A Malaysian Perspective on The Impact of Protection Motivation Behaviours on Robo-Advisor Adoption during Financial Crises

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ABSTRACT

The study integrated the Protection Motivation Theory into the Technology Acceptance Model to explore factors influencing robo-advisory service adoption. Robo-advisor adoption among retail investors in Malaysia was low during financial crises like COVID-19, necessitating an investigation into adoption determinants. Little is known about the drivers of robo-advisor adoption during financial crises and how investors perceive the effectiveness and reliability of AI-assisted services in such circumstances. The study contributes to existing literature by shedding light on investors' protection behaviors and AI adoption in the financial sector during challenging economic times. Quantitative data from 128 respondents revealed that response efficacy influences perceived usefulness, impacting investors' intentions to use robo-advisors. Behavioral intention significantly predicted actual usage during crises like COVID-19, highlighting challenges in translating knowledge into action. The study enhances understanding of investors' decision-making and offers insights for policymakers and financial services providers, amid evolving financial landscapes.

Keywords: Protection motivation theory, technology adoption model, perceived usefulness, actual use, robo-advisor

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INTRODUCTION

Robo-advisory services are software platforms that automate or aid in managing investments by substituting human advisory services and/or the customers' management (Goldstein et al., 2019). These automated platforms leverage sophisticated algorithms and technology to provide personalised investment recommendations and portfolio management services at a fraction of the cost typically associated with traditional human advisors. In Malaysia, regulatory initiatives from the Securities Commission (SC) have played a part in promoting transparency of automated discretionary portfolio management, thereby encouraging the adoption of robo-advisors in the country. However, based on Statista (2022), there is a low level of robo-advisor adoption amongst retail investors in Malaysia during a financial crisis such as COVID-19, prompting the need to investigate the adoption determinants. Little is known about the factors that drive the adoption of robo-advisors during financial crises and how investors perceive the effectiveness and reliability of AI-assisted services in such circumstances. Given the current situation, investors in Malaysia are missing out on the potential benefits offered by robo-advisors, which could serve as a valuable solution to navigate the heightened uncertainty during a crisis.

While past studies provide important insights of the factors influencing the adoption of robo-advisors (Atwal & Bryson, 2021; Seiler & Fanenbruck, 2021; Belanche et al., 2019), studies that aimed to understand factors such as protection motivation behaviours remain limited. Protection motivation behaviour encompasses the cognitive and emotional processes that drive individuals to adopt protective measures against perceived threats (Menard et al., 2017; Cummings et al., 2020). Exploring the impact of protection motivation allows us to delve into the psychological factors that drive individuals towards embracing robo-advisor as a means of safeguarding their financial well-being during times of crisis. Furthermore, unexplored research setting that is worthy of investigation includes the relationship between adoption intention and actual usage of robo-advisory services during a financial crisis. The current study attempted to provide empirical data to prepare the ground for more reasonable use of robo-advisor during a financial crisis.

To address the problems and the gaps aforementioned, the general objective of this study was to examine the determinants of robo-advisory services adoption amongst retail investors during a financial crisis by employing protection motivation behaviour as the external effects on technology acceptance model (TAM), with a specific focus on the understudied retail investors' behavior in Malaysia. While previous studies of robo-advisors explored continuance intention (Cheng, 2020), trust (Cheng et al., 2019; Zhang et al., 2021), and behavioral biases (Bhatia et al., 2021), the study would add to the existing body of research examining the relationship between the protection motivation behaviour and perceived usefulness of robo-advisor during a financial crisis. Furthermore, the study proposed examining the relationship between perceived usefulness and behavioural intention to use robo-advisor during a financial crisis. Finally, examining the relationship between behavioural intention and actual usage of robo-advisor during a financial crisis would provide novel insights into retail investors'adoption behavior.

LITERATURE REVIEW

The Adoption of Robo-Advisor

Previous studies of AI-assisted services focus on adoption (Flavián et al., 2021; Belanche et al., 2019), continuance intention (Cheng, 2020), trust (Cheng et al., 2019; Zhang et al., 2021), behavioural biases (Bhatia et al., 2021), banking (Boustani, 2020; Caron, 2019; Mogaji et al., 2021) and credit scoring (Aggarwal, 2021; Mhlanga, 2021). Previous adoption studies have argued that the low penetration rate and the novelty of robo-advisory services as their research gaps (Flavián et al., 2021; Belanche et al., 2019a). Meanwhile, Cheng (2020) identified a lack of understanding of continuance intention factors of robo-advisor as a research gap and examined the fit factor, network factors, and psychological factors amongst 360 end-users in Taiwan. Cheng et al. (2019) and Zhang et al. (2021) examined trust factors amongst users of robo-advisor in China and the United States, respectively. Another interesting study by Bhatia et al. (2021) surveyed 172 investors in India and concluded that robo-advisory services are still incapable of mitigating behavioural biases. Studies on banking and credit scoring are not directly related to robo-advisor, but they looked into the impact of AI and AI components. Still, the findings are significant to be discussed in the robo-advisory area as the system utilises analytical AI. Similar findings are reflected in a systematic literature review provided by Hentzen et al. (2022), whereby the study concludes that most studies either adopt an experimental research design focused on testing the accuracy and performance of AI algorithms to assist with credit scoring or investigating AI consumer adoption behaviours in a banking context.

