Factors Influencing the Intention to Use Robo-Advisors: A Hungarian Perspective

László Molnár, Szabolcs Nagy and Noémi Hajdú

Institute of Marketing and Tourism, Faculty of Economics, University of Miskolc, Egyetemváros út 1, H-3515 Miskolc, Hungary, email: laszlo.molnar@uni-miskolc.hu, szabolcs.nagy@uni-miskolc.hu, noemi.hajdu1@uni-miskolc.hu

Abstract: This study aims to investigate the factors influencing the intention to use robo-advisors, based on an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model, incorporating trust and perceived risk as new elements, alongside Artificial Intelligence attributes. To test our conceptual model, we conducted a survey in Hungary in 2024, with 249 respondents completing our online questionnaire. The model and hypotheses were evaluated using structural equation modeling (SEM). The results indicate that the intention to use robo-advisors is most significantly influenced by performance expectancy, trust, social influence, and facilitating conditions. Among the AI attributes, perceived intelligence stands out, exerting an indirect effect on the intention to use through the aforementioned factors. A limitation of our study is its' geographical focus on Hungary, restricting the generalizability of the findings to potential Hungarian users. Additionally, we were unable to investigate actual usage due to the currently low service penetration. Understanding the factors that influence the preference for automated investment management solutions over traditional advisors is essential for marketing managers in fintech companies to devise effective client acquisition and retention strategies. The findings highlight the importance of trust, security, and digital literacy. Addressing these factors is vital for maximizing the benefits and mitigating the risks associated with AI in financial services. The originality lies in its integrated examination of perceived intelligence and anthropomorphism within an extended UTAUT model, uncovering their combined effects on the intention to use robo-advisors.

Keywords: robo-advisors; consumer acceptance; intention; technology adoption; Hungary

1 Introduction

In recent decades, the services sector has significantly transformed due to technological advancements, notably in the banking sector, where recent developments have introduced a range of new financial services [1]. Digitalization and smart solutions are now essential for market success, impacting both fintech companies and traditional banks [2]. This necessity is highlighted by the fact that most new customers are from Generation Z and Alpha, who prioritize digital banking [3]. The early 2010s saw the rapid emergence of robo-advisors due to technological advances in the financial sector [4]. These platforms have gained popularity by eliminating bias and human error, appealing especially to younger, less experienced investors [5] [6]. The term "robo-advisor" was first used by Richard J. Koreto in Financial Planning in March 2002 [7] [8]. Robo-advisors are valued for reducing costs and enhancing the quality and transparency of financial advice [9], marking a revolutionary shift in investment management. The COVID-19 pandemic accelerated the digitalization process in financial services to mitigate economic impacts and support households and SMEs [10]. Social distancing increased reliance on online platforms, boosting the demand for robo-advisors. Many began investing during the pandemic, driven by accessible and affordable robo-advisor platforms, supported by stimulus checks and increased savings. Understanding user acceptance of robo-advisors is crucial for their success. While studies have examined consumer adoption of robo-advisors [11-14], none have analyzed it using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model in an EU emerging market. This gap is significant as neobanks offering robo-advisor services are popular in emerging economies [15], and the global market for robo-advisors is substantial. According to projections from Statista (2024), assets under management in the robo-advisor market will reach USD 1,802.00 billion in 2024, growing at a CAGR of 6.68% to USD 2,334.00 billion by 2028 [16]. The number of users is expected to reach 34.13 million by 2028, with the United States being the largest market [17]. In Hungary, the study's focus, assets under management are projected to reach USD 931.80 million in 2024 (Statista, 2024), increasing to USD 1,190.00 million and 17.07 thousand users by 2028, with an annual growth rate of 6.31% [17]. By examining the factors driving consumer adoption of robo-advisors in Hungary, this study enhances understanding of individual decision-making in the fintech sector. It also offers insights into how high-tech financial service providers can meet the specific needs of this consumer segment to promote financial inclusion. The study aims to analyze consumer intentions to use robo-advisors for investment decisions, focusing on technological innovation acceptance. The research extends a model originally used to investigate chatbot acceptance [18] to the context of robo-advisors. Using an extended UTAUT model, which includes trust, perceived risk, perceived intelligence, and anthropomorphism, this research proposes an integrated framework for understanding customer adoption of robo-advisors. This study presents its' theoretical framework, exploring robo-advisors' role in investment decisions and the foundational UTAUT theory. It then outlines hypotheses within the conceptual model, extends UTAUT, and includes additional factors. The methodology section details the research design and samples. This is followed by model tests, structural equation modeling results and the main findings. The paper concludes with a discussion on theoretical and managerial implications, limitations and future research directions.

