Promoting Robo-Advisor Adoption among B40 in Malaysia through Advisory Transparency and UTAUT Models

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ABSTRACT

The B40 is generally considered to have disadvantages in financial literacy and monetary resources, which often prevents them from making sound investment decisions. Therefore, based on recent advances in Artificial Intelligence (AI) and financial technologies, the Unified Theory of Acceptance and Use of Technology (UTAUT), and the notion of advisory transparency as a mediator, this study investigates factors influencing the intention to adopt financial robo-advisors among the B40 in Malaysia. The 217 responses collected using self-administered bilingual questionnaires were analyzed using Structural Equation Modeling (SEM). The results show that advisory transparency plays a significant role in mediating performance expectancy, facilitating conditions and effort expectancy to robo-advisor adoption intention. Specifically, the results imply that better advisory transparency, performance, and facilitating conditions of robo-advisor usage with minimal effort can, directly and indirectly, promote the intention of robo-advisor adoption. Consistent with the characteristics of B40, who are typically risk-averse and lack digital finance literacy, the findings suggest that more emphasis should be placed on the transparency of the robo-advisory process and digital financial education to promote robo-advisor adoption among the B40. This study fills a gap by integrating advisory transparency into the UTAUT model and providing insight into how advisory transparency interacts with UTAUT factors in promoting robo-advisor adoption. The results of this study can be a reference for policymakers, particularly in devising social welfare and educational policies to eradicate poverty in the country.

Keywords-poverty; fintech; low-income groups; robo-advisor; investment

I. INTRODUCTION

Financial technology (fintech) has grown exponentially worldwide in the last decade, and Malaysia is no exception, as its fintech companies increased by 27% in 2021 to 294 companies [1]. Among fintech solutions, financial robo-advisors have been introduced to provide alternatives to human financial advisors, incorporating AI and automated systems that require minimal human intervention [2]. The first robo-advisory platform for the Malaysian market, a Singapore-based company (StashAway), was approved by the Securities Commission Malaysia in 2018, while the first home-grown robo-advisor (Akru) was launched two years later [3-4]. According to Statista, the value of assets under management and the number of users of robo-advisors in Malaysia are expected to reach US$2,816 million and 57 thousand, respectively, with an average asset under management of US$48.81 million per user in 2027 [5]. However, the advanced and complex algorithms adopted by robo-advisors have, on the one hand, generated outstanding performance in portfolio management at low cost and reduced agency problems between fund managers and investors, but, on the other hand, caused drawbacks such as lack of transparency and trust, which in turn led to low adoption of robo-advisors by investors [6]. This is corroborated by [7], which shows that fee transparency, transaction security, and data privacy are the most influencing factors for robo-advisor adoption.

In Malaysia, financial robo-advisors are relatively new, and hence most Malaysian investors may lack knowledge and trust in fintech. This gets even worse for B40, who typically lack financial literacy and resources. Although the existing literature can provide a reference for the present study and a partial solution to the problem, there is room for supplementation. Most studies tried to investigate the antecedents of intention to adopt robo-advisory services as independent research objects and direct explanatory variables but did not incorporate advisory transparency and behavioral intention to adopt financial robo-advisors into a unified framework. Therefore, building on the well-established Unified Theory of Acceptance and Use of Technology (UTAUT) and the notion of advisory transparency as a mediator, this study aims to investigate the factors that influence the adoption intention of financial robo-advisor, filling the research gap and providing insight into how advisory transparency interacts with UTAUT factors in promoting robo-advisor adoption among B40 in Malaysia.

