's (2014) argument, who reported a strong significant positive correlation between reliance and behavior to consume conspicuous products. Considering the reduced close contact interaction, the likelihood of consumers relying on virtual platforms, that is, automated financial robo-advisors, might have increased amidst the COVID-19 crisis. In contrast to human advisors whose emotions may be affected by market volatility caused by the pandemic, the ability of robo-advisors to execute financial decisions without

emotional biases could have driven the tendency of consumers to rely more on the platform for financial wealth and investment management. This, in turn, enhanced the intention to adopt robo-advisory services.

## 6 | IMPLICATIONS

The findings of this study have implications for consumers, robo-advisory service providers, traditional financial advisory firms, and regulators. Based on our results, it was shown that performance expectancy and social influence have positive impacts on the adoption of financial robo-advisors. We conclude that the benefits of robo-advisory services are more apparent during critical situations such as the COVID-19 crisis, given that the platform provides automated financial planning with zero to minimal human contact at a low cost. Moreover, views and comments about automated online robo-advisory services are crucial in influencing the adoption of robo-advisors. Particularly during the COVID-19 pandemic, comments surrounding the performance and zero human contact can positively enhance consumer's perception and impression toward robo-advisors, thereby driving the intention to use robo-advisors. Regarding trust, the knowledge that robo-advisors utilize AI algorithms and are thus unbiased and free from human emotions can contribute to a trusting belief toward the technology. However, consumers should review the background of the companies providing the robo-advisory services before utilizing them. Companies with good reputations may lead to a high trust level, which is vital for adopting new services, especially during the pandemic that sees companies shutting down. By using robo-advisors, consumers may reduce information search costs as robo-advisors act as an information intermediary.

The findings of this study are beneficial to robo-advisory service providers in understanding the crucial factors driving robo-advisory adoption in Malaysia. As the results showed that performance expectancy and social influence were significant factors, service providers may encourage existing users of automated financial advisors to promote and share their experiences through ratings and evaluations on social media platforms. Exposure to such social information could encourage new potential users to adopt robo-advisory services. To build trust in robo-advisors among consumers, the robo-advisory industry could take initiatives such as awareness campaigns and advertisements to highlight the adherence to mechanisms that protect the privacy of a customer's data by robo-advisory service providers. Additionally, trust may breed if the companies customize services based on risk profiling. Increasing trust can, in turn, encourage the adoption of automated financial advisors

in Malaysia. Moreover, the robo-advisory service industry can increase potential consumers' financial knowledge and awareness about automated financial robo-advisors in Malaysia. Online education on this domain may be particularly effective in times of pandemic crisis. Moreover, robo-advisory providers may focus on investors' needs by highlighting the benefits of robo-advisors regarding cost, transparency, and unbiasedness compared with traditional human advisors. By focusing on the above factors, service providers could increase their customer base and gain a larger market share. Since the survey shows that about 80% of respondents are millennials (e.g., Gen Y), robo-advisory companies could target this potential market segment by understanding their needs and behaviors and catering robo-advisory services accordingly.

The findings of this study have implications for traditional financial advisory firms, as they would be affected by the introduction of robo-advisory services into the market. Hence, traditional financial advisory firms should consider offering robo-advisory services. During a prolonged pandemic (e.g., COVID-19), they could consider switching to online automated financial advisory platforms to sustain relevance and survivability. The findings of this study have implications for regulators as well. Regulators can initiate education programs to spread awareness on robo-advisory services, increasing the consumer's knowledge and confidence level.


## 7 | CONCLUSION, LIMITATION, AND FUTURE RESEARCH

This study examined the antecedents of the adoption of financial robo-advisors based on the data collected during the initial stages of the COVID-19 pandemic, just before the first nationwide lockdown in Malaysia was imposed. The data collection period is deemed crucial because it witnessed a significant shift toward digital and virtual activities. This study extended the unified theory of acceptance and use of the technology (UTAUT) model by incorporating three additional variables: trust in robo-advisors, perceived financial knowledge, and tendency to rely on robo-advisors. The findings of this study indicated that performance expectancy, social influence, trust in robo-advisors, perceived financial knowledge, and tendency to rely on robo-advisors were significant antecedents of the consumer's intention to adopt financial robo-advisors in Malaysia during the initial surge of the COVID-19 cases. Robo-advisory services are considered nascent in Malaysia and thus have the potential for increasing the consumer base.