2 Literature Review

2.1 Robo-Advisors

A robo-advisor is an automated brokerage account that streamlines the investment process using algorithms without human intervention [19, 20]. These platforms manage clients' investment portfolios and provide financial advice via computer algorithms, posing a significant challenge to traditional human financial advisors [21, 22]. Robo-advisors offer customized portfolio allocations that align with an investor’s risk tolerance and objectives, automating adjustments over time and providing accessible, affordable, and unbiased asset management services [23-26]. Key features that contribute to the popularity of robo-advisors include their low fees, accessibility, and the use of machine learning for creating customer profiles, managing risk, building portfolios, and executing algorithmic trading [27, 28]. They benefit specific population groups, such as low-income or highly educated investors, and apply machine learning to automate data processing for cryptocurrencies, reflecting a broader trend in the financial industry [29]. Robo-advisors offer comprehensive investment solutions with tools for automatic rebalancing and online financial planning. Robo-advisors have many advantages over traditional financial advisors, despite risks associated with their novelty and unfamiliarity. They offer lower costs due to their automated methodology, which appeals to cost-conscious investors [26, 34-36]. Natural Language Processing (NLP)-based chatbots have enhanced customer service by increasing engagement [34, 35]. The global expansion of robo-advisors influences their asset management effectiveness across different nations and companies [33]. The main differences between robo-advisors and traditional advisors are costs, knowledge, trust, investing methods, regulatory issues, and performance. Robo-advisors, with their low human involvement, create investment portfolios using algorithms tailored to clients' risk tolerances [4, 38]. They adhere to the same regulations as human advisors but present unique challenges for regulators, necessitating dynamic regulations and sandboxes for security and entrepreneurship balance [9, 31]. Robo-advisors often outperform traditional funds and indices in risk-adjusted performance [36]. However, robo-advisors lack human expertise and can have hidden costs. Their adoption is influenced by performance expectations, technological trust, financial knowledge, and risk perception [37]. Legal uncertainties and investor attitudes, influenced by fears, risk perception, behavioral biases, and data security concerns, also hinder adoption [38]. Robo-advisors are widely used in wealth and asset management, with benefits influenced by users' perceptions of competence and predicted returns [39]. Trust is crucial for adoption, with initial trust strongly related to perceived control and structural assurances [37]. Consumers generally prefer human financial advisors over robo-advisors due to trust and expertise valuation discrepancies [40]. Effective compliance regulations can enhance investor confidence by ensuring robo-advisors operate within a clear legal framework, boosting their legitimacy and reliability [41]. Many robo-advisors adhere to fiduciary guidelines, ensuring they act in clients' best interests, but unclear legal frameworks in some regions hinder their compliance and expansion [44-46]. The lack of human interaction can make understanding financial products more challenging [45]. As the industry matures, investor confidence in robo-advisors grows, with hybrid models combining automated and human support to promote acceptance and enhance personalized service [48-50]. The emergence of robo-advisors has driven innovation in socially responsible investing (SRI) techniques, integrating smart beta and ESG investing into their platforms to align with clients' sustainable and ethical preferences [51, 52].

