

**ADVANCED INTERNATIONAL JOURNAL
OF BANKING, ACCOUNTING
AND FINANCE
(AIJBAF)**www.gaexcellence.com/aijbaf**THE IMPACT OF FINANCIAL LITERACY ON ROBO-
ADVISOR ADOPTION DURING ECONOMIC CRISIS:
EVIDENCE FROM MALAYSIA**Najihah Abd Razak¹, Kamisah Ismail^{2*}¹Lecturer, Asia Pacific University, Malaysianajihah.razak@apu.edu.my<https://orcid.org/0009-0000-1154-0019>²Associate Professor, University of Malaya, Malaysiakamisah.ismail@um.edu.my;<https://orcid.org/0000-0001-8134-091X>

+603-79673810

*Corresponding Author

Article Info:**Abstract:****Article history:**

Received date: 22.06.2026

Revised date: 14.07.2026

Accepted date: 20.08.2026

Published date: 09.09.2026

To cite this document:

Razak, N. A., & Ismail, K. (2026). The Impact of Financial Literacy on Robo-Advisor Adoption During Economic Crisis: Evidence from Malaysia. *Advanced International Journal of Banking, Accounting and Finance*, 8(25), 01-26.

Despite the potential benefits of robo-advisors, their adoption in Malaysia lags other East Asian developing economies, particularly during the recent economic crisis. The connection between the dimensions of financial literacy and the use of robo-advisors has not been adequately studied in the context of AI-assisted services in the past. This gap highlights the need to explore underlying behavioral and perceptual factors influencing the adoption of robo-advisors. This study builds upon the Technology Acceptance Model (TAM) by adding the financial literacy dimensions as external antecedents of perceived usefulness and behavioural intention to adopt robo-advisors. This addition expands the traditional TAM by showing that the adoption of robo-advisors is not only influenced by the perceptions of the users towards the technology itself, but also by their financial capabilities and orientations. A survey questionnaire was used to collect data on 380 Malaysian retail investors, which was analyzed by Partial Least Squares Structural Equation Modeling (PLS-SEM). Financial knowledge ($\beta=0.613$, $p<0.05$) and financial attitude ($\beta=0.292$, $p<0.05$) were found to have significant positive effects on perceived usefulness, and perceived usefulness exhibited a significant positive effect on intention to use ($\beta=0.671$, $p<0.05$), confirming its central role as a determinant of behavioral intention in this model. The model was observed to have a moderate predictive ability of behavioral intention to use by 53.2%. The results add to the existing literature on the adoption of financial technologies in emerging markets and have a number of practical implications. The providers must make conscious efforts to demonstrate the practical worth of their services by case studies, live demonstrations and interactive simulations that display the performance of robo-advisors in volatile markets. To policymakers and regulators, the findings highlight the importance of focusing on how individuals can

use their skills with technology to deal with risk and improve financial decision-making in crisis situations.

DOI:10.35631/AIJBAF.825001

Keywords:

Economic Crisis; Financial Literacy; Malaysia; Perceived Usefulness; Retail Investor; Robo-Advisors; Technology Acceptance Model, JEL Classification: M40



© The authors (2026). This is an Open Access article distributed under the terms of the Creative Commons Attribution (CC BY NC) (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact aijbaf@gaexcellence.com.

Introduction

Robo-advisors are low-cost, low-interaction, algorithm-driven investing investment portfolio management services. The platforms provide a variety of advantages such as reduced costs, easy access, and personalization (Belanche et al., 2019). However, compared with other developing economies in East Asia, widespread adoption has not taken place in Malaysia, particularly in the last economic crisis which occurs between the period of 2020 to 2023. The time frame is characterized by high economic uncertainty, beginning with the shocks of the pandemic and proceeding to inflationary pressures, rising interest rates, limiting supply chains and economic uncertainty on the global level. In addition, the financial landscape in Malaysia is very different. The Malaysian Financial Literacy Survey (RinggitPlus, 2021) shows that a significant number of Malaysians have poor financial habits. The chairman of the Securities Commission has claimed that the financial knowledge of Malaysian investors is still relatively low, which exposes them to illegal activities and fraud (Mardhiah, 2022). These findings pose significant questions concerning the role of financial literacy in the uptake of new financial technologies such as robo-advisors, especially in times of financial turmoil.

The connection between the dimensions of financial literacy and the adoption of robo-advisors has not been adequately studied in previous research on AI-assisted services, which has investigated adoption (Flavián et al., 2021; Belanche et al., 2019), continuance intention (Cheng, 2020), trust (Cheng et al., 2019; Zhang et al., 2021), behavioral biases (Bhatia et al., 2021), the banking industry (Boustani, 2020; Caron, 2019; Mogaji et al., 2021) and credit scoring (Aggarwal, 2021; Mhlanga, 2021). Therefore, the research questions in this study are:

- I. Is there any relationship between financial literacy and perceived usefulness of robo-advisors during an economic crisis?

- II. Is there any relationship between financial literacy and behavioral intention to use robo-advisors during an economic crisis?
- III. Is there any relationship between perceived usefulness of robo-advisors during an economic crisis and behavioral intention to use robo-advisors during an economic crisis?
- IV. Is there any mediating effect of perceived usefulness in the relationship between financial literacy and behavioral intention to use robo-advisors during an economic crisis?

Through answering these questions, this study adds to the body of research on the adoption of robo-advisory services and expands the use of the Technology Acceptance Model (TAM) in the context of financial technology adoption in times of crisis. The results offer useful information to financial institutions, policymakers, and educational institutions in Malaysia to improve the adoption of robo-advisors.

Literature Review

Robo-Advisory Services

Robo-advisors are an important technological change in the wealth management sector, which provides automated investment recommendations and portfolio management through algorithms with minimal human intervention (Flavián et al., 2021). Such platforms usually offer services like portfolio allocation, rebalancing, and tax optimization at reduced costs than traditional financial advisors, and investment advice is more available to retail investors (Belanche et al., 2019). The introduction of robo-advisors has also upset the conventional financial advisory business by democratizing the access to advanced investment strategies that were only accessible to affluent clients. According to Jung et al. (2018), robo-advisors are online services that offer financial guidance and automatically make purchases and sales with little human oversight. The services are usually based on algorithms that assign assets to the clients according to their risk profiles, goals, and investment horizons (Phoon & Koh, 2018).

Robo-advisors have a number of benefits compared to conventional investment practices in the case of an economic crisis. According to Beketov et al. (2018), automated advisory systems can be used to reduce behavioral biases, which in most cases result in poor investment decisions in times of market volatility. Moreover, Lopez et al. (2015) indicate that the rule-based investment strategies of robo-advisors may offer consistency and disciplined management of a portfolio in economic recessions. Although these benefits exist, there is a wide variation in the uptake of robo-advisory services across markets. Robo-advisors have received a significant momentum in developed economies such as the United States and the United Kingdom, and the assets under management are increasing at a fast rate (Statista, 2021). Nevertheless, in developing economies such as Malaysia, the uptake is at an early stage even though it has the potential to be beneficial (RinggitPlus, 2021).