There are plenty of research opportunities in the area of robo-advisor. For example, Flavián et al. (2021), Bhatia et al. (2021), Zhang et al. (2021), Cheng (2020), Belanche et al. (2019a), and Cheng et al. (2019) encouraged future researchers to examine other influencing factors and determinants that may impact the different context of robo-advisor. Furthermore, Bhatia et al. (2021), Mogaji et al. (2021), Cheng (2020), Belanche et al. (2019a), and Boustani (2020) suggested future researchers to expand the studies into different socio-cultural backgrounds. Moreover, Mogaji et al. (2021), Boustani (2020) and Cheng et al. (2019) addressed recommendations to increase the diversity and size of the sample of studies related to the robo-advisory area. Hentzen et al. (2022) called for more research on building overarching theories or extending existing theoretical perspectives. The burgeoning field of robo-advisor research offers ample opportunities for future exploration, as highlighted by various scholars, encompassing the investigation of additional influencing factors, diverse socio-cultural contexts, and expanded sample sizes. Also, the development of overarching theories to enhance our understanding of robo-advisory services adoption, with the present study contributing by examining Malaysian retail investors' adoption determinants during a financial crisis through the lenses of PMT and TAM.

Crisis and Financial Market

A crisis can have drastic consequences on individuals, organisations, and countries. Hence, research on crisis and financial markets has been gaining attention from practitioners and academicians. Previous studies examined the effect of a crisis at an individual level (Messaoud et al., 2023; Prorokowski, 2011; Bansal, 2020; Parveen et al., 2023; Lippi & Rossi, 2020; Misra et al., 2022; Leo et al., 2023, Mirbabaie et al., 2022), sector level (Rubbaniy et al., 2021; Al Refai et al., 2016; Bahloul et al., 2021; Mezghani et al., 2021; Kakinuma, 2021; Singh & Singh, 2016; Sumer & Ozorhon, 2020; Singh & Sharma, 2018), market level (Cardoso et al., 2020; Ah Mand et al., 2023; Mezghani & Boujelbène-Abbes, 2023) and organisational level (Sherman & Roberto, 2020; Mokline & Abdallah, 2021). COVID-19 was the most highlighted crisis in previous studies published from 2020 to 2022 (Bansal, 2020; Parveen et al., 2023; Rubbaniy et al., 2021; Misra et al., 2022; Bahloul et al., 2021; Mezghani et al., 2021; Kakinuma, 2021; Mokline & Abdallah, 2021; Leo et al., 2023), followed by the 2008 global financial crisis (Messaoud et al., 2023; Prorokowski, 2011; Lippi & Rossi, 2020; Al Refai et al., 2016; Singh & Singh, 2016; Cardoso et al., 2020; Mezghani & Boujelbène-Abbes, 2023; Singh & Sharma, 2018). Meanwhile, Sumer and Ozorhon (2020) brought the 2018 Turkish currency crisis into the discussion together with the 2008 financial crisis and COVID-19. Ah Mand et al. (2023) included the 1998 Asian financial crisis and 2008 financial crisis to examine the herding strategy. Misra et al. (2022) mentioned a scarcity of research on survey-based studies of investment behaviour and COVID-19. Even though retail investors play an important role in the stock market, there have been few studies on retail investors, their investment behaviour, and its psychological underpinnings. Amidst the rising significance of modern automation technology, there is an urgent need for research to ascertain the potential adoption of robo-advisors by retail investors as a protective measure in financial crises, addressing the critical gaps in understanding the key determinants of such adoption and recognising the vulnerability of retail investors in volatile markets.

Protection Motivation Theory

The PMT was proposed by Rogers (1975) assuming that motivation for protection stems from a perceived threat and a desire to avoid a potentially negative outcome (Menard et al., 2017; Cummings et al., 2020). The Drive Theory, which holds that people are motivated to lessen unfavourable emotional states elicited by signals of fear, forms the basis of PMT (Sternthal & Craig, 1974). According to PMT, when an individual is confronted with a threat, he or she cognitively assesses the threat as well as any potential associated remedy (Menard et al., 2017; Cummings et al., 2020). Therefore, the PMT is divided into threat and coping appraisal by individuals who are facing threats or dangers. The PMT has been adapted in previous research to understand what motivates individuals to protect information security (Menard et al., 2017), continuance intention of mobile health apps (Luo et al., 2021), intention to take vaccine (Cummings et al., 2020), and adoption of protective technologies (Chenoweth et al., 2009). Individuals use cognitive process to conduct threat appraisal in terms of perceived vulnerability, perceived severity, and intrinsic or extrinsic rewards achieved by performing maladaptive behaviour (Menard et al., 2017). According to Menard et al. (2017), perceived vulnerability refers to how much an individual feels exposed to a specific threat, and perceived severity refers to how much an individual assess the seriousness of a threat. An intrinsic reward refers to the pleasure of engaging in a maladaptive behaviour, whereas an extrinsic reward could be something valuable that could not reasonably be gotten without doing the act.

Subsequent to threat appraisal, an evaluation of the possible coping techniques is done by the individual. Response efficacy, self-efficacy, and response cost are evaluated during the coping appraisal. Response efficacy is an assessment by the individual of how effective the suggested action responds to the current threat, for example, to follow security policy. Self-efficacy is the assurance a person has in his/her ability to carry out the advised action. Response costs comprise perceived extrinsic or intrinsic costs of engaging in the advised action. Response cost can be interpreted in a variety of ways, such as in terms of time, money, or effort. Protective motivation behaviour are the product of threat and coping appraisals. The PMT examines the causes and processes of behaviours by using external information and internal cognitive characteristics (Liu, 2015). For threat appraisal, perceived vulnerability and perceived severity have beneficial effects on threat adaptive behaviour (Cummings et al., 2020), whereas intrinsic and extrinsic rewards reduce individuals' sensitivity to threats and negatively affect threat adaptive behaviour (Menard et al., 2017). For coping appraisal, intentions to engage in threat adaptive behaviour are positively influenced by response efficacy and self-efficacy (Cummings et al., 2020), and it is negatively influenced by response cost (Menard et al., 2017).