A. Robo-advisors in Malaysia

The adoption of robo-advisory services has received considerable attention recently following the rise of AI and awareness in personal financial management. For example, in [8], it was found that the adoption of robo-advisors among millennials in Malaysia is influenced by financial knowledge, perceived usability, and trust, while in [9], it was observed that perceived usefulness, social influence, relative advantage, and transparency are important factors in the intention of adopting robo-advisors. The studies in [6, 10] investigated financial robo-advisor acceptance in Malaysia during the COVID-19 outbreak. In [10], using various Technology Acceptance Models (TAM), it was found that social influence, effort expectancy, and relative advantage of using robo-advisors increase the intention to adopt them, while in [6] it was revealed that consumers who have trust, a greater tendency to rely on robo-advisors, and have higher perceived financial knowledge are more inclined to adopt financial robo-advisors in times of crisis. UTAUT factors, such as social influence and performance expectancy, are drivers of consumers' intention to use robo-advisors, particularly during the pandemic crisis. Other studies that used TAM showed that attitude, perceived usefulness, subjective norms, perceived behavioral control, and perceived risk are significant predictors of robo-advisor adoption intention [11], while in [12], it was shown that perceived usefulness, optimism, insecurity, and innovativeness are significant antecedents of behavioral intention to adopt robo-advisors. The studies in [13, 14] adopted UTAUT to explain the association between factors and the intention to adopt financial robo-advisors. The findings in [13] showed that trust, performance expectancy, social influence, hedonic motivation, and price value are important factors in the intention to adopt robo-advisors among individuals in the M40 income group in Malaysia. In [14], it was found that performance expectancy, trust propensity, and hedonic motivation are significant antecedents to building initial trust in financial robo-advisors among young retail investors prior to their intention to adopt robo-advisory services.

B. Advisory Transparency

Advisory transparency plays an important role in investment as it determines the accessibility of investors to necessary financial information, including fees [15]. Although investors are often price-sensitive, transparency is one of the essential criteria in their investment decision-making process, as it reduces information asymmetries and skepticism about the validity of financial advice between investors and managers [7]. Transparency can be further classified into cost transparency, process transparency, and information transparency [16]. In [17], it was found that cost transparency is correlated with customer satisfaction and willingness to pay, where customers must be able to quickly locate and comprehend information about costs associated with advice products. Businesses with good cost transparency often differentiate themselves from competitors by having more loyal client bases and operational effectiveness [18]. Process transparency, on the other hand, is associated with the internal and external process communication pertaining to the extent of "clients' understanding of the performed actions (what comprises an activity and why it is performed) and their succession in advisory services" [19]. Information transparency, as defined in [17], is the "explanation to the client why each piece of information is required during the advisory process, as well as enabling the client to monitor and interpret the information used as the foundation for decision-making". Studies have shown that an interactive portfolio with comparison and graphical features, and greater information transparency would encourage the adoption of robo-advisors, as investors can easily understand the product and gain quick access to platforms [17]. Hence, advisory transparency is posited to have a positive effect on the intention of robo-advisor intention.

C. UTAUT Model and Research Framework

Behavioral intention is the likelihood that an individual will adopt an application [20] and is commonly explained by behavioral models such as the UTAUT [21]. The UTAUT model consists of four main factors to explain behavioral intention, namely, performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy reflects the level of usefulness that people feel when using a technology to perform a certain task, while effort expectancy reflects the extent of usability and convenience that people feel when using it [22]. Social influence reflects how much a user believes that other people close to him think that he should adopt the technology, and facilitating conditions are the availability of resources and a conducive environment that would encourage a user to adopt it [22]. Previous empirical studies have shown that robo-advisor adoption intention is significantly influenced by performance expectancy [8, 14], effort expectancy [10], social influence [9, 13], and facilitating conditions [23]. Considering that transparency has also been shown to be an important determinant of the adoption of financial advisory services [17, 15], the direct effect of UTAUT factors on robo-advisor adoption intention may be mediated by advisory transparency. In other words, the adoption of robo-advisory services may be directly subjected to the extent of advisory transparency, and indirectly conditioned on the level of performance expectancy, effort expectancy,

social influence, and facilitating conditions. Therefore, a high degree of performance expectancy, effort expectancy, social influence, and facilitating conditions is expected to positively influence advisory transparency and be conducive to the behavioral intention of adopting robo-advisors [24].

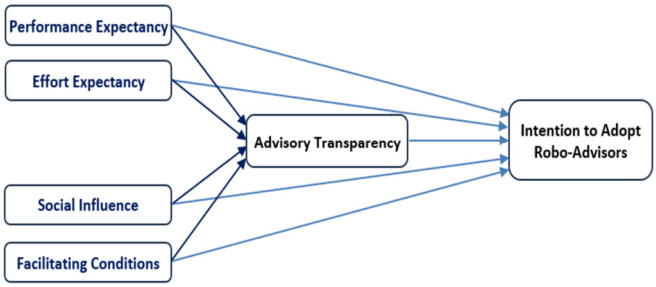

Fig. 1. Research framework.