The latest literature has found that there are many research opportunities in the field of robo-advisors. The works of Flavián et al. (2021), Bhatia et al. (2021), Zhang et al. (2021), Cheng (2020), Belanche et al. (2019), and Cheng et al. (2019) enable future researchers to investigate other factors that can affect the adoption of robo-advisors in other settings. Moreover, Bhatia et al. (2021), Mogaji et al. (2021), Cheng (2020), and Belanche et al. (2019) recommend the extension of research to other socio-cultural backgrounds. Hentzen et al. (2022) particularly

emphasize the necessity of research on the impact of financial literacy of consumers on the use of robo-advisors, which is one of the under-researched areas.

Financial Literacy

Financial literacy refers to the knowledge, behavior, and attitude that help one to make sound financial choices (OECD, 2016). Financial knowledge is the knowledge about financial concepts and products; financial behavior is the behavior taken in respect to money management and financial attitude is the perception and beliefs about money. Financial literacy has been transformed into a concept of multidimensionality as opposed to the limited scope of financial literacy in terms of financial knowledge. Huston (2010) conceptualizes financial literacy as a concept with both knowledge and application aspects, which implies that people need to not only be aware of the financial concepts, but also be able to apply them in decision-making. Lusardi and Mitchell (2014) also add that financial literacy is numeracy and the capacity to carry out calculations connected with interest rates and comprehend simple financial notions.

OECD (2016) has created a financial literacy framework that includes three dimensions, i.e., knowledge, behavior, and attitudes. Financial knowledge entails the knowledge of the simple financial principles like interest, inflation and diversification of risk (van Rooij et al., 2011). Financial behavior describes behaviors like budgeting, saving and not being in too much debt (Robb and Woodyard, 2011). Financial attitudes include orientations toward long-term financial planning and money management (OECD, 2016). Financial literacy has been observed to vary among the studies in the Malaysian context. Financial Education Network (2019) states that merely 43% of Malaysians are financially knowledgeable, and 1 in 10 Malaysians perceives that they are not disciplined when it comes to managing their finances. Such a low financial literacy level could have consequences regarding the use of new financial technologies like robo-advisors. Although financial literacy is a crucial factor in investment decision-making, the existing body of research on the effects of financial literacy on the adoption of robo-advisors is sparse. Hentzen et al. (2022) noted this gap and called for studies investigating the relationship between financial literacy and robo-advisory services adoption. This relationship is especially important to understand in the context of economic crises, when the decision-making process regarding investment becomes more complicated and decisive.

Financial Literacy

Davis (1989) developed the Technology Acceptance Model that is extensively applied to understand user acceptance of new technologies. According to the model, behavioral intention to use a technology is mainly determined by perceived usefulness and perceived ease of use. Within the framework of financial technologies, TAM has been utilized to comprehend adoption behaviors of different innovations (Cheng, 2020). Since its inception, TAM has been widely used to forecast the adoption of technology in many areas, including financial technologies. Davis (1989) defined perceived usefulness as the extent to which an individual believes that the use of a given system would help him/her in improving his/her job and perceived ease of use as the extent to which an individual believes that the use of a given system would be effortless. These constructs have always been strong predictors of technology adoption intentions (Venkatesh and Davis, 2000).

Applied to financial technologies, TAM has been used to learn about user acceptance of mobile banking (Alalwan et al., 2016), online investment platforms (Tai and Ku, 2013), and most recently, robo-advisory services (Belanche et al., 2019). Singh and Srivastava (2018) established that the perceived usefulness is a significant determinant of the behavioral intention to use mobile banking services, whereas Belanche et al. (2019) established the same effect of robo-advisors. The perceived usefulness of financial technologies can be especially acute during economic crises when people are in need of efficient means to cope with their investments in the state of uncertainty. According to Cheng (2020), economic crises may hasten the implementation of financial technologies when the technologies are seen as effective in reducing financial risks.

Technology Acceptance Model (TAM)

Davis (1989) developed the Technology Acceptance Model that is extensively applied to understand user acceptance of new technologies. According to the model, behavioral intention to use a technology is mainly determined by perceived usefulness and perceived ease of use. Within the framework of financial technologies, TAM has been utilized to comprehend adoption behaviors of different innovations (Cheng, 2020). Since its inception, TAM has been widely used to forecast the adoption of technology in many areas, including financial technologies. Davis (1989) defined perceived usefulness as the extent to which an individual believes that the use of a given system would help him/her in improving his/her job and perceived ease of use as the extent to which an individual believes that the use of a given system would be effortless. These constructs have always been strong predictors of technology adoption intentions (Venkatesh and Davis, 2000).

Applied to financial technologies, TAM has been used to learn about user acceptance of mobile banking (Alalwan et al., 2016), online investment platforms (Tai and Ku, 2013), and most recently, robo-advisory services (Belanche et al., 2019). Singh and Srivastava (2018) established that the perceived usefulness is a significant determinant of the behavioral intention to use mobile banking services, whereas Belanche et al. (2019) established the same effect of robo-advisors. The perceived usefulness of financial technologies can be especially acute during economic crises when people are in need of efficient means to cope with their investments in the state of uncertainty. According to Cheng (2020), economic crises may hasten the implementation of financial technologies when the technologies are seen as effective in reducing financial risks.

Economic Crises and Technology Adoption

Economic crises provide special circumstances in which to examine technology adoption behaviors. In the past, these crises have been known to spur technological innovation and adoption in the financial sector. An example is the 2008 global economic crisis, which triggered the development of fintech solutions as consumers wanted to find an alternative to traditional financial institutions (Arner et al., 2016). When there is a financial or economic uncertainty, the decision-making process of the people is likely to alter. Fear and anxiety are some of the emotional reactions that are caused by economic crisis and can result in poor financial choices (Loewenstein et al., 2001). This situation renders the role of financial literacy especially significant, as it can assist individuals to make more reasonable choices even when they are under the influence of emotions. COVID-19, in its turn, put a lot of financial pressure on numerous households. The pandemic caused job losses, loss of income, and market volatility

in Malaysia, leaving many people in a precarious financial situation (Habibullah et al., 2024). This climate possibly augmented the worth of low-cost, accessible investment choices such as robo-advisors.

Conceptual Framework and Hypothesis Development

Conceptual Framework

The conceptual framework focuses on the relationship between financial literacy (financial knowledge, financial behavior and financial attitude) and behavioral intention to use robo-advisors in economic crisis, where perceived usefulness is used as a mediating variable. This model hypothesizes that more financially literate people might have a better grasp of investment concepts and risk tolerance, which could influence their perceptions of the utility of robo-advisory services in times of market volatility. The perceived usefulness of robo-advisors, defined as algorithmic decision-making, portfolio rebalancing, and lack of emotions, then mediates the connection between the financial literacy of an individual and his or her final decision to use these digital tools in times of financial turmoil.