Technology Acceptance Model

Researchers have repeatedly and successfully used the TAM in modelling technology and system-based acceptance by employing a variety of technical features and contextual aspects (Sohn & Kwon, 2020; Okpala et al., 2021). The TAM evolved from Theory of Reasoned Action (TRA) to give an explanation of the determinants of computer acceptance that is generic, capable of describing user behaviour across a broad range of end-user computing technology and user groups, while at the same time being both parsimonious and theoretically justified (Davis et al., 1989). The TAM is similar with TRA where both of the theories propose that behavioural intention determines actual technology usage (Bradley, 2012). However, the TAM eliminates subjective norm of the TRA component (Bradley, 2012). Davis et al. (1989) proposed that the direct effects of subjective norm on behavioural intention is difficult to distinguish from indirect effects via attitude. The original TAM introduces two key variables that influences attitude toward use of system – perceived usefulness (PU) and perceived ease of use (PEOU). Each of these variables can be individually linked to external effects on the model (Bradley, 2012). The PU is based on the extent that if people perceived technology is useful to increase their job performance, they will use it (Davis, 1989). The PU also directly influences behavioural intention to use (BI). PEOU is based on the user's expectation that the system will be simple and easy to use (Bradley, 2012). The original TAM postulates that attitude influences behavioural intention to use, and behavioural intention influences actual use. However, the final TAM did not include the attitude component because attitude did not completely mediate the effect of perceived usefulness on intention based on empirical evidence (Davis & Venkatesh, 1996). The following sub-section presents the conceptual framework for the current study based on theories discussed above.

CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

This study is based on the TAM to build the AI adoption model which examines the determinants of robo-advisory services adoption amongst retail investors during a financial crisis. Drawing on the TAM, this study proposed a research model and three hypotheses as shown in Figure 1. Five elements of protection motivation behaviour relevant to the study were included in the research model, excluding intrinsic and extrinsic rewards. Intrinsic and extrinsic rewards are used to understand why individual choose to engage in unhealthy behaviour. This study was targeted at retail investors who adopted robo-advisor as protective behaviour against financial crisis, and non-adoption of robo-advisor was not considered as unhealthy behaviour as there are a variety of other low-risk investment products and services in the financial market. The TAM has been used to support the conceptual framework in many studies with external variables comprises various contexts (Tarhini et al., 2015). Protection motivation behaviours are the external effects in this study, influencing the PU of robo-advisor. The PEOU is omitted in the current research model as self-efficacy in the PMT is a similar construct with PEOU, whereby they measure individuals' belief that the technology is easy to use. Based on TAM principle, PU directly influences behavioural intention to use, which influences actual use. COVID-19, as a recent financial crisis has provided a laboratory to examine the actual use of robo-advisor against a backdrop of economic shocks.

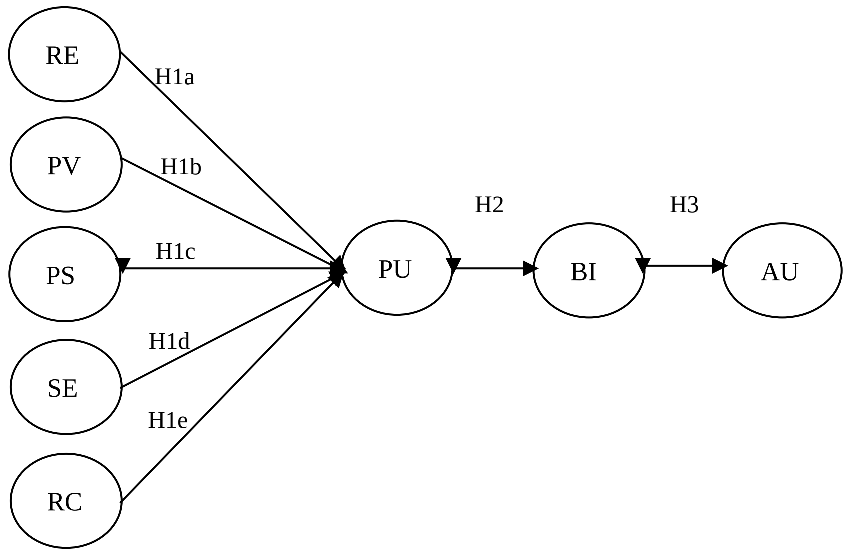

Figure 1: Conceptual Framework

PS: Perceived severity; PV: Perceived vulnerability; RE: Response efficacy; SE: Self-efficacy; RC: Response cost; PU: Perceived usefulness; BI: Behavioral intention to use; AU: Actual use

Based on the PMT, information about threats obtained from the environment aid an individual's judgement on the threats, thereby stimulating the threat appraisal and the coping appraisal in the cognitive process (Luo et al., 2021). Luo et al. (2021) reported that self-efficacy and response efficacy have positive effects on continuance intention mediated by attitude. A post-COVID-19 study by Joung et al. (2022) demonstrated that perceived severity, perceived vulnerability, response efficacy, and self-efficacy have a significant impact on perceived usefulness of trading app. Rahi et al. (2021) showed a positive significant relationship between perceived vulnerability, perceived severity, and response efficacy on attitude, and self- efficacy moderates the relationship between patient attitude and patient intention to adopt telemedicine healthcare services. During a financial crisis, retail investors perceive the situation as a threat to their financial well-being. They become concerned about potential losses, market volatility, and uncertainty. The current study argued that investors with higher protection motivation are more likely to recognise the importance of taking proactive measures to protect their investments. Robo-advisors offer a structured and automated approach to investment management, which may be seen as a reliable coping mechanism during times of market turmoil. Individual with high protection motivation behaviour examine the severity of a financial crisis and respond to it by assessing the usefulness of robo-advisor as a protection tool against investment losses. If investors believe that robo-advisors have the ability to provide sound investment advice and protect their assets during a financial crisis, they are more inclined to use these platforms.