II. RESEARCH METHODOLOGY

The households in Malaysia are classified into three different income groups, that is, the Top 20% (T20), Middle 40% (M40), and Bottom 40% (B40). The target population of this study is the B40 group, which falls into the lower bracket of income classification with a median monthly household income of RM4850 or less and comprises almost 2.91 million or 34.92% of households in Malaysia [25]. The minimum sample size was determined using the 10-times rule, which recommends that the minimum sample size of a structural model should be equal to, whichever larger, the ten times the largest number of formative indicators of a construct or ten times the largest number of structural paths directed to a particular latent construct [26]. Since this study uses reflective indicators and contains at most four structural paths directed from constructs performance expectancy, effort expectancy, social influence, and facilitating conditions toward advisory transparency, the minimum sample size recommended for this study is at least 10×4 paths = 40. However, considering that the preferable sample for PLS-SEM is around 200 [27], a total of 217 responses were collected from the heads or representatives of B40 households by purposive sampling and self-administered bilingual (English and Malay) questionnaires distributed through non-government organizations and government agencies. The items of the constructs, as presented in Table I, were either adopted or adapted from literature and then validated by two academics and an industry expert in the field. The two-stage approach (i.e. items and construct specifications and validation assessments followed by model estimation and path analysis) was used to estimate the SEM, which relaxes the distributional assumptions and fits well with the complex structural model [28].

III. RESULTS AND DISCUSSION

Table II shows the demographic information of the 217 respondents. Nearly 42.4% of the respondents were from the central region, followed by northern (26.3%), southern (19.4%), and eastern (12.0%) regions of peninsular Malaysia, and the distribution is comparable with the household distribution in 2022 (Eastern 15.27%, Central 39.88%, Northern 25.98%, and Southern 18.86%) [32].

TABLE I. THE CONSTRUCTS AND ITEMS

Construct	Items	Ref.
Intention (INT)	1. I intend to use robo-advisors for managing investments. 2. Using robo-advisors for managing investments is something I would do. 3. My intention is to use robo-advisors rather than any human financial advisor.	[29]
Performance Expectancy (PE)	1. I would find a financial robo-advisor useful in making financial decisions. 2. Using a financial robo-advisor would increase my chances of achieving things that are important to me. 3. Using a financial robo-advisor would help me accomplish financial goals more quickly. 4. Using a financial robo-advisor would increase my financial profitability.	[30]
Effort Expectancy (EE)	1. Learning how to use a robo-advisor would be easy for me. 2. My interaction with a robo-advisor would be clear. 3. My interaction with a robo-advisor would be understandable. 4. I would find a robo-advisor easy to use. 5. It would be easy for me to become skillful in using a robo-advisor.	[6]
Social Influence (SI)	1. People who influence my behavior do use a robo-advisor. 2. People important to me will influence my intention to use a robo-advisor. 3. People who influence my behavior think that I should use a robo-advisor. 4. People important to me support that I should use a robo-advisor in the future.	[23]
Facilitating Conditions (FC)	1. I have the necessary resources to use the robo-advisor. 2. I have the necessary knowledge to use the robo-advisor. 3. The robo-advisor is compatible with other systems I use. 4. A specific person (or group) is available for assistance with system difficulties.	[23]
Advisory Transparency (AT	Cost Transparency 1. I prefer a robo-advisor that provides cost comparison information with other robo-advisors. 2. I prefer a robo-advisor that shows the total cost of the service. 3. I prefer a robo-advisor that shows the expected returns for the investments that I make. Information Transparency 4. I prefer a website/application with information that helps me understand the robo-advisor. 5. I prefer a website/application with information that gives me a clear idea about the robo-advisor. 6. I prefer website/application information that gives me a clear understanding of the robo-advisor. 7. I prefer a website/application with information that helps me know the robo-advisor. 8. I prefer a website/application that makes the robo-advisory information transparent to me. Process Transparency 9. I prefer a robo-advisor that indicates how the service can be subscribed to step by step. 10. I prefer a robo-advisor that offers instructions for the whole process of subscription. 11. I prefer a robo-advisor that describes the way to subscribe to the service in detail.	[24], [31]

The respondents were 66.4% female and 33.6% male, and 68.2% of them were aged 29 years old or less, followed by 24.4% in the range of 30-49 years old, and 10.1% aged more

than 50 years old. The breakdown of the B40 income shows that 64.1% of the households earned no more than RM3170 per month, followed by 9.7% having monthly income between RM3171-RM3970, and 26.3% RM3970-RM4850.