One of the limitations of this study is the focus on only one country, namely Malaysia. However, as robo-advisors provide online services, the findings of this study (the antecedents) are applicable beyond borders. Another limitation is that regulatory issues are ignored in adopting financial robo-advisors. Other variables such as extrinsic and intrinsic motivations may drive the behavioral intention to adopt robo-advisors, which were not within the scope of this study.

Future studies may consider more than one country in studying the adoption of robo-advisors. Regulatory issues, together with the antecedents of this study, may be taken into account in future studies. Extrinsic and intrinsic motivations could be considered to improve the predictive power of the proposed model. Moreover, future research could focus on the actual usage behavior of robo-advisory consumers using a large-scale survey.

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## ENDNOTE

<sup>1</sup> Robo-Advisor (Video 1) - YouTube

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## APPENDIX A.

Table A1 and Figure A1

**TABLE A1** Definition of variables

Variables	Items	References
Performance expectancy	PE_1: I would find robo-advisor useful in making financial decisions. PE_2: Using robo-advisor would increase my chances of achieving things that are important to me. PE_3: Using robo-advisor would help me accomplish financial goals more quickly. PE_4: Using robo-advisor would increase my financial profitability.	Venkatesh et al. (2003, 2012) Moore & Benbasat, 1991
Effort expectancy	EE_1: Learning how to use robo-advisor would be easy for me. EE_2: My interaction with robo-advisor would be clear. EE_3: My interaction with robo-advisor would be understandable. EE_4: I would find robo-advisor easy to use. EE_5: It would be easy for me to become skillful in using robo-advisor.	Venkatesh et al. (2003, 2012) Moore & Benbasat, 1991
Social influence	SI_1: People who are important to me would think that I should use robo-advisor. SI_2: People who influence my behavior would think that I should use robo-advisor. SI_3: People whose opinions that I value would prefer that I use robo-advisor. SI_4: People who use robo-advisor have a high profile.	Venkatesh et al. (2003, 2012) Moore & Benbasat, 1991



TABLE A1 (Continued)

Variables	Items	References
Facilitating conditions	<p>FC_1: I have the resources necessary (smartphone or computer with internet connection) to use robo-advisor.</p> <p>FC_2: I have the knowledge necessary to use robo-advisor.</p> <p>FC_3: Robo-advisor is compatible with other technologies I use.</p> <p>FC_4: I can get help from others when I have difficulties using robo-advisor.</p>	Venkatesh et al. (2003, 2012) Moore & Benbasat, 1991
Trust in robo-advisors	<p>T_1: I would trust the portfolios recommended by robo-advisor.</p> <p>T_2: I am willing to reveal the personal sensitive information to robo-advisor.</p> <p>T_3: I believe that robo-advisor is trustworthy.</p>	Zhou et al. (2019)
Perceived financial knowledge	<p>PFK_1: I am well informed about the financial market.</p> <p>PFK_2: I am familiar with the stocks I trade (e.g., their business, financial status).</p> <p>PFK_3: I am well informed about the major economic news that impacts the stock market.</p> <p>PFK_4: I have high level of financial knowledge.</p>	Robb et al. (2012) Park et al., (2010)
Tendency to rely on robo-advisors	<p>R_1: Compared with seeking advice from human advisor, I will seek advice from robo-advisors for financial services.</p> <p>R_2: Compared with seeking advice from human advisor, I will rely on robo-advisors in financial planning.</p> <p>R_3: Compared with seeking advice from human advisor, I will rely on robo-advisors in investment management.</p> <p>R_4: Compared with seeking advice from human advisor, I would rely on robo-advisor in making financial decision.</p>	Bachmann and Hens (2015); Safari et al., (2016)
Intention to adopt financial robo-advisors	<p>INT_1: I intend to use robo-advisor in the next 6 months.</p> <p>INT_2: I predict I would use robo-advisor in the next 6 months.</p> <p>INT_3: I plan to use robo-advisor in the next 6 months.</p>	Venkatesh et al. (2003); Venkatesh et al. (2012); Surendran (2012)

Note: Responses are recorded on a 5-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree."