When investors perceive that a financial crisis could have a substantial impact on their wealth, financial stability, or future prospects, they are more inclined to view the severity of the crisis as significant. Based on Cummings et al. (2020), perceived severity has beneficial effects on threat adaptive behavior. Threat adaptive behavior or “risk response action” are specific action that may lessen or mitigate potential harm brought on by threats (Cummings et al., 2020, pg. 1). Consistent with past studies on technological innovation such as Joung et al. (2022), Nguyen and Tang (2022), Rahi et al. (2021), Chen and Yeh (2017), and Chenoweth et al. (2009), the study argued that when perceived severity of a financial crisis increases, this triggers “risk response action” of robo-advisor’s perceived usefulness. The heightened perception of usefulness stems from the ability of robo-advisors to provide automated, data-driven investment strategies that can adapt to rapidly changing economic circumstances.

H1a: Perceived severity has a positive effect on retail investors’ perceived usefulness of robo-advisor during a financial crisis.

During financial crises such as COVID-19, investors may experience heightened feelings of vulnerability due to increased market volatility, economic uncertainty, and potential financial losses. Perceived vulnerability leads to positive outcomes in terms of adaptive responses to threats (Cummings et al., 2020). This sense of vulnerability can influence investors' perceptions and decision-making regarding the adoption of robo-advisor services. In line with prior research findings (Nguyen & Tang, 2022; Rahi et al., 2021; Chenoweth et al., 2009), the study posited as investors perceive themselves to be more vulnerable to the impacts of a crisis, they are more likely to view robo-advisor services as valuable tools for managing risks, making informed investment decisions, and protecting their financial well-being.

H1b: Perceived vulnerability has a positive effect on retail investors’ perceived usefulness of robo-advisor during a financial crisis.

Response efficacy, or perceived effectiveness of financial solutions amid economic upheaval becomes crucial in shaping investors' perceptions and behaviors. In the context of robo-advisor, this perception is influenced by factors such as the accuracy of advice provided, the ability to diversify risk, and the timeliness of recommendations. Response efficacy positively impacts intentions to engage in threat adaptive behavior (Cummings et al., 2020). When investors believe that using robo-advisors is an effective strategy for navigating and mitigating financial risks during crises, they are more likely to perceive robo-advisors as valuable tools. Aligned with the conclusions of earlier investigations by Rahi et al. (2021), Luo et al. (2021), Johnston and Warkentin (2010), Chen and Yeh (2017), and Chenoweth et al. (2009), the following positive relationship was proposed.

H1c: Response efficacy has a positive effect on retail investors’ perceived usefulness of robo-advisor during a financial crisis.

Retail investors' self-efficacy in using robo-advisors during a financial crisis relates to their confidence in utilizing these tools effectively to manage investments, make informed decisions, and mitigate risks. Factors influencing self-efficacy may include familiarity with technology, financial literacy, and past experiences with investment platforms. When investors have high self-efficacy in using robo-advisors, they are more likely to perceive these tools as valuable assets for navigating financial challenges and achieving positive outcomes during crises. Echoing the findings of past investigations from Luo et al. (2021), Johnston and Warkentin (2010), and Chen and Yeh (2017), the study argues that self-efficacy positively influences retail investors’ perception of robo-advisors' usefulness during financial crises.

H1d: Self-efficacy has a positive effect on retail investors’ perceived usefulness of robo-advisor during a financial crisis.

Response cost represents the perceived barriers or challenges that investors face when using robo-advisory services. Retail investors may perceive response costs associated with robo-advisor usage, such as fees, learning curves, or technical complexities. Response cost negatively impacts intentions to engage in threat adaptive behavior (Menard et al., 2017). These costs can create barriers to adoption and influence investors' perceptions of robo-advisors' usefulness. As response costs increase, investors are more likely to view robo-advisors as less useful for their financial decision-making needs during crises. Menard et al. (2017) and Hanus and Wu (2016) reported an insignificant negative relationship between response cost and individual's behavioral intention. Nevertheless, this study argued that it is important to include response cost in the conceptual framework as the current study is different from previous studies where it measures behavioral intention during a financial crisis. Investors want to protect their capital during a financial crisis, therefore associated cost related to the threat adaptive behavior may influence their behavioral intention.