TABLE II. DEMOGRAPHIC INFORMATION

Demographic		Frequency	Percentage (%)
Region	Eastern	26	12.0
	Central	92	42.4
	Northern	57	26.3
	Southern	42	19.4
Gender	Female	144	66.4
	Male	73	33.6
Age (year)	< 29	148	68.2
	30 - 49	53	24.4
	> 50	22	10.1
Household Income	< RM3170	139	64.1
	RM3171 - RM3970	21	9.7
	RM3970 - RM4850	57	26.3

Table III presents the descriptive statistics and the results of the convergent validity tests. The mean of the Intention (INT) was 3.687, out of a 5-point scale, being almost the same as the mean of Intention to use robo-advisor (3.352) in [12]. The variables that reported the highest (3.888) and lowest means (3.506) were Advisory Transparency (AT) and Social Influence (SI). The convergent validity of the construct items was also examined. The range of the outer loading of the items was 0.769 to 0.934, where the lowest and the highest outer loadings were respectively given by the item FC2 of Facilitating Conditions (FC) and item INT2 of Intention (INT). The Cronbach's alpha was 0.813 (FC), 0.963 (AT), 0.875 (FC), and 0.968 (AT). The lowest and highest Average Variance Extracted (AVE) were given by Facilitating Conditions (FC) and Intention (INT), with 0.637 and 0.822, respectively. Therefore, all the items satisfied the criteria of the convergent validity tests, i.e. Cronbach's alpha and composite reliability for the constructs' internal consistency must exceed 0.70, and the item loading and AVE must exceed 0.50 [26]. Table IV shows the discriminant validity test using the Heterotrait-monotrait (HTMT) criterion. The HTMT values ranged from 0.675 (AT-SI) to 0.867 (FC-EE) and were below the recommended HTMT threshold value of 0.90 [28]. The highest upper limit value of the bias-corrected 95% bootstrapped confidence intervals is 0.937, given by FC-EE, which is below the threshold of 1.00 [33]. Hence, the HTMT results indicate that the discriminant validity of the constructs used in this study is justified.

TABLE III. DESCRIPTIVE STATISTICS, AND THE RESULT OF THE CONVERGENT VALIDITY TESTS

Variable	Descriptive Statistics		Convergent Validity Tests			
	Mean	Std. Dev.	Outer Loading	Cronbach's alpha	Composite reliability	AVE
Intention (INT)	3.687	0.906		0.891	0.933	0.822
INT1			0.929			
INT2			0.934			
INT3			0.854			
Performance Expectancy (PE)	3.811	0.823		0.905	0.933	0.778
PE1			0.878			
PE2			0.892			
PE3			0.879			
PE4			0.879			
Effort Expectancy (EE)	3.752	0.832		0.925	0.944	0.770
EE1			0.873			
EE2			0.901			
EE3			0.898			
EE4			0.886			
EE5			0.830			
Social Influence (SI)	3.506	0.928		0.896	0.927	0.761
SI1			0.844			
SI2			0.864			
SI3			0.888			
SI4			0.894			
Facilitating Conditions (FC)	3.732	0.817		0.813	0.875	0.637
FC1			0.781			
FC2			0.769			
FC3			0.860			
FC4			0.789			
Advisory Transparency (AT)	3.888	0.789		0.963	0.968	0.734
AT1			0.777			
AT2			0.783			
AT3			0.853			
AT4			0.878			
AT5			0.895			
AT6			0.849			
AT7			0.896			
AT8			0.881			
AT9			0.900			
AT10			0.882			
AT11			0.816			

TABLE IV. DISCRIMINANT VALIDITY (HTMT)

	INT	PE	EE	SI	FC	AT
PE	0.828					
	(0.755, 0.896)					
EE	0.811	0.827				
	(0.724, 0.883)	(0.758, 0.886)				
SI	0.719	0.711	0.767			
	(0.587, 0.829)	(0.573, 0.830)	(0.674, 0.849)			
FC	0.804	0.806	0.867	0.830		
	(0.708, 0.887)	(0.710, 0.895)	(0.784, 0.937)	(0.726, 0.925)		
AT	0.864	0.786	0.785	0.675	0.828	
	(0.803, 0.918)	(0.717, 0.849)	(0.696, 0.857)	(0.542, 0.792)	(0.747, 0.892)	

Notes: The bootstrapped bias-corrected 95% confidence intervals are presented in brackets.