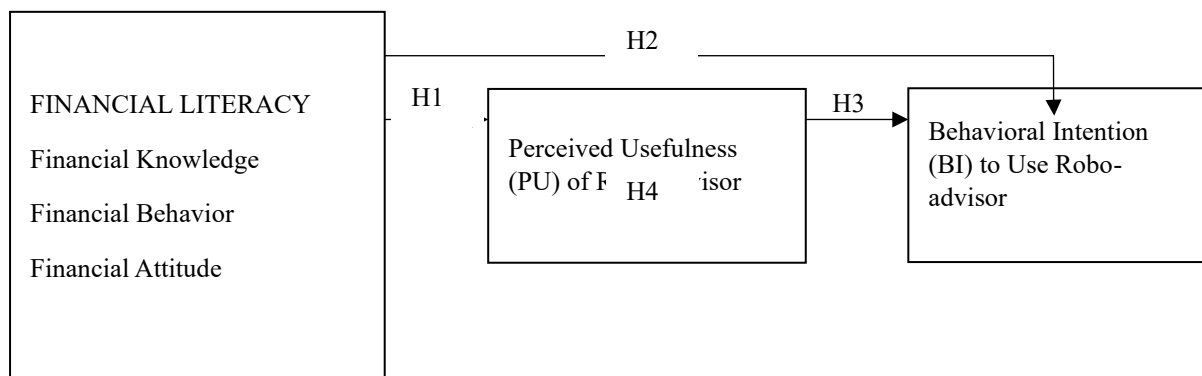


Figure 1: Conceptual Framework

Hypothesis Development

Based on the literature review and the research gaps identified, this study proposes the following hypotheses:

H1a: Financial knowledge has a positive relationship with perceived usefulness of robo-advisors during an economic crisis.

Financial knowledge is a measure of how well a person can comprehend and use basic financial principles like diversification, risk-return trade-offs, compounding, and algorithmic asset allocation (Lusardi and Mitchell, 2014). More financially educated people are in a better position to assess the advantages of financial technologies, such as robo-advisors, which are based on these principles using automated portfolio management and data-driven decision-making (Jung et al., 2018). In times of economic crises, the skill to understand systematic approaches to investment is especially important, when fluctuating markets require more knowledgeable, disciplined strategies. Past research (van Rooij et al., 2011) has shown that financial knowledge has a positive effect on financial decision-making and the use of advanced

financial instruments. Thus, those who are more financially savvy are likely to find robo-advisors more helpful in times of economic insecurity.

H1b: Financial behavior has a positive relationship with perceived usefulness of robo-advisors during an economic crisis.

Financial behavior is defined as the real financial activities of the individuals, including budgeting, saving, and investing (OECD, 2016). Good financial practices, especially, frequent saving and responsible investing, are associated with improved financial performance and receptiveness to technological applications that facilitate financial management (Robb and Woodyard, 2011). The automated asset allocation and rebalancing functions of robo-advisors fit such behaviors with cost-effective and systematic investment strategies. In times of economic crises, people who have developed positive financial behaviors might be more concerned about how robo-advisors can keep their investments disciplined and reduce the impact of emotional biases. Thus, financial behavior is anticipated to enhance the perceived usefulness of robo-advisors.

H1c: Financial attitude has a positive relationship with perceived usefulness of robo-advisors during an economic crisis.

Financial attitude is an individual attitude towards financial planning, risk management and long-term investment strategies (OECD, 2016). Positive financial attitude is usually linked to proactive financial management and willingness to innovative financial solutions (Woodyard and Robb, 2016). Robo-advisors, which enable long-term portfolio planning by applying algorithmic accuracy and diversification, could be of interest to people with prospective financial mindsets. In economic crisis situations, people having such attitudes might find robo-advisors as a more valuable tool to maintain long-term objectives in the face of short-term market fluctuations.

H2a: Financial knowledge has a positive relationship with behavioral intention to use robo-advisors during an economic crisis.

Behavioral intention to use robo-advisors can be directly affected by financial knowledge because more knowledgeable people might be more confident in their skills to effectively use financial technologies. Lusardi and Mitchell (2014) discovered that more advanced financial products were correlated with financial knowledge. In times of economic crisis, more financially savvy individuals might be willing to consider new innovative services such as robo-advisors to streamline their investment plans.

H2b: Financial behavior has a positive relationship with behavioral intention to use robo-advisors during an economic crisis.

Good financial habits like saving on a regular basis, investing regularly, and monitoring of expenses are positive financial habits that signify an active attitude towards personal finances (Robb and Woodyard, 2011). Those who practice these behaviors are more likely to embrace tools that will improve their financial behaviors. Such users are well-suited to robo-advisors, which provide systematic and automated investment solutions, especially in times of economic crisis when it is important to have structured behaviors.

H2c: Financial attitude has a positive relationship with behavioral intention to use robo-advisors during an economic crisis.

Behavioral intentions are heavily dependent on attitudes towards financial planning and technology adoption (OECD, 2016). Individuals who have a positive attitude towards finance i.e. forward-thinking and goal-oriented tend to value the digital investment options like robo-advisors. In times of economic crisis, people with optimistic financial attitudes can be interested in technologies that can assist them in following long-term financial goals in the face of market instability.

H3: Perceived usefulness has a positive relationship with behavioral intention to use robo-advisors during an economic crisis.

This hypothesis is based on the direct result of the Technology Acceptance Model (Davis, 1989) that perceived usefulness is a significant predictor of behavioral intention to use a technology. When considering robo-advisors, Belanche et al. (2019) discovered that perceived usefulness is a key factor in intention to use such services. In the case of robo-advisors, perceived usefulness is based on the perception that these services have the potential to enhance the performance of investments by automation, diversification, and cost-efficiency. The perceived usefulness and behavioral intention relationship can be especially high during economic crises as people are willing to find effective instruments to deal with their investments in the face of uncertainty.

H4: Perceived usefulness mediates the relationship between financial literacy and behavioral intention to use robo-advisors during an economic crisis.

This hypothesis combines the earlier hypotheses in that it hypothesizes that financial literacy has a direct and indirect effect on behavioral intention via perceived usefulness. Financially literate people might know about the technological benefits of robo-advisors, which will make them feel more useful and, in turn, will make them more willing to use such services. This mediating role can be especially significant during economic crises when people of a higher financial literacy can be more aware of the usefulness of robo-advisors in overcoming the market fluctuations.

Research Methodology***Research Design***

This study employed a quantitative research approach using a survey questionnaire to collect data from retail investors in Malaysia. The research design allowed for testing the proposed hypotheses and examining the relationships between financial literacy, perceived usefulness, and behavioral intention to use robo-advisors during an economic crisis.

Sampling and Data Collection

The target population for this study was retail investors in Malaysia. Retail investors are the right respondents in this study as they are the main target population of robo-advisory services, especially in the emerging markets where availability of affordable and technology-based investment solutions is taking off. Retail investors are likely to be hindered by financial knowledge, resources, and access to personalized advice compared to institutional investors,

who already have professional advisors and access to sophisticated tools. Robo-advisors are meant to fill these gaps by providing low-cost, automated, and easy-to-use platforms that democratize investment opportunities. The analysis of the behavioral intention of retail investors thus gives direct information on the adoption potential of robo-advisory services, which are specifically promoted as an easy-to-use service among people with little investing experience or smaller amounts to invest.

Non-probability sampling methods were, however, employed as suggested by Saunders et al. (2019) because a sampling frame (which is a confidential data) was not available. The survey will only select the targeted respondent who meets two criteria i) retail investors, who buy assets in the form of stocks, bonds, securities, mutual funds, and exchange-traded funds, and ii) Malaysian residents. The initial target sample size was 384 respondents to provide sufficient statistical power.