2.2 Theoretical Framework

Our research employed the model developed by Liew et al. [18], initially used to investigate the acceptance of chatbots. Despite robo-advisors and chatbots representing distinct technologies, they share notable similarities – both can operate without human intervention and provide automated information or services – justifying the adaptation of this model. The Unified Theory of Acceptance and Use of Technology (UTAUT) model, first introduced by Venkatesh et al. [51], underpins the model by Liew et al. [18] and offers a robust framework for understanding the variables influencing user acceptance of technology. This model's comprehensive scope has facilitated its application across various technological contexts. Notably, Nain and Rajan [40], Eren [54] and Yeh et al. [55] have applied the UTAUT or UTAUT2 model to examine the acceptance of robo-advisors. The model developed by Liew et al. [18] serves as a foundational framework for our research on robo-advisors. This adapted model maintains the core structure of the UTAUT model while extending it to encompass the specific characteristics of AI technology pertinent to robo-advisors. The model by [18] comprises four distinct components: attributes, functional elements, relational elements, and contextual factors. Perceived intelligence and anthropomorphism are central components of AI attributes. Perceived intelligence refers to users' perception of artificial intelligence as competent, appropriate, and trustworthy in executing its intended tasks [54-56]. Anthropomorphism denotes the attribution of human characteristics to non-human animals and objects [57]. The UTAUT model [51] and its extended version incorporate performance expectancy, effort expectancy, trust, perceived risk, social influence, and facilitating conditions. Within the functional elements component, performance expectancy (PE) and effort expectancy (EE) can be distinguished. Performance expectancy (PE) is a crucial element influencing the intention to use technology and is defined as the extent to which using a technology benefits users [58]. In the context of robo-advisors, PE refers to users' expectations of achieving better financial results through these automated systems, including the system's efficiency, reliability, and accuracy in financial planning and investment recommendations. Effort expectancy (EE) pertains to the ease of use of a technology [58]. For robo-advisors, EE includes the simplicity of the platform, user-friendliness, intuitive interface, and ease of account setup and management, significantly influencing users' willingness to adopt the technology. The contextual factors component comprises social influence and facilitating conditions. Social influence is defined as the extent to which individuals perceive that important others (e.g., family, friends) believe they should use the new system [51], influenced by recommendations, social media endorsements, and perceived popularity. Facilitating conditions refer to the belief in the availability of organizational and technical infrastructure supporting the use of the system [51], including customer support availability, platform accessibility and compatibility with various tools. Trust and perceived risk are key elements of relational factors. Trust is defined as the user's belief that the technology will not lead to negative outcomes, implying secure and effective investment management [58]. encompassing data protection, investment decision trust, and platform reliability. Perceived risk is defined as users' concerns about potential negative consequences of using the technology, such as financial loss and data protection issues [58] and worries about inadequacies compared to human advisors.

Although MCDM methods were not used in this study, their application in future research could help refine robo-advisor recommendation engines by incorporating multidimensional user priorities. Methods such as AHP (Analytic Hierarchy Process), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and DEMATEL were used to model investor preferences, risk tolerances and product comparisons [59].

3 Hypotheses and Conceptual Model

Based on the comprehensive literature review presented in the previous chapter, the following hypotheses were formulated.

- *H1. Perceived intelligence has…*
    - *(a)… positive impact on performance expectancy*
    - *(b)… positive impact on effort expectancy*
    - *(c)… positive impact on trust*
    - *(d)… negative impact on perceived risk*
    - *(e)… positive impact on anthropomorphism*
- *H2. Antropomorphism influences…*
    - *(a)… positively the performance expectancy*
    - *(b)… positively the effort expectancy*
    - *(c)… positively the trust*

(d)… negatively the perceived risk

- *H3. Performace expectancy positively affects the intention to adopt robo-advisors*
- *H4. Effort expectancy positively impacts the intention to adopt robo-advisors*
- *H5. Trust influences positively the intention to adopt robo-advisors*
- *H6. Perceived risk affects negatively the intention to adopt robo-advisors*
- *H7. Social infulence positively impacts the intention to adopt robo-advisors*
- *H8. Facilitating conditions positively influences the intention to adopt robo-advisors*

To summarize the above hypotheses, the following conceptual model (Figure 1) has been developed, which includes both the measurement models and the relationships between the constructs under investigation.