*H1e: Response cost has a negative effect on retail investors' perceived usefulness of robo-*advisor *during a financial crisis.*

A robust study of TAM has analysed the relationship between PU and behavioural intention to use. Previous research had examined the relationship to determine the intention to use technologies, such as mobile money (Ha et al., 2023), virtual fitting applications (Park, 2022), Go-Pay (Nugroho & Apriliana, 2022), and higher education content on TikTok (Rahimullah et al., 2022). These past studies found that PU had a positive impact on behavioural intention. Hence, based on previous findings, this study argued that PU of robo-advisor during a financial crisis positively influenced intention to adopt robo-advisor during a financial crisis amongst retail investors. PU arises when retail investors believe that robo-advisor could effectively address their specific needs and requirements during a financial crisis. This may include risk management, portfolio diversification, automatic rebalancing, and data-driven decision-making. When investors perceive that robo-advisor aligns with their crisis-related needs, they are more inclined to use it as means to safeguard their investments. More importantly, PU of robo-advisor extends to the platform's ability to make timely adjustments to the investment portfolio in response to changing market conditions. Investors may value the agility of robo-advisors to adapt to evolving market dynamics, enhancing their willingness to use the platform during a financial crisis. Therefore, the following hypothesis is derived:

H2: Perceived usefulness of robo-advisor during a financial crisis has a positive effect on Behavioural intention to use robo-advisor during a financial crisis.

Previous research has found that actual adoption is primarily driven by users' desire to test and evaluate new technologies. Joo et al. (2016) reported that continuance intention predicted actual usage of mobile learning management system. Wang et al. (2022) suggested that in both urban and rural areas, behavioural intention is the strongest positive predictor of university students' use of tablet computers as learning tools. In Malaysia, a study by Munikrishnan et al. (2022) found that behavioural intention to use had a significant positive effect on adoption of cashless payment amongst youth. In this present study context, robo-advisor is proposed as an effective crisis-response tool for several reasons. It presents digital touchpoints between retail investors and "robot" fund managers when people have to be in lockdowns and practice social distancing. Furthermore, investors who needed to rethink about their investment portfolio during a financial crisis might use robo-advisory services as it is a lower-cost alternative when savings are crushed due to the volatility in stock markets. This demonstrates that users can respond competitively towards financial crisis-related market challenges through robo-advisors. Thus, retail investors' enthusiasm to explore and assess robo-advisor positively determines the actual usage of robo-advisor during a financial crisis. When investors develop a behavioural intention to use a robo-advisor during a financial crisis, they form a psychological commitment or decision to act in a certain way. This intention reflects their willingness and motivation to take action. Investors who intend to use a robo-advisor during a financial crisis are more likely to take the necessary steps to initiate and set up their accounts, input relevant information, and fund their investments. Thus, the following hypothesis was derived:

H3: Behavioural intention to use robo-advisor has a positive effect on actual usage of robo-advisor during a financial crisis.

RESEARCH METHODOLOGY

In this study the data were collected on a sample of retail investors in Malaysia. To identify the right targeted respondent, the survey required the respondents to indicate that they have fulfilled two criteria, which are (a) retail investors who purchase assets, such as stocks, bonds, securities, mutual funds, and exchange-traded funds, and (b) Malaysian residents. This study used two non-probability sampling techniques (Saunders et al., 2019) as the sampling frame of retail investors in Malaysia is unavailable because it is considered as confidential data. The first sampling technique was self-selection sampling which is one of the volunteer sampling techniques. Self-selection sampling is when an individual is allowed to express their desire to be part of the sample (Saunders et al., 2019). Once a pool of self-selected participants is collected, snowball sampling is utilized to expand the sample through participant referrals. Participants who have already joined the study can refer to other individuals they know who meet the eligibility criteria. This creates a network effect, where new participants are added through the referrals of existing participants. Snowball sampling can be particularly useful in accessing hard-to-reach populations or individuals who may not be easily identifiable through other means.

According to Table 1, the questions used to measure the constructs were adopted and adapted from previous studies aforementioned in the literature and hypotheses development with relevant modifications. The respondents were given a predetermined set of responses on a 5-point Likert scale (Ismail et al., 2018a, 2018b) with “strongly agree” and “strongly disagree” at both ends. SPSS software version 29.0 was chosen for the data analysis because of its capabilities in assessing the validity and reliability of the constructs, generating descriptive statistics, evaluating multicollinearity, and performing linear regression analysis. It was the preferred data analysis method for the context of the study as these analyses are relevant for evaluating the reliability of measurement instruments and assessing relationship between variables.

Table 1: Measurement of Variables

Construct	Measurement Items	Source of Measurement of Construct
Perceived severity	PS1: If my investment is impacted by a financial crisis, it would be serious.	Adapted from Rahi et al. (2021)
	PS2: If my investment is impacted by a financial crisis, it would be severe.	
	PS3: If my investment is impacted by a financial crisis, it would be dangerous.	
Perceived vulnerability	PV1: It is likely that my investment value will decline due to a financial crisis.	
	PV2: It is possible that my investment value will decline due to a financial crisis.	
	PV3: It is expected that my investment value will decline due to a financial crisis.	
	PV4: If my investment value declines due to a financial crisis, my life will be at risk.	
Response efficacy	RE1: With the use of robo-advisor, solving my investment management issues during a financial crisis is more likely to be guaranteed.	
	RE2: Using robo-advisor helps in solving my investment management problems during a financial crisis.	