Measurement Instruments

The questionnaire also contained financial literacy, perceived usefulness of robo-advisors, and behavioral intention to use robo-advisors in case of an economic crisis. All the measures were taken and modified according to the existing scales in the literature with appropriate changes to fit the context of the current research.

Financial Literacy

Adopted from van Rooij et al. (2011), responses to five multiple-choice questions designed to test different aspects of knowledge widely considered to be useful to individuals when making financial decisions are used to assess basic financial knowledge, as shown in Table 1. These questions form the foundation of simple financial transactions, financial planning and day-to-day financial decision making (van Rooij et al., 2011).

Table 1: Measurement of Financial Knowledge

Financial Knowledge: Choose the most correct answer from the following multiple-choice questions.		
No.	Question	Answer
1	Numeracy: Suppose you had RM100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?	More than RM102; Exactly RM102; Less than RM102; Do not know; Refusal.
2	Interest compounding: Suppose you had RM100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have on this account in total?	More than RM200; Exactly RM200; Less than RM200; Do not know; Refusal.
3	Inflation: Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?	More than today; Exactly the same; Less than today; Do not know;

		Refusal.
4	Time value of money: Assume a friend inherits RM10,000 today and his sibling inherits RM10,000 3 years from now. Who is richer because of the inheritance?	My friend; His sibling; They are equally rich; Do not know; Refusal.
5	Money illusion: Suppose that in the year 2023, your income has doubled and the prices of all goods have doubled too. In 2023, how much will you be able to buy with your income?	More than today; The same; Less than today; Do not know; Refusal.

Source: van Rooij et al. (2011)

Table 2 looks at levels of financial behavior by assessing the extent to which respondents are behaving in financially literate ways. Most people consider creating an emergency fund, checking one's credit report/score, avoiding bank overdrafts, saving for retirement, and paying with credit card balances on time and in full to be positive financial behaviors, or best practices (Robb & Woodyard, 2011; Allgood & Walstad, 2016). This research took all the six measures of financial behavior as used by Robb and Woodyard (2011) research.

Table 2: Measurement of Financial Behavior

Financial Behavior: Choose “Yes” if you agree with the following statement, and choose “No” if you disagree with the following statement.			
No.	Question	Yes	No
1	Have you set aside emergency funds that would cover your expenses for 3 months in case of sickness, job loss, economic downturn, or other emergency?		
2	Have you obtained a copy of your credit report or checked your credit score in the last 12 months? Note: A credit report is a statement that has information about your credit activity and current credit situation such as loan paying history and the status of your credit accounts.		
3	Do you have a retirement account established privately or through an employer (example: Employees Provident Fund account)?		
4	Do you have at least two of the four categories of risk management policies: health insurance, homeowner's or renter's insurance, life insurance and auto insurance?		
5	I have overdrawn my current account (at least) occasionally. Note: If you do not own a current account, please tick N/A ()		
6	I always paid my credit card in full in the past 12 months. Note: If you do not own a credit card, please tick N/A ()		

Source: Robb and Woodyard (2011)

The attitudes of respondents towards money and future planning are determined by using four questions as shown in Table 3. The questions are based on the survey of OECD (2016) which has been modified. Such preferences will tend to motivate individuals to behave in a manner

that would enhance their financial stability and overall wellbeing. Everything was estimated based on a five-point Likert scale based on the range of 1 to strongly disagree and 5 to strongly agree.

Table 3: Measurement of Financial Attitude

Financial Attitude: Please rate how strongly you agree or disagree with each of the following statements by placing a checkmark in the appropriate box.						
No.	Question	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
1	I tend to live for my future					
2	I tend to take care of my future					
3	I find it more satisfying to save money for the long term than to spend money					
4	Money is there to be saved or to be invested					

Source: OECD (2016)

Technology Acceptance Model Constructs

In order to quantify the perceived usefulness, the study will use the question items of a study by Belanche et al. (2019) on the adoption of robo-advisor. Table 4 shows that there are four questions to determine whether the respondent feels that the use of robo-advisor would improve his or her performance in managing investments in the event of an economic crisis. The estimation of all items was done by a five-point Likert scale in accordance with a range of 1 strongly disagree to 5 strongly agree.

Table 4: Measurement of Perceived Usefulness

No.	Question	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
1	Using robo-advisor would improve my performance in managing investments during an economic crisis					
2	Using robo-advisor would improve my productivity in managing investments during an economic crisis					
3	Using robo-advisor would enhance my effectiveness in managing investments during an economic crisis					

4	I would find robo-advisor useful in managing investments during an economic crisis					
---	--	--	--	--	--	--

Source: Belanche et. al. (2019)

This study also uses the question items of Belanche et al. (2019) study to measure behavioral intention to use. Three questions are used to assess the intention to use robo-advisor to manage his or her investments during an economic crisis as indicated in Table 5. Everything was estimated on a five-point Likert scale based on a scale of 1 to strongly disagree and 5 to strongly agree.

Table 5: Measurement of Behavioral Intention to Use

No.	Question	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
1	I plan to use robo-advisor to manage my investments during an economic crisis					
2	Using robo-advisor to manage my investments during an economic crisis is something I would do					
3	I plan to use robo-advisor during an economic crisis rather than any human financial advisor					

Source: Belanche et. al. (2019)

Instrument Validation

Expert reviews were done before data collection to validate the questionnaire. Three field experts assessed the extent to which the items were a good reflection of the intended constructs. Some adjustments were done according to their feedback:

Expert A and B doubted the applicability of COVID-19 as the crisis of interest in a survey in 2023. As a result, the emphasis was shifted to the economic crisis in general, and the respondents could assess their behavior during COVID-19 as an instance of a previous economic crisis.

The objective items of Financial Behavior that were questioned by Expert C were whether binary responses were analyzable. The researcher chose to keep these items as binary responses can be recoded and examined in SPSS.

Expert A was concerned with the level of difficulty of Accounting Knowledge measurement items. This was later put to test in the pilot study where respondents reported no problems in comprehending the questions.

Expert A recommended the inclusion of additional questions in the demographic profile section about investment. As a result, gross income and investment risk tolerance were added to the demographic questions.

All expert comments and suggestions were incorporated prior to conducting the pilot study.

Data Analysis Techniques

Data were analyzed with the help of Partial Least Squares Structural Equation Modeling (PLS-SEM) that is appropriate in predictive research models and able to deal with complex models including multiple constructs. The analysis was performed in two phases: measurement model (reliability and validity) assessment and structural model (hypothesis testing) assessment.

Results

Sample Profile and Non-Response Bias

The survey was shared in 39 investment-related social media groups, 11 open Telegram channels, 35 WhatsApp groups, and 4 investment forums, with an estimated total reach of more than 100,000 members. The use of non-probability sampling methods and open channels of distribution did not allow a traditional response rate to be determined. Engagement was however monitored through a Bitly link which registered 500 unique clicks within the time frame of the data collection. Though precise numbers of distribution cannot be confirmed because of the snowball sampling method, all these methods made sure that the survey covered a lot more than the target of 384 potential participants as the final sample of 380 valid responses proves. To check the non-response bias, respondents were divided into early respondents (199) who submitted their answers on time and late respondents (181) who submitted their answers after the due date. Table 6 is the independent sample t-test, which was used to compare the mean scores of all the main variables in these two groups, according to the method used by Ismail et al. (2018a). The findings indicated that there were no significant differences at the 5% level of significance, meaning that non-response bias was not a problem in this study.