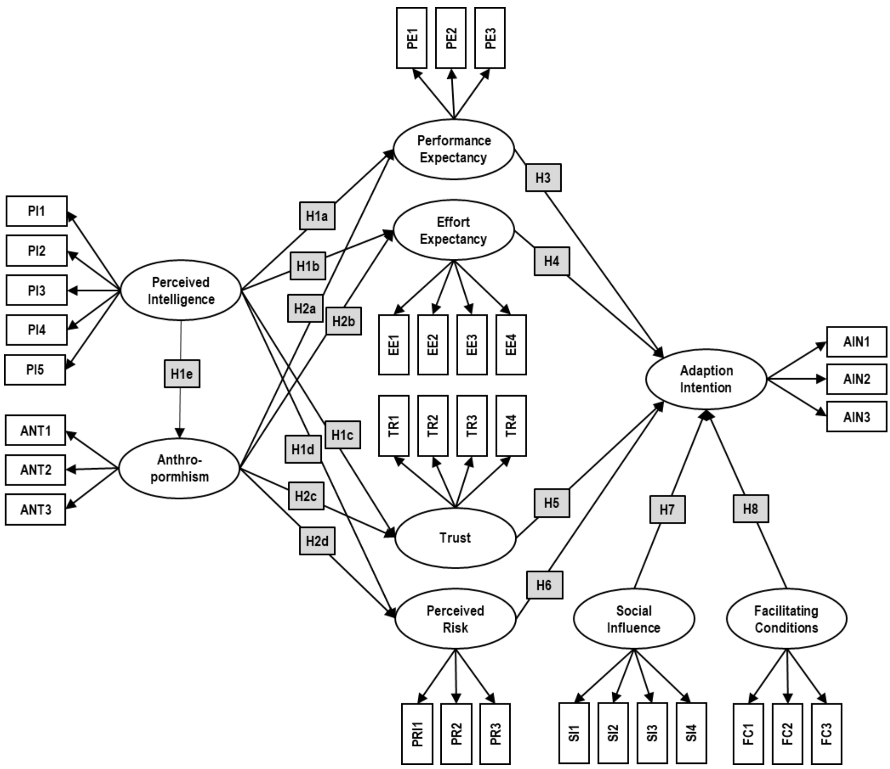

Figure 1

Conceptual model based on the extended UTAUT framework for robo-advisor adoption in Hungary

The dependent variable in our model is the intention to use, which is directly influenced by six factors: the functional elements: performance expectancy and effort expectancy; the relational elements: trust and perceived risk; and the contextual factors: social influence and facilitating conditions. In our model, the AI attributes, specifically perceived intelligence and anthropomorphism, directly impact the functional and relational elements. We anticipate that our model will elucidate the intention to use robo-advisors by these factors, determine the magnitude of the effect of each construct, and underscore the influential role of AI attributes on functional and relational elements.

4 Method

4.1 Research Design and Sampling

During the research, we conducted a cross-sectional study among respondents who had already heard of robot advisors. (Many such services are already available in Hungary.) Respondents were invited to participate in the study by posting our invitation in groups interested in investing on various social media platforms. In March-April 2024 (in 2 months) 309 people completed the questionnaire, but after data cleaning only 249 analyzable respondents remained. Statistical analyses were conducted in SPSS, and the research hypotheses were tested by structural equation modelling (SEM) in AMOS. Reference [60] recommended a minimum sample size of 200 for SEM in AMOS, so the actual sample size of 249 respondents met this criterion.

The demographic characteristics of the respondents were as follows: By gender: 60.2% were men and 39.8% were women. By age: 36.1% were between 18-29 years old, 33.7% were between 30-39 years old, 13.3% were between 40-49 years old, 9.6% were between 50-59 years old and 7.2% were over 59 years old. In terms of education, 20.5% had completed secondary school and 79.5% had a university degree. Their subjective financial situation was categorized as average on a seven-point scale (M=4.49 SD=0.885), where (1) means "very below average", (4) "corresponds to the domestic average" and (7) means "vary above average". Only 7.2% of respondents had ever used a robot-advisor, the rest (92.8%) had only heard of them. Accordingly, we did not analyze any actual use in our survey, only the intention to use them.

4.2 Measures

Table 1 presents the measurement constructs and corresponding items. The measurement items were crafted by the authors, adapting original items of the Adoption Intention of SRH Chatbot model to align with the measurement of behavioral intention to use robo-advisors. Data collection involved a questionnaire encompassing 32 variables related to using robo-advisors. All entries in Table 1 were assessed using a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7).