	RE3: Using robo-advisor is effective in improving my investment management problems during a financial crisis.	
	RE4: Using robo-advisor is an effective way to improve my investment management during a financial crisis.	
Self-efficacy	SE1: Robo-advisor platform is easy to use.	Adapted from Johnston & Warkentin (2010)
	SE2: Robo-advisor platform is convenient to use.	
	SE3: I am able to use robo-advisor platform without much effort.	
Response cost	RC1: Installing robo-advisor app requires a significant financial cost.	Adapted from Crossler (2010)
	RC2: Installing robo-advisor app requires a significant amount of time.	
	RC3: Installing robo-advisor app requires a significant cognitive effort (brain power).	
	RC4: Updating robo-advisor app requires a significant financial cost.	
	RC5: Updating robo-advisor app requires a significant amount of time.	
	RC6: Updating robo-advisor app requires a significant cognitive effort (brain power).	
	RC7: Checking my investment through robo-advisor app requires a significant financial cost.	
	RC8: Checking my investment through robo-advisor app requires a significant amount of time.	
	RC9: Checking my investment through robo-advisor app requires a significant cognitive effort (brain power).	
Perceived usefulness	PU1: Using robo-advisor would improve my performance in managing investments during a financial crisis	Adopted from Belanche et al. (2019a)
	PU2: Using robo-advisor would improve my productivity in managing investments during a financial crisis	
	PU3: Using robo-advisor would enhance my effectiveness in managing investments during a financial crisis	
	PU4: I would find robo-advisor useful in managing investments during a financial crisis	
Behavioral Intention to Use	BI1: I plan to use robo-advisor to manage my investments during a financial crisis	
	BI2: Using robo-advisor to manage my investments during a financial crisis is something I would do	
	BI3: I plan to use robo-advisor during a financial crisis rather than any human financial advisor	

Actual Use	During the past financial crisis such as the COVID-19 pandemic, AU1: I use a robo-advisor frequently AU2: I use a robo-advisor as the main tool to manage my investment AU3: I recommend robo-advisors platform to other investors to manage their investments	Adapted from Wang et al. (2022)

RESEARCH FINDINGS

The demographic profile of 128 respondents is presented in Table 2. To test convergent validity, item-total correlations were calculated to assess how each individual item contribute meaningfully to the total score (Schober et al., 2018). Table 3 presents the item-total correlation results assessed by using Pearson correlation coefficients. The results revealed statistically significant positive correlations for all items, indicating that higher scores on each item were associated with higher total scores on the scale. The internal consistency of the variables is calculated by using Cronbach's alpha, and the results are presented in Table 4. Cronbach's reliabilities for all scales were above the recommended threshold of 0.70 (Nunnally & Bernstein, 1994). The results indicated a strong level of internal consistency amongst the items, suggesting that they were highly correlated with each other.

Table 2: Demographic Profile of Respondents

Demographic Information	Categories	N	%
Gender	Male	56	43.8
	Female	72	56.3
Age	18 – 23 years old	82	64.1
	24 – 29 years old	18	14.1
	30 – 35 years old	10	7.8
	36 – 41 years old	6	4.7
	42 – 47 years old	4	3.1
	48 – 53 years old	6	4.7
	54 years old and above	2	1.6
Education Level	Certificate	4	3.1
	Diploma	58	45.3
	Bachelor's Degree	46	35.9
	Master's Degree	20	15.6
Years of Investment Experience	0 – 2 years	74	57.8
	3 – 5 years	36	28.1

	6 – 8 years	2	1.6
	9 – 11 years	4	3.1
	12 years and above	12	9.4
Gross Income	Less than RM2,500	82	64.1
	RM2,500 – RM3,169	8	6.3
	RM3,170 – RM3,969	2	1.6
	RM3,970 – RM4,849	10	7.8
	RM4,850 – RM5,879	2	1.6
	RM5,880 – RM7,099	4	3.1
	RM7,110 – RM8,699	8	6.3
	RM10,960 – RM15,039	6	4.7
	RM15,039 and above	6	4.7
Investment Risk Tolerance	Conservative low-risk, focus on capital preservation	50	39.1
	Moderate-risk, balance between capital preservation and growth	66	51.6
	Aggressive high-risk, focus on capital appreciation	12	9.4

Table 3: Item-Total Correlations

Variables	Measurement Items	Pearson's r
Perceived Severity	PS1	0.915**
	PS2	0.816**
	PS3	0.863**
Perceived Vulnerability	PV1	0.770**
	PV2	0.870**
	PV3	0.825**
	PV4	0.759**
Response Efficacy	RE1	0.820**
	RE2	0.918**
	RE3	0.928**
	RE4	0.869**
Self-Efficacy	SE1	0.877**

	SE2	0.913**
	SE3	0.842**
Response Cost	RC1	0.712**
	RC2	0.857**
	RC3	0.813**
	RC4	0.885**
	RC5	0.870**
	RC6	0.862**
	RC7	0.837**
	RC8	0.723**
	RC9	0.705**
Perceived Usefulness	PU1	0.868**
	PU2	0.807**
	PU3	0.856**
	PU4	0.859**
Behavioral Intention to Use	BI1	0.901**
	BI2	0.883**
	BI3	0.723**
Actual Use	AU1	0.861**
	AU2	0.914**
	AU3	0.828**

***correlation is significant at the 0.01 level (2-tailed).*

Table 4: Cronbach's Alpha

Variables	Cronbach's alpha
Perceived Severity	0.851
Perceived Vulnerability	0.815
Response Efficacy	0.837
Self-Efficacy	0.856
Response Cost	0.786
Perceived Usefulness	0.829
Behavioral Intention to Use	0.842
Actual Use	0.852

After ensuring that all variables employed in the current study satisfied the tests of validity and reliability, descriptive statistics were performed for all variables. Descriptive statistics including mean, standard deviation, minimum, and maximum values for all variables are presented in Table 5. The overall mean score for perceived severity was approximately [(3.64+3.33+3.50)/3] = 3.49. This indicated that the respondents perceive a moderate level of severity regarding the potential threat or harm associated with the financial crisis impact on their investment. Meanwhile, the respondents generally exhibited a positive inclination in their responses to items PV1, PV2, and PV3, while their level of agreement with item PV4 tended to be slightly lower. The overall mean score across the four items was approximately [3.61+3.67+3.50+3.19/4] = 3.49, which was the same with perceived severity's overall mean score. The respondents perceived a moderate level of vulnerability or susceptibility to the impact of financial crisis on their investment.