Table 6: Independent Sample t-test

Indicators	Early responses (n = 199)		Late responses (n = 181)		T	P
	Mean	S.D.	Mean	S.D.		
FK1	0.81	0.390	0.88	0.328	-1.733	0.084
FK2	0.70	0.458	0.71	0.456	-0.078	0.938
FK3	0.67	0.472	0.71	0.454	-0.932	0.352
FK4	0.59	0.493	0.61	0.490	-0.392	0.695
FK5	0.71	0.453	0.76	0.427	-1.079	0.281

FB1	0.78	0.413	0.75	0.437	0.874	0.383
FB2	0.40	0.491	0.41	0.494	-0.344	0.731
FB3	0.56	0.498	0.60	0.491	-0.875	0.382
FB4	0.61	0.482	0.61	0.488	0.501	0.617
FB5	0.79	0.405	0.87	0.340	-1.903	0.058
FB6	0.23	0.423	0.27	0.446	-0.888	0.375
FA1	3.96	1.032	3.89	0.999	0.721	0.471
FA2	4.20	1.010	4.10	0.972	0.996	0.320
FA3	3.93	0.982	3.81	1.042	1.131	0.259
FA4	3.97	0.828	4.00	0.816	-0.357	0.721
PU1	3.57	0.647	3.59	0.675	-0.262	0.793
PU2	3.46	0.664	3.44	0.660	0.306	0.760
PU3	3.46	0.723	3.51	0.696	-0.775	0.439
PU4	3.47	0.771	3.56	0.725	-1.185	0.237
BI1	3.34	0.884	3.30	0.817	0.432	0.666
BI2	3.40	0.864	3.42	0.782	-0.270	0.787
BI3	3.02	0.759	3.10	0.778	-1.076	0.283

Measurement Model Assessment

The measurement model was evaluated by measuring reliability and validity. Table 7 indicates that the majority of the outer loadings were above the recommended value of 0.70, which is a good indicator of reliability in the indicators (Hair et al., 2022). FB1, FB2, FB5, FK1 and FK2 are dropped since they are below the threshold and their dropping increases the composite reliability of the construct. Items whose loadings were 0.40 to 0.70 were not dropped because their dropping did not contribute much to the composite reliability or AVE.

Table 7: Outer Loadings

Indicators	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)
BI1	0.918	0.918	0.009	98.52*
BI2	0.906	0.906	0.012	74.25*

BI3	0.682	0.680	0.047	14.629*
FA1	0.847	0.841	0.038	22.038*
FA2	0.894	0.888	0.026	34.279*
FA3	0.719	0.720	0.058	12.366*
FA4	0.479	0.472	0.077	6.207*
FB1	0.356	0.349	0.115	3.091*
FB2	0.041	0.041	0.139	0.295
FB3	0.602	0.585	0.093	6.487*
FB4	0.766	0.748	0.057	13.464*
FB5	0.096	0.093	0.097	0.984
FB6	0.855	0.839	0.041	20.704*
FK1	-0.125	0.061	0.204	0.613
FK2	-0.676	-0.128	0.664	1.018
FK3	0.620	0.288	0.535	1.158
FK4	0.370	0.220	0.317	1.169
FK5	0.457	0.227	0.387	1.179
PU1	0.878	0.879	0.013	69.179*
PU2	0.813	0.812	0.031	26.526*
PU3	0.847	0.847	0.025	33.362*
PU4	0.855	0.855	0.018	47.125*

The results of composite reliability, AVE, square root of AVE and latent variable correlations are presented in Table 8. All constructs had composite reliability values that were greater than 0.70, which is sufficient to establish reliability (Hair et al., 1998; Chin, 1998; Henseler et al., 2009). The constructs all have AVE values of over 0.50, which validates convergent validity (Fornell and Larcker, 1981). This was followed by the determination of discriminant validity in which the square root of the AVE of each construct was greater than the correlations of all the constructs (Fornell and Larcker, 1981).

Table 8: Composite Reliability, AVE, Square Root of AVE, and Correlations

Construct	CR	AVE	BI	FA	FB	FK	PU
BI	0.876	0.707	0.841				
FA	0.832	0.566	0.270	0.752			
FB	0.803	0.580	-0.315	-0.093	0.762		
FK	0.742	0.502	0.010	0.044	0.210	0.708	
PU	0.911	0.720	0.668	0.315	-0.079	0.274	0.849

The cross-loadings were evaluated to further determine discriminant validity as indicated in Table 9. The outer loadings of each indicator on its respective construct were larger than its loadings on any other construct, which means that each item had more variance with its respective latent variable than with any other variable in the model. This indicates that the indicators were discriminant enough, which justifies the idea that the constructs in the measurement model were different. These findings are consistent with the criteria suggested by Hair et al. (2022), which supports the strength of the reflective measurement model.

Table 9: Cross-loadings

Item/Construct	BI	FA	FB	FK	PU
BI1	0.924	0.320	-0.316	0.010	0.599
BI2	0.921	0.226	-0.237	0.128	0.711
BI3	0.647	0.097	-0.258	-0.214	0.289
FA1	0.196	0.849	-0.038	0.189	0.291
FA2	0.211	0.896	-0.056	0.039	0.264
FA3	0.259	0.717	-0.155	-0.078	0.251
FA4	0.119	0.477	0.031	-0.095	0.051
FB3	-0.116	-0.045	0.612	0.217	-0.043
FB4	-0.223	-0.199	0.779	0.079	0.009
FB6	-0.322	0.003	0.872	0.205	-0.120
FK3	0.038	0.130	0.139	0.902	0.281
FK4	-0.056	-0.060	0.164	0.547	0.132
FK5	0.009	-0.135	0.216	0.625	0.091
PU1	0.605	0.242	-0.086	0.269	0.878
PU2	0.513	0.342	-0.055	0.157	0.808
PU3	0.495	0.267	0.034	0.393	0.852
PU4	0.646	0.226	-0.154	0.114	0.855

Next, discriminant validity was assessed using the Heterotrait-Monotrait ratio of correlations (HTMT), following the guidelines by Hair et al. (2022). As shown in Table 10, all HTMT values were below the conservative threshold of 0.90, indicating acceptable discriminant validity between most constructs.

Table 10: HTMT Matrix

Construct	BI	FA	FB	FK	PU
BI					
FA	0.326				
FB	0.407	0.203			
FK	0.226	0.277	0.426		
PU	0.764	0.369	0.156	0.361	

Structural Model Assessment and Hypothesis Testing

In order to determine the multicollinearity between the predictor constructs in the inner model, the values of Variance Inflation Factor (VIF) were analyzed as indicated in Table 11. The value of all inner VIFs was determined to be less than the suggested value of 5.0, which means that there were no serious problems with multicollinearity. This indicates that the predictor constructs were independent enough of each other, and thus the path coefficients could be estimated reliably. These findings meet the multicollinearity assumption recommended by Hair et al. (2022), hence, the stability and interpretability of the structural model estimates.