Table 1

Constructs and measurement instruments

Construct	Measurement items	Code
Performance Expectancy (PE)	I find robo-advisors useful for making investment decisions.	PE1
	Using robo-advisors enables me to make more informed decisions about my investments	PE2
	Using robo-advisors increases my knowledge about investing	PE3
Effort Expectancy (EE)	My engagement with robo-advisors is simple and straightforward	EE1
	It is simple for me to learn how to use robo-advisors and become proficient at it	EE2
	I find robo-advisors easy to use	EE3
	Learning to operate robo-advisors is easy for me	EE4
Social Influence (SI)	People who influence my financial decisions will think that I should use robo-advisors	SI1
	People who are important to me will think that I should use robo-advisors	SI2
	In general , the community will support the use of robo-advisors	SI3
	If I use a robo-advisor, I will also meet social expectations	SI4
Facilitating Conditions (FC)	I have the resources necessary to use robo-advisors	FC1
	I have the knowledge necessary to use robo-advisors	FC2
	The robo-advisors are compatible with the devices I use.	FC3
Anthropo-morphism (ANT)	I feel like I am conversing with human being when using robo-advisors	ANT1
	My interaction with the robo-advisors I use feels completely natural	ANT2
	My conversations with robo-advisors do not appear to be artificial	ANT3
Trust (TR)	I feel that the investment information provided by robo-advisors is honest and authentic	TR1
	I feel that the robo-advisors have clarity of services provided	TR2
	I feel that the robo-advisors are trustworthy	TR3
	I feel that the robo-advisors have the necessary ability to provide accurate investment information	TR4
Perceived Intelligence (PI)	I believe that robo-advisors are competent	PI1
	I believe that robo-advisors are knowledgeable	PI2
	I believe that robo-advisors are intelligent	PI3
	I believe that robot advisors are responsible	PI4
	I believe that robot advisors are sensible	PI5
Perceived Risk (PR)	The security systems built into the robo-advisors may not be strong enough to protect my account	PR1

Construct	Measurement items	Code
	My decision to use robo-advisors involves high risk	PR2
	If I use robo-advisors, internet hackers might have gain access to my account	PR3
Adoption Intention (AIN)	I will use robo-advisors for investment information in the future	AIN1
	I believe that I will use robo-advisors for my investment decisions in the future	AIN2
	I will continue to use robo-advisors for investment information in the future	AIN3

5 Results

5.1 Convergent and Discriminant Validity; Reliability and Model Fit

We evaluated both convergent and discriminant validity for our model. Following the Fornell-Larcker criterion [61], convergent validity requires the Average Variance Extracted (AVE) to surpass 0.5. Additionally, in line with Hair [62] recommendations, AVE should exceed 0.5, standardized factor loadings of all items should surpass 0.5, and Composite Reliability (CR) should be above 0.7 to establish convergent validity. Our nested model successfully fulfilled all these criteria, as indicated in Table 2.

Table 2

Summary table of means, standard deviations, validity and reliability measures

Constructs	Items	M	SD	Load.	Alpha	AVE	CR
Performance Expectancy (PE)	PE1	4.16	2.00	0.93	0.93	0.83	0.93
	PE2	3.96	1.99	0.95			
	PE3	4.23	2.07	0.84			
Effort Expectancy (EE)	EE1	4.39	1.75	0.76	0.94	0.80	0.94
	EE2	4.31	1.69	0.73			
	EE3	4.07	1.72	0.93			
	EE4	4.05	1.76	0.94			
Social Influence (SI)	SI1	2.83	1.82	0.86	0.90	0.71	0.91
	SI2	2.60	1.72	0.93			
	SI3	2.51	1.71	0.82			
	SI4	2.41	1.58	0.74			
Facilitating Conditions (FC)	FC1	5.01	1.89	0.71	0.85	0.67	0.82
	FC2	3.73	1.99	0.80			
	FC3	4.27	1.81	0.94			
Anthropo-morphism (ANT)	ANT1	3.42	1.85	0.77	0.88	0.72	0.88
	ANT2	2.87	1.67	0.94			
	ANT3	2.88	1.65	0.83			
Trust (TR)	TR1	4.16	1.83	0.90	0.84	0.83	0.94
	TR2	3.54	1.93	0.89			

Constructs	**Items**	**M**	**SD**	**Load.**	**Alpha**	**AVE**	**CR**
	TR3	3.57	1.93	0.95			
Perceived Intelligence (PI)	PI1	3.89	1.97	0.95	0.94	0.74	0.93
	PI2	3.77	1.93	0.94			
	PI3	4.17	2.08	0.84			
	PI4	3.00	1.90	0.74			
	PI5	3.72	1.96	0.82			
Perceived Risk (PR)	PR1	3.92	1.86	0.58	0.68	0.56	0.71
	PR2	4.55	1.69	0.89			
Adoption Intention (AIN)	AIN1	3.51	1.89	0.87	0.91	0.77	0.91
	AIN2	3.34	1.81	0.84			
	AIN3	3.55	1.91	0.93			

Our model demonstrates satisfactory discriminant validity, as none of the correlations surpassed the threshold limit of 0.85, indicating poor discriminant validity according to [63]. The observed correlations are represented in Table 3.