With an overall mean score of 3.44, the respondents, on average, were slightly leaning towards the positive side of response efficacy. This indicated that the respondents, on average, believed moderately in the effectiveness of the recommended protective behaviour. For self-efficacy, all three items received mean scores above than 3.40. With an overall mean score of 3.47, the respondents tended to slightly favour the positive end of the scale, suggesting a moderate level of self-efficacy amongst the respondents, indicating their perceived ability to carry out the recommended protective behaviour. For response cost, the respondents, on average, were taking a neutral position regarding the statements or items assessed. The responses did not lean significantly towards agreement or disagreement, suggesting a lack of strong positive or negative opinions on the cost or inconvenience associated with adopting the protective behaviour. Generally, the respondents seemed to have moderate perceptions of severity and vulnerability, moderate beliefs in the effectiveness of the recommended behaviour (response efficacy), and moderate confidence in their ability to perform the behaviour (self-efficacy). However, the perceived cost associated with the protective behaviour (response cost) was somewhat lower, indicating that the respondents, on average, may perceive the adoption of the protective behaviour as less burdensome, as supported by Hanus and Wu (2016).

The overall mean score for perceived usefulness was 3.50 suggesting that, on average, the respondents tended to express a positive stance towards the perceived usefulness of robo-advisor during a financial crisis. However, the respondents were expressing a stance that was neither strongly positive nor strongly negative on their behavioural intention to use as the overall mean score was 3.26. It can be inferred that, on average, the respondents were neither strongly inclined nor strongly disinclined to use robo-advisor during a financial crisis. This may indicate a degree of uncertainty or mixed opinions amongst the respondents. Lastly, the overall mean score for actual use is 2.12, indicating a tendency towards disagreement amongst the respondents. The respondents were expressing a lower level of endorsement regarding the actual use of robo-advisor during a financial crisis. In summary, the results highlighted a nuanced landscape where moderate protective behaviours, and behavioural intentions were accompanied by challenges in consistently translating knowledge into actions.

Table 5: Descriptive Statistics

Variables	Item	Mean	Overall Mean	S.D.	Min	Max
Perceived Severity	PS1	3.64		1.089	1	5
	PS2	3.33	3.49	1.055	1	5
	PS3	3.50		1.182	1	5
Perceived Vulnerability	PV1	3.61		1.033	1	5
	PV2	3.67	3.49	0.977	1	5
	PV3	3.50		1.098	1	5
	PV4	3.19		1.320	1	5

Response Efficacy	RE1	3.52		0.836	2	5
	RE2	3.39	3.44	0.748	2	5
	RE3	3.44		0.774	2	5
	RE4	3.44		0.852	1	5
Self-Efficacy	SE1	3.47		0.755	2	5
	SE2	3.53	3.47	0.796	2	5
	SE3	3.42		0.752	2	5
Response Cost	RC1	2.97		0.854	1	5
	RC2	2.92		0.965	1	5
	RC3	3.08		1.013	1	5
	RC4	3.00		0.943	1	5
	RC5	2.94	3.01	0.957	1	5
	RC6	3.02		1.046	1	5
	RC7	3.02		0.787	1	5
	RC8	3.05		0.862	1	5
	RC9	3.13		0.968	1	5
Perceived Usefulness	PU1	3.58		0.662	2	5
	PU2	3.45	3.50	0.665	2	5
	PU3	3.48		0.713	2	5
	PU4	3.52		0.756	1	5
Behavioral Intention to Use	BI1	3.33		0.856	1	5
	BI2	3.41	3.26	0.830	1	5
	BI3	3.06		0.774	1	5
Actual Use	AU1	2.50		1.024	1	4
	AU2	3.02	2.12	1.105	1	5
	AU3	0.84		0.366	0	1

The collinearity tolerance and variance inflation factor (VIF) values were calculated for each predictor variable in the regression model to evaluate the extent of multicollinearity. The purpose of this analysis was to assess the correlation amongst the predictors and identify any potential issues that might affect the stability and reliability of the regression coefficients. The results are presented in Table 6. All collinearity tolerance values were comfortably close to 1, and all VIF values were well below the common threshold of 10. These results collectively indicated a lack of problematic multicollinearity amongst the predictor variables.

Table 6: Variance Inflation Factor

Independent Variable	Dependent Variable	Collinearity Tolerance	VIF
Perceived Severity	Perceived Usefulness	0.416	2.402
Perceived Vulnerability		0.420	2.381
Response Efficacy		0.536	1.864
Self-Efficacy		0.702	1.425
Response Cost		0.862	1.160
Perceived Usefulness	Behavioral Intention to Use	1.000	1.000
Behavioral Intention to Use	Actual Use	1.000	1.000