Table 11: Inner VIF

Path	VIF
H1a: FK -> PU	1.050
H1b: FB -> PU	1.058
H1c: FA -> PU	1.013
H2a: FK -> BI	1.149
H2b: FB -> BI	1.073
H2c: FA -> BI	1.117
H3: PU -> BI	1.218

The structural model was evaluated to test the hypotheses. Financial knowledge (H1a) and financial attitude (H1c) were identified to have significant positive impact on PU, but financial behavior (H1b) had significant negative impact and was rejected even though statistically significant. Conversely, none of the three financial literacy dimensions significantly influenced direct effects on BI, indicating that they might have an indirect influence on intention. Lastly, the relationship between perceived usefulness (H3) and BI was significant and positive, which validates its centrality as a behavioral intention determinant in this model. These results highlight the significance of perceived usefulness as a mediator variable in the relationship between the dimensions of financial literacy and behavioral intention. Table 12 shows the results.

Table 12: Structural Model Findings

Paths	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	Decision
H1a: FK -> PU	0.613	0.624	0.090	6.828*	Supported
H1b: FB -> PU	-0.245	-0.250	0.101	2.416*	Not supported
H1c: FA -> PU	0.292	0.297	0.046	6.292*	Supported
H2a: FK -> BI	-0.274	-0.269	0.084	3.255*	Not supported
H2b: FB -> BI	-0.506	-0.513	0.072	7.067*	Not supported
H2c: FA -> BI	0.043	0.044	0.031	1.413	Not supported
H3: PU -> BI	0.671	0.670	0.030	22.149*	Supported

*Significant at $p < 0.05$

The R^2 value measures the predictive power of a model and is obtained from the squared correlation between an endogenous latent variable's actual and predicted values (Hair et al., 2022). Table 13 presents the results for R^2 values for the endogenous latent variables employed in the current study. The model explains 17.9% of the variance in perceived usefulness,

indicating a weak predictive power. However, the model has a moderate predictive power in explaining behavioral intention to use by 53.2%.

Table 13: R²

Constructs	R-square
PU	0.179
BI	0.532

Table 14 presents the results of f^2 . The f^2 values reveal the effect sizes of various relationships in the research model, providing insights into the relative importance of different predictors. Notably, the effect size of perceived usefulness on behavioral intention exceeds the threshold for a large effect ($f^2 > 0.35$) as suggested by Cohen (1988). This indicates that perceived usefulness has a substantial impact on behavioral intention, contributing significantly to the explanatory power of the structural model. The result reinforces the critical role of perceived usefulness in shaping individuals' intention to use robo-advisors during a economic crisis, consistent with the core tenets of the TAM.

Table 14: f^2

Paths	f-square
H1a: FK -> PU	0.094
H1b: FB -> PU	0.014
H1c: FA -> PU	0.102
H2a: FK -> BI	0.030
H2b: FB -> BI	0.106
H2c: FA -> BI	0.004
H3: PU -> BI	0.790

Predictive relevance is a prediction of the predictive power of a model (Hair et al., 2022). The test of predictive relevance is represented by Q² values (Hair et al., 2022). The results of the PLSpredict are presented in Table 15. Behavioral intention had a Q² value of 0.086, which is not below zero, meaning that it has small but significant predictive relevance to this endogenous construct (Hair et al., 2022). On the other hand, the Q² of perceived usefulness was -0.015 and this indicates that the model does not have predictive relevance to this construct. A negative Q² suggests that the predictive power of the model is less than just using the mean as a predictor and it means that the exogenous variables in the model are not predictive enough of the perceived usefulness. The results suggest the necessity to reevaluate the antecedents of perceived usefulness or take into account the possible missing variables that might enhance the predictive power of the model.

Table 15: Q²

Constructs	Q ²
PU	-0.015
BI	0.086

Table 16 shows the direct effect of financial literacy on behavioral intention that was found to be statistically significant and had a p-value of less than 0.05. The 95% bias-corrected confidence interval was between 0.010 (2.5%) and 0.100 (97.5%), which means that the indirect effect is not zero and thus significant. This finding supports the mediating influence of perceived usefulness in the association between financial literacy and behavioral intention. It means that more financially literate people will be more inclined to view robo-advisors as helpful, which, in turn, will increase their desire to use these platforms. The result confirms the theoretical assumption of the TAM, in which the perceived usefulness is a key process through which background factors are linked to technology adoption behavior.

Table 16: Specific Indirect Effects

Paths	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Confidence Interval Bias Corrected	
						2.5%	97.5%
H4: FL - > PU -> BI	0.051	0.040	0.024	2.148	0.032	0.010	0.100

Discussion and Implications

Discussion of Findings

The antecedent patterns to perceived usefulness are nuanced. There are positive and significant trends of financial knowledge and financial attitude to perceived usefulness, which is also in line with the perception of the usefulness of an automated advisory tool in productivity value recognition (Jung et al., 2018; van Rooij et al., 2011). Conversely, financial behavior shows a very strong negative correlation with perceived usefulness, and this rejection of the hypothesis because the sign is of the opposite direction as the theorized direction. The most likely explanation is that people who already adopt disciplined habits like budgeting and regular check-ins see a smaller marginal value in robo advisors, or they consider the automation as providing less marginal utility compared to their existing self-managed habits.

There is no support in the direct paths between three financial literacy dimensions and behavioral intention, although two of them are statistically significant. Financial knowledge and financial behavior have significant negative coefficients to intention, and financial attitude is small and insignificant. These trends show inconsistency of signs with the hypothesized positive effects and hence these are rejected on theoretical grounds. The existence of a strong perceived usefulness to intention relationship and negative or negligible direct effects would indicate a competitive or inconsistent mediation structure. Increased behaviorally prudent and more knowledgeable individuals can be more critical and risk aware in the face of a crisis and this depresses their stated intention when considered at constant perceived usefulness. In other words, once usefulness beliefs are removed, remaining effect of knowledge and disciplined action can be biased towards caution, doubt about the performance of algorithms in volatile markets or may be biased towards wanting to retain control and this decreases the direct intention to adopt.

The mediation of the relationship between financial literacy and intention is supported by the large specific indirect effect of perceived usefulness between financial literacy and intention. The bias adjusted interval is completely positive, which confirms the existence of mediation according to the theoretical rationale of the TAM (Belanche et al., 2019; Davis, 1989). Substantively, the total positive indirect effect is that the positive contribution of financial knowledge and financial attitude to usefulness is more than the minor negative contribution of financial behavior to usefulness, which results in a net positive path of literacy to intention through usefulness. This is what the model aims to capture in a crisis situation where adoption choices will not be highly dependent on background characteristics per se but rather the degree to which the technology is perceived to provide value in stressful situations.

The trend of accepted and rejected hypotheses thus has definite theoretical and practical consequences. Theoretically, the results confirm the TAM in a crisis context by demonstrating that usefulness judgments prevail intention formation (Belanche et al., 2019; Davis, 1989). Simultaneously, they warn that one should not expect the same positive direct effects of financial literacy to intention. The sign reversal of knowledge and behavior indicates a more discriminating adoption calculus in the case of financially able users who might require a higher level of value demonstration before engaging in automated services in turbulent environments. In practical terms, platforms aiming to increase adoption must target levers that have a direct positive impact on perceived usefulness. Measures involve communicating verifiable performance in volatility, exposing risk management characteristics and guardrails in the interface, demonstrating scenarios that relate literacy to concrete system advantages, and offering guided trials that lessen the distance between assessment and perceived value. These precautions are aimed at the construct with which the data locate themselves as definitive and aid in overcoming the scruples which may arise in the minds of the knowledgeable and wise users.