Table 3

Heterotrait-monotrait ratio (HTMT) matrix

	AIN	**ANT**	**EE**	**FC**	**PE**	**PI**	**PR**	**SI**	**TR**
AIN									
ANT	0.625								
EE	0.372	0.462							
FC	0.145	0.280	0.432						
PE	0.812	0.610	0.353	0.069					
PI	0.744	0.636	0.503	0.141	0.847				
PR	0.172	0.129	0.062	0.344	0.386	0.396			
SI	0.627	0.666	0.130	0.108	0.546	0.385	0.163		
TR	0.744	0.620	0.488	0.070	0.845	0.813	0.337	0.478	

We assessed the precision and consistency of the nested model through three reliability tests: Cronbach's alpha (α), the Average Variance Extracted index (AVE), and Composite Reliability (CR). A measurement model is deemed acceptable when all estimates are significant, α is greater than 0.5 or ideally 0.7, AVEs for all constructs are above 0.5 [61], CRs for all constructs are above 0.7 [64]. As presented in Table 2, all constructs exhibited Cronbach's alphas of 0.68 or higher, AVE scores exceeding 0.56, and CRs surpassing 0.71. These results indicate that the reliability of the measurement model is optimal.

We assessed both absolute and relative model fits, and all absolute measures demonstrated statistical significance, indicating a favorable fit. Specifically, the Chi-square test yielded a value of 203.605 (DF=128), with a probability level of 0.000. Additionally, the CMIN/DF ratio was 1.591, GFI stood at 0.792, AGFI at 0.722, RMSEA at 0.085, and SRMR at 0.0773.

For the evaluation of relative model fit, we employed TLI/NNFI, NFI, IFI, and CFI, all of which exhibited either acceptable or commendable values (TLI/NNFI=0.936; NFI=0.870; IFI=0.948; CFI=0.947). Following [65] guidelines, values exceeding 0.9 indicate an acceptable fit, while those surpassing 0.95 suggest a good fit. Both absolute and relative model fit tests affirmed that the structural nested model is well-suited for the analysis and interpretation of parameter estimates.

5.2 Hypothesis Testing and Estimates

The structural model was employed to test hypotheses and extract insights regarding behavioral intention to use robo-advisors. The results of the hypothesis tests, encompassing unstandardized and standardized regression weights as measured within the model, are presented in Table 4.

Table 4
Unstandardized and standardized regression weights and hypothesis testing

Hypothesis	Relationship	Regression Weights				Standardized Regression Weights	Result
		Est.	*S.E.*	*C.R.*	*P*		
H1a	PI → PE	0.87	0.09	10.27	<0.001	0.87	accepted
H1b	PI → EE	0.24	0.11	2.17	0.03	0.28	accepted
H1c	PI → TR	0.87	0.08	11.09	<0.001	0.94	accepted
H1d	PI → PR	-0.48	0.12	-4.04	<0.001	-0.60	accepted
H1e	PI → ANT	0.43	0.08	5.35	<0.001	0.59	accepted
H2a	ANT → PE	0.08	0.11	0.73	0.47	0.06	rejected
H2b	ANT→EE	0.36	0.16	2.30	0.02	0.31	accepted
H2c	ANT→TR	0.02	0.08	0.27	0.79	0.02	rejected
H2d	ANT→PR	0.36	0.17	2.15	0.03	0.33	rejected
H3	PE → AIN	0.45	0.14	3.31	<0.001	0.52	accepted
H4	EE → AIN	-0.03	0.08	-0.35	0.73	-0.03	rejected
H5	TR → AIN	0.26	0.15	1.75	0.05	0.28	accepted
H6	PR → AIN	0.10	0.09	1.12	0.27	0.10	rejected
H7	SI → AIN	0.27	0.08	3.34	<0.001	0.26	accepted
H8	FC → AIN	0.12	0.07	1.84	0.05	0.13	accepted

Figure 2 displays the standardized estimates and loadings depicting the relationships between the constructs and the observed indicators. Confirmation of a statistically significant relationship ($p<0.05$) in the predicted direction, led to the acceptance of the corresponding hypothesis.