This study uses SEM, considering its advantage in modeling higher-order constructs. As shown in Table V, the estimated model is considered a good fit, as indicated by the model's standardized root mean square residual (SRMR) value of 0.061 (estimated model), which is less than the threshold of 0.08 [34], an NFI of 0.809 that is greater than 0.800 [35], an R^2 of 0.671 to 0.714, and an adjusted R^2 of 0.665 to 0.708. The model is also not affected by multicollinearity issues, as all VIF values, ranging from 2.351 to 3.440, are lower than the threshold value of 5.0 [28]. From the results of the test statistics *t*-value, *p*-value, and bias-corrected at 95% confidence intervals (BCLL, BCUL), the Performance Expectancy (PE), Effort Expectancy (EE), and Facilitating Conditions (FC) are shown to be statistically significant and positively related to Advisory Transparency (AT), where the highest effect (0.122), as indicated by f^2, is given by Facilitating Conditions (FC). This finding suggests that individuals in the B40 group prioritize expected performance and effort needed, as well as the facilitating conditions and support given to them, but the transparency of financial robo-advisory services precedes. In other words, B40 individuals who expected good performance from robo-advisors and perceived minimal effort required and anticipated support will be provided when using them will tend to expect and demand more information (high transparency) about robo-advisory services. The result also shows that Performance Expectancy (PE), Effort Expectancy (EE), and Advisory Transparency (AT) are significant positive determinants of Intention (INT) to adopt robo-advisors, and it is notable that Advisory Transparency (AT) reported the highest effect size of 0.242 among the factors. This implies the importance of advisory transparency in encouraging the adoption of robo-advisory services among the B40. The finding is consistent with previous studies that demonstrated that performance expectancy [13, 14], effort expectancy [10], and transparency [9] are significant antecedents in increasing the intention to use financial robo-advisors among Malaysians.

TABLE V. RESULT OF STRUCTURAL EQUATION MODELING (DIRECT EFFECT)

Path	coefficient	std. dev.	*t*-value	*p*-value	BCLL	BCUL	f^2	VIF
$R^2 = 0.671;\ R_a^2 = 0.665$								
PE→AT	0.303***	0.069	4.380	<0.001	0.171	0.439	0.105	2.650
EE→AT	0.235**	0.101	2.326	0.020	0.024	0.422	0.051	3.272
SI→ AT	0.038	0.081	0.472	0.637	-0.111	0.204	0.002	2.347
FC→AT	0.335***	0.074	4.533	<0.001	0.192	0.481	0.122	2.795
$R^2 = 0.714; R_a^2 = 0.708$								
PE → INT	0.227***	0.085	2.678	0.007	0.067	0.395	0.062	2.929
EE → INT	0.158*	0.096	1.653	0.098	-0.032	0.342	0.025	3.440
SI → INT	0.095	0.080	1.186	0.236	-0.060	0.256	0.013	2.351
FC → INT	-0.001	0.095	0.012	0.991	-0.183	0.183	<0.001	3.136
AT→ INT	0.459***	0.087	5.285	<0.001	0.281	0.619	0.242	3.041

Notes: The BCLL and BCUL, f^2 and VIF denote the lower and upper limits of the bias-corrected 95% confidence intervals, the effect size, and the variance inflation factor, respectively.
*, **, and *** indicate significance levels at the 1%, 5%, and 10%, respectively.

A mediation analysis was performed to examine the role of advisory transparency as a mediator between the UTAUT factors and robo-advisor adoption intention. The result of the mediation analysis presented in Table VI shows that both the indirect and total effects for the respective paths from Performance Expectancy (EE), Effort Expectancy (EE), and Facilitating Conditions (FC), through Advisory Transparency (AT) to Intention (INT) are statistically significant. This implies the mediating effect of advisory transparency on relationships between the factors and intention to adopt robo-advisors. More specifically, the results show that Advisory Transparency (AT) plays a complementary mediation role (both direct and indirect effects are significant and in the same algebraic sign) between the relationships of Performance Expectancy (EE) and Effort Expectancy (EE) with Intention (INT), while a competitive mediation role (direct and indirect effects are significant but in the opposite algebraic sign) between Facilitating Conditions (FC) and Intention (INT) [36]. In other words, the presence of advisory transparency as a mediator strengthens (complementary) the total effect of performance expectancy and effort expectancy while suppressing (competitive) the total effect of facilitating conditions on robo-advisor adoption intention [37]. This finding implies that the role of facilitating conditions becomes less important in the presence of advisory transparency, as the latter may be a substitute for the former in facilitating and

encouraging the intention and adoption of robo-advisory services among the B40 in Malaysia.