A regression analysis was conducted to examine the relationships amongst the variables in the conceptual framework. Based on Table 7, the results showed that some of the predictor variables yielded p-values above the conventional significance threshold of 0.05, indicating an insignificant relationship with the dependent variable. Perceived severity, perceived vulnerability, self-efficacy, and response cost demonstrated insignificant relationships with PU (β =0.076, p =0.609; β =-0.080, p =0.589; β =0.096; p =0.402; β =-0.178, p =0.088, respectively). Possible reasons for this lack of significance may include inadequate sample size, moderate level of perceptions, factors not considered in the current model or the potential presence of complex interactions that warrant further investigation. Although this result contradicted the theoretical predictions of the PMT, numerous prior studies utilizing PMT have consistently demonstrated that threat appraisal has limited predictive power for both behavioral intentions and actual behaviors (Hodgkins & Orbell, 1998). However, the results revealed that response efficacy significantly predicts PU (β = 0.659, $p<0.001$), indicating positive associations. This suggested that changes in response efficacy were linked to meaningful variations in PU, providing empirical support for H1c. The respondents believed that robo-advisor is a useful and effective investing platform to be employed during a financial crisis. The result was supported by previous studies such as Joung et al. (2022), Rahi et al. (2020), Menard et al. (2017), Hanus and Wu (2016), and Chenoweth et al. (2009) who proved that response efficacy is a determinant of protective behavior. This finding aligns with earlier studies, indicating that response efficacy remains one of the most reliable predictors of protective behaviors (Crossler, 2010).

Moreover, the current study yielded results that aligned with previously established theory. PU, as posited by the existing theoretical framework, demonstrated a significant positive relationship with BI (β = 0.641, $p<0.001$), thus supporting hypothesis H2. This result was congruent with the underlying theory of TAM, and supported by previous studies that had brought to light significant positive correlation between PU and behavioural intention to use technological innovations, such as mobile money (Ha et al., 2023), virtual fitting applications (Park, 2022), Go-Pay (Nugroho & Apriliana, 2022), and higher education content on TikTok (Rahimullah et al., 2022).

BI revealed a significant positive relationship with actual use of robo-advisor (β = 0.478, $p<0.001$), thus supporting hypothesis H3. This indicated for each percentage rise in behavioural intention to use, actual usage will increase by 47.8%. This finding aligned seamlessly with the TAM model, and consistent with prior research that had revealed substantial positive relationship between behavioural intention to use and actual use of technological innovations, such as cashless payments (Munikrishnan et al., 2022), tablet computers (Wang et al., 2022), and e-learning system (Joo et al., 2016). Overall, the results suggested that response efficacy and TAM constructs posited prior to the empirical investigation accurately capture the dynamics of the studied phenomenon. This alignment provided empirical grounding for the conceptual framework, contributing to the credibility and generalisability of the theories within the context of the current study.

Table 7: Regression Analysis

Paths		*b (t-values)*	Conclusion
H1a: Perceived Severity	Perceived Usefulness	0.076 (0.514)	Not supported
H1b: Perceived Vulnerability		-0.080 (-0.544)	Not supported
H1c: Response Efficacy		0.659 (5.064)*	Supported
H1d: Self-Efficacy		0.096 (0.844)	Not supported
H1e: Response Cost		-0.178 (-1.734)	Not supported
H2: Perceived Usefulness	Behavioral Intention to Use	0.641 (6.568)*	Supported
H3: Behavioral Intention to Use	Actual Use	0.478 (4.286)*	Supported

**p<0.001*

CONCLUSION

Theoretical and Managerial Implications

The study highlighted the efficacy of TAM in understanding user adoption decisions, particularly with AI technologies like robo-advisors. It delved into protection motivation behaviors within this framework, showing how perceptions of efficacy influence protective actions, crucial for safeguarding financial well-being. Understanding protective actions was essential as it helped predict how individuals will respond to the crisis and what factors will influence their decision-making regarding risk management and protective behaviors. This deeper understanding uncovered the intricacies driving robo-advisor adoption, especially during financial crises. Insights gained illuminate factors influencing adoption, paving the way for targeted interventions and educational initiatives aimed at retail investors. Stakeholders benefitted by grasping how robo-advisors protect wealth and empower informed decision-making in turbulent times. This would be valuable for vendors seeking to gauge user interest in novel design concepts, as well as for information systems managers within user organizations aiming to assess these vendor solutions.

Investment banks and asset managers can refine marketing and communication strategies to resonate with users' protection motivations and adoption factors. Aligning strategies with wealth protection motives enhances robo-advisory services' appeal and drives adoption rates. Improving user experiences by incorporating feedback and emphasizing confidence-boosting features fosters trust and loyalty, ensuring long-term customer relationships and revenue streams. Utilizing behavioral nudges in robo-advisory platforms encourages desired behaviors, such as portfolio reviews and risk diversification, further solidifying market leadership in AI-driven financial services. Understanding adoption determinants, especially in crises, optimizes firms' position in the value chain, boosting overall business performance.

Limitations and Future Research

The generalisability of the findings from this study may be limited as the impact of protection motivation behaviour could vary in different technological or economic contexts. It is suggested that future research explore the influence of protection motivation behaviour across various investment scenarios. While the study measured all constructs at a single point in time, there is a need for investigations into the longitudinal impact of protection motivation behaviour on actual usage patterns, shedding light on the dynamics of adoption behaviour over time. An alternative approach, such as experimental design, could also be considered for future research. It is worth noting that the study captured a specific group of novice retail investors, which may constrain the applicability of the findings. To enhance the generalisability, future research could employ a more diverse sample to enable meaningful comparisons. Additionally, given the absence of prior research examining the effects of protection motivation behaviour on the use of robo-advisors during financial crises, this study contributes significantly to stakeholders' understanding of retail investors' adoption behaviour in challenging economic conditions.

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