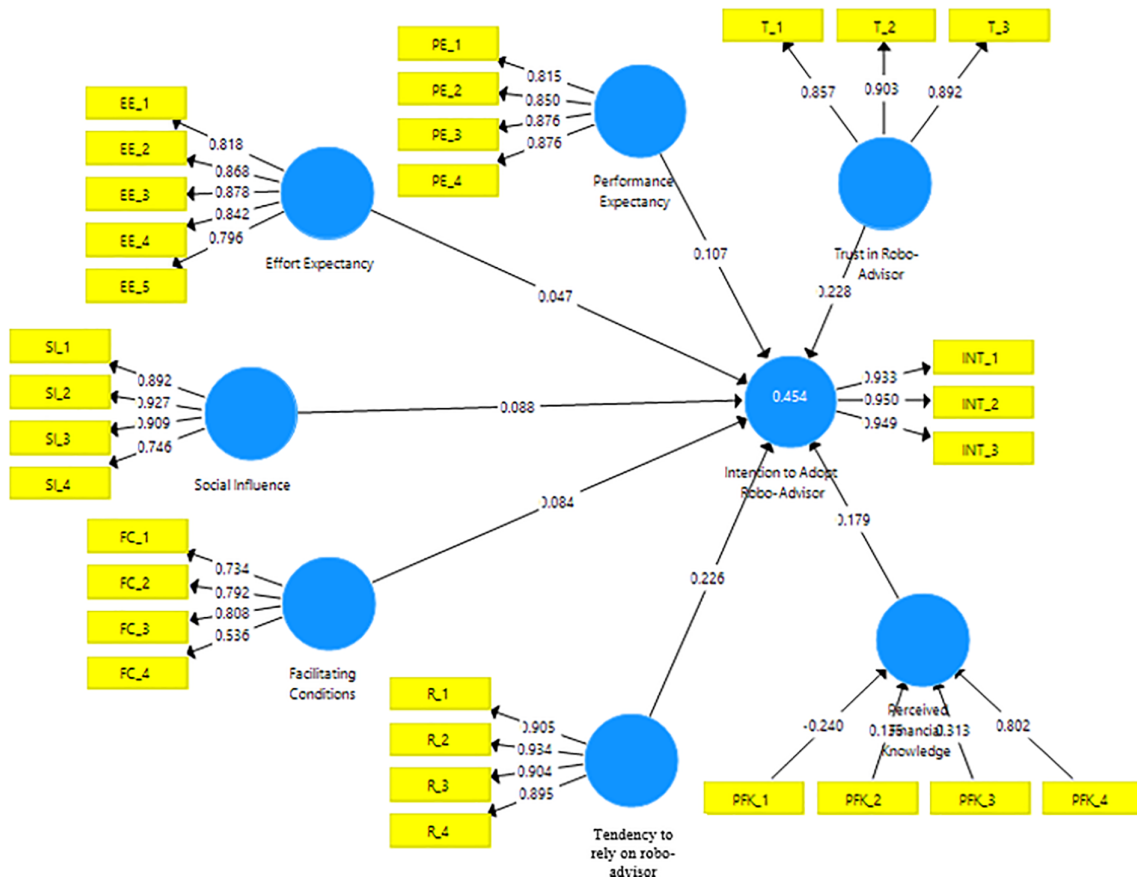


FIGURE A1 PLS-SEM diagram