H1a: Perceived intelligence → Performance expectancy

Hypothesis H1a was supported. The results showed that perceived intelligence significantly and positively influenced performance expectancy ($\beta = 0.87$, $p < 0.001$). This indicates that the more intelligent users perceive robo-advisors to be, the more they expect these tools to improve their financial performance.

H1b: Perceived intelligence → Effort expectancy

Hypothesis H1b was supported. A significant positive correlation was found between perceived intelligence and effort expectancy ($\beta = 0.28$, $p = 0.03$), indicating that intelligent robo-advisors are perceived by users as easier to use and more intuitive.

H1c: Perceived intelligence → Trust

Hypothesis H1c was supported. The results showed a strong positive influence of perceived intelligence on trust ($\beta = 0.94$, $p < 0.001$). This shows that perceived cognitive ability directly contributes to users' trust in robo-advisors.

H1d: Perceived intelligence → Perceived risk

Hypothesis H1d was supported. Interestingly, contrary to our initial expectations, the results showed a significant positive relationship between perceived intelligence and perceived risk ($\beta = 0.59$, $p < 0.001$). This means that higher intelligence can also raise concerns about complexity, automation or loss of control.

H1e: Perceived intelligence → Anthropomorphism

Hypothesis H1e was supported. Perceived intelligence had a significant positive effect on anthropomorphism ($\beta = 0.59$, $p < 0.001$), suggesting that intelligent behavior increases the likelihood that users attribute human-like characteristics to robo-advisors.

H2a: Anthropomorphism → Performance expectancy

Hypothesis H2a was not supported. Anthropomorphism had no significant effect on performance expectancy, indicating that human-like traits alone do not enhance users' belief in the effectiveness of robo-advisors.

H2b: Anthropomorphism → Effort expectancy

Hypothesis H2b was supported. The model revealed a significant positive influence of anthropomorphism on effort expectancy ($\beta = 0.31$, $p = 0.02$). This means that the more human-like a robo-advisor appears, the easier it is perceived to be to use.

H2c: Anthropomorphism → Trust

Hypothesis H2c was not supported. No significant correlation was found between anthropomorphism and trust. This indicates that the addition of human-like features does not automatically increase users trust in robo-advisors.

H2d: Anthropomorphism → Perceived risk

Hypothesis H2d was not supported. Rather, anthropomorphism significantly increased the perceived risk. This result suggests that human-like features may lead to uncertainty or discomfort among users, possibly due to the "uncanny valley" .

H3: Performance expectancy → Intention to use

Hypothesis H3 was supported. The results showed a strong positive influence of performance expectancy on intention to use ($\beta = 0.52$, $p < 0.001$), confirming that users who find robo-advisors useful are more likely to intend to use them.

H4: Effort expectancy → Intention to use

Hypothesis H4 was not supported. There was no statistically significant effect of effort expectancy on intention to use. This suggests that although ease of use is important, it may not be a decisive factor for acceptance if other factors such as trust or usefulness are more dominant.

H5: Trust → Intention to use

Hypothesis H5 was supported. Trust was found to positively influence the intention to use robo-advisors ($\beta = 0.28$, $p = 0.05$), emphasizing the central role of trust in the adoption of financial technology.

H6: Perceived risk → Intention to use

Hypothesis H6 was not supported. The analysis revealed no significant negative impact of perceived risk on intention to use, suggesting that perceived concerns or threats do not strongly deter users in this context.

H7: Social influence → Intention to use

Hypothesis H7 was supported. Social influence had a significant positive effect on intention to use ($\beta = 0.26$, $p < 0.001$), which means that recommendations or norms from peers and influencers can influence user behavior towards robo-advisors.

H8: Facilitating conditions → Intention to use

Hypothesis H8 was supported. Facilitating conditions also had a positive effect on intention to use ($\beta = 0.13$, $p = 0.05$), suggesting that access to the right tools, knowledge and support systems increases the likelihood of adoption.