TABLE VI. RESULTS OF THE MEDIATION ANALYSIS

Effect Type	Path	Effects	Std. Dev.	*t*-value	*p*-value	BCLL	BCUL	Result
Indirect	PE→ AT → INT	0.139	0.042	3.305	0.001	0.071	0.238	Complementary Mediation
Total	PE → INT	0.366	0.074	4.971	<0.001	0.225	0.512	
Indirect	EE→AT → INT	0.108	0.050	2.168	0.030	0.022	0.217	Complementary Mediation
Total	EE → INT	0.266	0.098	2.71	0.007	0.067	0.447	
Indirect	SI→AT→ INT	0.017	0.038	0.453	0.651	-0.047	0.103	Non-mediation (no effect)
Total	SI → INT	0.112	0.089	1.265	0.206	-0.054	0.294	
Indirect	FC→AT → INT	0.153	0.045	3.439	0.001	0.079	0.256	Competitive Mediation
Total	FC→ INT	0.152	0.085	1.789	0.074	-0.011	0.324	

IV. CONCLUSION

This study aimed to investigate the potential of robo-advisors in supporting B40 in Malaysia to perform sound investments and personal financial management, despite their disadvantages in financial literacy and monetary resources, and to support the government's initiative to alleviate poverty in the country. Building on the UTAUT and the notion of advisory transparency as a mediator, this study determines the antecedents of the intention to adopt financial robo-advisory services. The findings suggest that B40 placed performance expectancy, effort expectancy, and facilitating conditions as a prior of advisory transparency, highlighting the importance of advisory transparency in increasing the intention to adopt financial robo-advisory services. The finding of the mediation analysis also implies that advisory transparency, as a mediator, complements the role of performance expectancy and effort expectancy while substituting the role of facilitating conditions in encouraging the robo-advisor adoption intention among the B40 in Malaysia.

This study can be distinguished from previous ones, as it examined the role of advisory transparency as a mediator between the UTAUT factors and adoption intention, revealing that advisory transparency has a complementary mediation on the relationships of performance expectancy and effort expectancy with intention and a competitive mediation on the relationship between facilitating conditions and robo-advisor adoption intention. This contrasts with previous studies on robo-advisor adoption in Malaysia, which mainly focused on the direct effect of selected factors from the TAM or UTAUT models [6, 10, 11, 14]. Furthermore, this study is among the first to focus on the robo-advisor adoption intention among the B40 income group in Malaysia. Although the study in [13] focused on M40 [13] using the UTAUT model, no study has integrated advisory transparency into the UTAUT framework. Therefore, the contributions of this study are twofold. First, this study contributes to the literature by providing new empirical evidence and fills a research gap by providing insight into how advisory transparency, as a mediator, interacts with other UTAUT factors in a unified framework. Second, this study fills a gap by providing better insight into how low-income and poverty issues can be potentially addressed through the adoption of robo-advisors among the B40 low-income group, which can be a reference for policymakers in eradicating poverty in the country and supports the no poverty goal of the Malaysian government MADANI framework and the United Nations Sustainable Development Goals (UN SDG1).

This study has some limitations. First, it used a modified UTAUT model that does not include the use behavior construct, considering that financial robo-advisory services are relatively new and are yet to be widely accepted in Malaysia, and, hence, would face challenges if data collection is extended to existing robo-advisor customers. Future research may consider extending the dataset to cover robo-advisor users and can also consider expanding the theoretical framework to cover factors of the extended UTAUT model, such as price value, hedonic motivation, and habits. Second, the data of this study are constrained by self-administered questionnaires. Future research may consider using other data collection approaches, such as qualitative or mixed methods. Lastly, this study focuses only on the mediating effect of advisory transparency. However, the moderating effect of advisory transparency on the UTAUT factors and the adoption of robo-advisors also deserves attention from future studies.

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