Combined, the structural findings place perceived usefulness as the key explanatory variable in the model. The explained variance of perceived usefulness is small at 17.9 percent and the perceived usefulness at 53.2 percent, which means that after introducing perceived usefulness into the model, a significant portion of behavioral intention to use robo advisors can be explained. The influence of perceived usefulness on behavioral intention is statistically significant and substantively significant, with an effect size greater than the standard of a large effect as proposed by Cohen, thus supporting the main hypothesis of the TAM that usefulness beliefs are the most proximate antecedent of intention is strong especially in situations of increased uncertainty like in an economic crisis. Overall, the model describes a moderate proportion of intention largely due to the perceived usefulness, reports a large and significant usefulness to intention correlation, and demonstrates that financial literacy has its effect by influencing usefulness beliefs more than by acting directly to persuade. Enhancing the antecedents of usefulness that are relevant in times of crisis provides a clear route to improving the explanatory power and predictive relevance in future refinements of models.

Theoretical Implications

The study has a number of contributions to the literature. First, it generalizes the use of TAM to the particular context of robo-advisor adoption during economic crises to show how it remains relevant in elucidating the behaviors of financial technology adoption. Second, by focusing on the multidimensionality of financial literacy, the study offers a more detailed

insight into the effect of various dimensions of financial literacy on technology adoption decisions. The fact that the most important predictors of financial literacy in various settings are the financial knowledge and financial attitude among the three dimensions adds to the current debate that has been going on to determine the most important of the three dimensions of financial literacy.

Third, this study addresses the gaps in the literature by responding to the calls by Hentzen et al. (2022) and other researchers to examine the correlation between financial literacy and the adoption of robot's advisors, which is a significant gap in the literature. The results are empirical evidence that can be used to inform future studies in this field. Fourth, this study adds to the knowledge regarding the impact of economic uncertainties in determining the technology adoption choices in the financial sector by emphasizing on adoption behaviors in economic crisis.

Practical Implications

The findings are an indication that the perceived usefulness should be placed at the core of the strategies of robo-advisory practitioners and service providers. Providers ought to make conscious efforts to demonstrate the practical worth of their services by providing case studies, real-time demonstrations, and interactive simulations that demonstrate how robo-advisors work in volatile markets. The communication must be attentively adapted to the various groups of users, specifically those who are financially literate, and are likely to be suspicious of automated tools. In this category, platforms should provide tailored investment capabilities, clear descriptions on how the algorithms work, and sophisticated features that can fit in their current financial habits. Meanwhile, the trust and transparency should be strengthened by the apparent adherence to regulatory requirements, the presence of effective data protection mechanisms, and a clear explanation of the manner in which recommendations are developed. Improving the user experience by providing user-friendly dashboards, scenario-planning features, and tutorials will be another way to bridge the digital divide between financial literacy and technology adoption.

The findings highlight the necessity of policymakers and regulators to incorporate the awareness of robo-advisory in the wider financial literacy efforts. Such programs should not solely concentrate on general financial knowledge but on how people can use their skills with the help of technology to deal with risk and improve financial decision-making in times of crisis. The policymakers are also supposed to come up with effective regulatory frameworks that enhance consumer protection, transparency, and data security in robo-advisory services. These measures will minimize perceived risks and create more confidence in potential users. Moreover, the public sector and robo-advisory providers should be encouraged to cooperate to provide accessible education programs, demonstration platforms, and outreach initiatives to younger investors and households that have been impacted by financial uncertainty.

To financial educators and institutions, the results indicate that the efforts to enhance literacy must be linked to the use of technology. Training programs should extend beyond theory and include practical learning tasks that show how financial knowledge, behavior, and attitudes can be implemented using robo-advisors. It will enable the learners to feel the benefits of these technologies in practical decision-making scenarios through simulations, practice and actual application of the demo platforms. Teachers' ought to also discuss the skepticism by portraying

the advantages and disadvantages of robo-advisors so that students and professionals could be able to examine automated advice critically, but still, should be willing to benefit.

To individual users and investors, the research recommends a change in emphasis to consider robo-advisors based on value creation and not necessarily based on the prior knowledge or financial behavior. It is recommended that users should use trial versions or low commitment portfolios as a means of experimenting with the usefulness of robo-advisors in managing their finances before committing to larger amounts of money. Meanwhile, informed oversight is still critical. Financial literacy should allow investors to critically oversee the advice produced by robo-advisors and make sure that it aligns with their objectives, as well as understand the effectiveness and stability that artificial intelligence platforms can offer when financial markets become volatile.

Limitations and Future Research Directions

The research has a number of limitations that can be used in the future as research. To begin with, the cross-sectional data restricts us in making causal relationships between the variables. Longitudinal designs may offer more information on the role of financial literacy in driving the uptake of robo-advisors over the years, especially as economic crises transform. Second, the research was only done in Malaysia, which did not broaden the generalizability of the results to other cultural and economic settings. Further studies might take a comparative methodology, and how the relationships found in this study differ in various countries and cultural contexts. Third, the research used self-reported measures that could be prone to social desirability bias and common method variance. Objective measures of financial literacy and actual usage behavior, as opposed to behavioral intentions, could be introduced into future research. Fourth, although this research involved three aspects of financial literacy, the future research might consider other variables like financial self-efficacy, risk-taking behavior, and trust in financial institutions that could affect the adoption of robo-advisors during economic crises. Fifth, the research focused on the adoption of robo-advisors in the recent economic crisis caused by the COVID-19 pandemic. Future studies may examine the differences in adoption behaviors between different forms of economic crises (e.g., banking crises, market crashes, inflation crises) and how these behaviors change over the course of the crisis.

Sixth, the sampling method employed in this study is not probability sampling, and thus it might be limiting the representativeness of the findings. Further studies may use more intensive sampling methods in case extensive sampling frames will be accessible. Lastly, the qualitative research methods might be used to supplement the quantitative results of the research since the study will give a clearer understanding of the psychological and behavioral processes that support the relationships that are established.

Conclusion

In conclusion, this study indicates that perceived usefulness is the key factor that determines behavioral intention to use robo-advisors in the case of economic crisis, which aligns with the key principles of the TAM. Although financial knowledge and financial attitude influence the perceptions of usefulness positively, financial behavior has a surprisingly negative influence, and no financial literacy dimension has a direct positive impact on intention. Rather, they have an indirect effect on influence via perceived usefulness, highlighting the importance of this factor as an important mediator. The model describes a medium percentage of the variation in

behavioral intention and a weak percentage in perceived usefulness indicating that other antecedents like trust, perceived risk, or transparency ought to be included in future studies. These results underscore the potential and the constraints of the existing framework, as well as support the necessity of the strategies that will help to increase the perceived value of robo-advisors in order to make them more acceptable in the times of financial insecurity.