Conclusions

Our analysis confirms that perceived intelligence significantly enhances performance expectancy, effort expectancy, trust and anthropomorphism, while reducing perceived risk. Specifically, the results indicate that the more intelligent users perceive robo-advisors to be, the more they regard these tools as useful and easy to use. Additionally, perceived intelligence bolsters trust and anthropomorphism, yet paradoxically increases perceived risk. These findings are in line with Aw et al. [66] who found that perceived intelligence is the most important determinant of robo-advisory service acceptance.

Contrary to our expectations and previous findings [66], anthropomorphism positively impacts effort expectancy but does not significantly affect performance expectancy or trust. Moreover, anthropomorphism unexpectedly increases perceived risk, suggesting a complex relationship between human-like characteristics and risk perception in robo-advisors. Our hypotheses regarding performance expectancy and trust were confirmed, with both factors positively influencing the intention to use robo-advisors, which is also supported by [13] results. However, effort expectancy did not significantly impact the intention to use. The hypothesized negative effect of perceived risk on intention to use was also not supported by our findings. Additionally, social influence and facilitating conditions were found to significantly enhance the intention to use, underscoring the importance of external factors and resource availability in shaping user intentions.

The positive influence of perceived intelligence on performance expectancy, effort expectancy, trust, and anthropomorphism underscores the critical role of cognitive perceptions in technology acceptance, as noted by Flavián [67]. Users are more likely to adopt robo-advisors that exhibit high levels of perceived intelligence, as these are seen as more capable, trustworthy, and easier to use [68]. However, the concurrent increase in perceived risk highlights a potential barrier to adoption, suggesting that users may associate higher intelligence with greater complexity and vulnerability. The unexpected findings regarding anthropomorphism – its limited impact on performance expectancy and trust, and its positive effect on perceived risk – suggest that while human-like characteristics may simplify interactions, they also introduce concerns about reliability and security. This dichotomy indicates that anthropomorphism alone is insufficient to foster trust and reduce perceived risk, and must be complemented by other factors such as transparency and security assurances.

Our study provides compelling evidence that perceived intelligence is a pivotal driver of user acceptance of robo-advisors, significantly shaping functional and relational perceptions. However, the complexity introduced by anthropomorphism necessitates a balanced approach in designing robo-advisors. Developers should focus on enhancing perceived intelligence while mitigating perceived risks through robust security features and clear communication about the capabilities and limitations of these AI tools.

In conclusion, understanding the interplay between perceived intelligence, anthropomorphism, and other influencing factors offers valuable insights for enhancing the design and adoption of robo-advisors. By addressing the nuanced perceptions of usefulness, ease of use, trust, and risk, stakeholders can better align these technologies with user expectations and foster greater acceptance in financial decision-making processes.

From a theoretical perspective, this paper enhances our understanding of individual decision-making in the fintech sector, by investigating customer adoption of robo-advisors. The extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) to include trust, perceived risk, perceived intelligence, and anthropomorphism has proven to be a robust theoretical framework for comprehending the drivers of individuals' behavioral intentions to use digital platforms that offer automated, algorithm-driven financial planning and investment services with minimal human supervision.

Furthermore, this article contributes to the body of knowledge on individual decision-making by providing new insights into the decision-making processes of high-tech-oriented customers. The novelty of this research lies in addressing a gap in the literature: while numerous studies have examined consumer adoption of various technologies such as e-commerce, online banking, and mobile banking, no studies have focused on customer adoption of automated investment advisors within an emerging market in the European Union.

From a managerial perspective, this paper provides valuable customer insights for the fintech industry. Understanding the critical factors influencing the choice of automated investment management solutions over traditional investment advisors is crucial for marketing managers in fintech companies to develop effective strategies to attract and retain clients.

One limitation of our study is the geographical focus on Hungary, which could limit the generalizability of the results. To overcome this, future research could extend the model and test it in different national and cultural contexts. In addition, conducting longitudinal studies would allow the assessment of behavioral intentions and actual usage over time. Finally, combining quantitative methods with qualitative approaches – such as interviews or focus groups – could provide deeper insights into users' motivations and barriers. These extensions would improve the international relevance and practical implications of the results.

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