Acknowledgements:	The authors would like to acknowledge the support provided by the Faculty of Business and Economics, Universiti Malaya, throughout the completion of this study.
Funding Statement:	This research received no external funding.
Conflict of Interest Statement:	The authors declare that there is no conflict of interest regarding the publication of this paper.
Ethics Statement:	The authors confirm that this study was conducted in accordance with accepted academic integrity and ethical research standards. The research involved survey data collected from Malaysian retail investors and was undertaken solely for academic purposes.
Author Contribution Statement:	Najihah Abd Razak contributed to the data collection, data analysis, literature review, and writing of the manuscript. Kamisah Ismail contributed to the research methodology and supervision of the study. Both authors reviewed and approved the final version of the manuscript prior to submission.

References

- Aggarwal, N. (2021). The norms of algorithmic credit scoring. *Cambridge Law Journal*, 80(1), 42-73.
- Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Williams, M. D. (2016). Consumer adoption of mobile banking in Jordan: Examining the role of usefulness, ease of use, perceived risk and self-efficacy. *Journal of Enterprise Information Management*, 29(1), 118-139.
- Allgood, S., & Walstad, W. B. (2015). The effect of perceived and actual financial literacy on financial behaviors. *Economic Inquiry*, 54(1), 675-697. <https://doi.org/10.1111/ecin.12255>
- Arner, D. W., Barberis, J., & Buckley, R. P. (2016). The evolution of Fintech: A new post-crisis paradigm. *Georgetown Journal of International Law*, 47, 1271-1319.
- Beketov, M., Lehmann, K., & Wittke, M. (2018). Robo advisors: Quantitative methods inside the robots. *Journal of Asset Management*, 19(6), 363-370.
- Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*, 119(7), 1411-1430.
- Bhatia, A., Chandani, A., & Chhateja, J. (2021). Robo-advisory and its potential in addressing the behavioral biases of investors—A qualitative study in Indian context. *Journal of Behavioral and Experimental Finance*, 30, 100466.
- Boustani, N.M. (2020). Artificial intelligence impact on banks clients and employees in an Asian developing country. *Journal of Asia Business Studies*, 16(2), 267-278.
- Caron, M.S. (2019). The transformative effect of AI on the banking industry. *Banking and Finance Law Review*, 34(2), 169-214.
- Cheng, X., Guo, F., Chen, J., Li, K., Zhang, Y., & Gao, P. (2019). Exploring the trust influencing mechanism of robo-advisor service: a mixed method approach. *Sustainability*, 11(18), 4917.
- Cheng, Y. M. (2020). Understanding cloud ERP continuance intention and individual performance: A TTF-driven perspective. *Benchmarking: An International Journal*, 27(4), 1591-1614.
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, 295(2), 295-336.
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers.
- Das, A., & Das, D. (2023). Adoption of FinTech services amidst COVID-19 pandemic: empirical evidence from Assam. *Managerial Finance*, 49(6), 1075-1093.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340.
- Financial Education Network. (2019). *Malaysia National Strategy for Financial Literacy 2019-2023*. <https://fenetwork.my/wp-content/uploads/2020/07/National-Strategy-ENG-F.pdf>
- Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2021). Intention to use analytical artificial intelligence (AI) in services—the effect of technology readiness and awareness. *Journal of Service Management*, 33(20), 293-320.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.
- Fu, J., & Mishra, M. (2022). Fintech in the time of COVID– 19: Technological adoption during crises. *Journal of Financial Intermediation*, 50, 100945.

- Habibullah, M. S., Saari, M. Y., Maji, I. K., Din, B. H., & Saudi, N. S. M. (2024). Modelling volatility in job loss during the COVID-19 pandemic: The Malaysian case. *Cogent Economics & Finance* 12: 2291886.
- Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis* (5th ed.). Prentice Hall.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed. Thousand Oaks, CA: Sage.
- Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). *The use of partial least squares path modeling in international marketing*. In R. R. Sinkovics & P. N. Ghauri (Eds.), *New challenges to international marketing* (pp. 277-319). Emerald Group Publishing Limited.
- Hentzen, J. K., Hoffmann, A., Dolan, R., & Pala, E. (2022). Artificial intelligence in customer-facing financial services: a systematic literature review and agenda for future research. *International Journal of Bank Marketing*, 40(6), 1299-1336.
- Huston, S. J. (2010). Measuring financial literacy. *Journal of Consumer Affairs*, 44(2), 296-316.
- Ismail, K., Isa, C. R., & Mia, L. (2018a). Market competition, lean manufacturing practices and the role of management accounting systems (MAS) information. *Jurnal Pengurusan (UKM Journal of Management)*, 52, 47-61.
- Ismail, K., Isa, C. R., & Mia, L. (2018b). Evidence on the usefulness of management accounting systems in integrated manufacturing environment. *Pacific Accounting Review*, 30(1), 2-19.
- Jung, D., Dorner, V., Weinhardt, C., & Puzmaz, H. (2018). Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets*, 28(3), 367-380.
- Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, 127(2), 267-286.
- Lopez, J. C., Babovic, S., & De La Ossa, A. (2015). Advice goes virtual: How new digital investment services are changing the wealth management landscape. *Journal of Financial Perspectives*, 3(3), 156-164.
- Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, 52(1), 5-44.
- Mardhiah, A. (2022, October 19). *SC: Malaysia recorded 1,800 investment scams for 9M22*. The Malaysian Reserve.
- Mhlanga, D. (2021). Financial inclusion in emerging economies: the application of machine learning and artificial intelligence in credit risk assessment. *International Journal of Financial Studies*, 9(3), 1-16.
- Mogaji, E., Soetan, T. O., & Kieu, T. A. (2021). The implications of artificial intelligence on the digital marketing of financial services to vulnerable customers. *Australasian Marketing Journal*, 29(3), 235-242.
- OECD (2016). *OECD/INFE international survey of adult financial literacy competencies*. OECD, Paris, www.oecd.org/finance/OECD-INFE-International-Survey-of-Adult-Financial-Literacy-Competencies.pdf
- Phoon, K. F., & Koh, F. C. (2018). Robo-advisors and wealth management. *Journal of Alternative Investments*, 20(3), 79-94.
- RinggitPlus. (2021). *Malaysian Financial Literacy Survey 2021*.
- Robb, C. A., & Woodyard, A. (2011). Financial knowledge and best practice behavior. *Journal of Financial Counseling and Planning*, 22(1), 60-70.

- Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson.
- Singh, S., & Srivastava, R. K. (2018). Predicting the intention to use mobile banking in India. *International Journal of Bank Marketing*, 36(2), 357-378.
- Statista. (2022). *Robo-advisors | Statista market forecast*. <https://www.statista.com/>
- Tai, Y. M., & Ku, Y. C. (2013). Will stock investors use mobile stock trading? A benefit-risk assessment based on a modified UTAUT model. *Journal of Electronic Commerce Research*, 14(1), 67-84.
- Tut, D. (2023). FinTech and the COVID-19 pandemic: Evidence from electronic payment systems. *Emerging Markets Review*, 54, 100999.
- van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, 101(2), 449-472.
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186-204.
- Woodyard, A., & Robb, C. (2016). Consideration of financial satisfaction: What consumers know, feel and do from a financial perspective. *Journal of Financial Therapy*, 7(2), 41-61.
- Zhang, L., Pentina, I., & Fan, Y. (2021). Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services. *Journal of Services Marketing*, 35(5), 634-646.