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MODELLING THE FACTORS INFLUENCING CUSTOMER ADOPTION OF FINANCIAL ROBO-ADVISORS

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ABSTRACT

In this study, we examine the intention to use robo-advisors among potential users by employing an extended UTAUT model. The novelty of this model lies in its incorporation of constructs such as trust and perceived risk. Furthermore, it also builds upon artificial intelligence attributes, including perceived intelligence and anthropomorphism. To test the theoretical model, we conducted an online questionnaire survey in 2024, which yielded 249 valid responses. Structural equation modelling (CB-SEM) was applied to assess the extended model and its associated hypotheses. The findings indicate that performance expectancy and social influence exert significant effects on the intention to use robo-advisors. Among the AI attributes, perceived intelligence has an indirect impact on usage intention. The results show that fostering trust, enhancing security, and promoting digital literacy are critical for attracting potential users. Proper management of these factors is indispensable for fintech companies seeking to maximize the benefits of AI-based financial services while minimizing the associated perceived risks. The originality of this research lies in its integrated analysis of perceived intelligence and anthropomorphism within an extended UTAUT model, highlighting their combined impact in shaping the social acceptance of robot advisors.

JEL codes: G41

Keywords: robo-advisors, consumer adoption, usage intention, technology adaptation

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1 INTRODUCTION

Robo-advice is a modern and rapidly evolving field of artificial intelligence, which aims to support and facilitate the decision-making process of customers. At the moment, its importance in the financial sector can be considered marginal, limited mainly to investment advice and the implementation of investment strategies. However, the ongoing digital transformation of the economy suggests that this technology will be used for more banking transactions in the near future. Although some customers are reluctant to use robo-advisors (Hildebrand–Bergner, 2021; Zheng et al., 2019), the widespread adoption of this advisory format is fundamentally supported by its lower cost compared to traditional advisory services (Isaia–Oggero, 2022). According to Statista (2024), in 2023, assets managed in the robo-advisor segment reached $1.3 billion and it is estimated that by 2028, this amount could be close to $2.5 billion. It is therefore of paramount importance that credit institutions prepare to expand their service portfolio in this direction.

As the popularity of robo-advice grows, so does the number of publications on the subject. Most of the literature approaches the service from a technological, technical perspective (Belanche et al., 2019a; Nguyen et al., 2023; Nourallah et al., 2023; Rühr, 2020; Sabir et al., 2023; Zheng et al., 2019), presenting the underlying investment strategies (Babaei et al., 2022), analyse the role of trust in technology (Nourallah et al., 2023; Yi et al., 2023), investigate the design of algorithms behind effective advice (Bhatia et al., 2020; Day et al., 2018; Musto et al., 2015) or even evaluate the topic from a legal perspective (Jung et al., 2019; Ződi, 2020). Overall, there is relatively little literature that analyses the factors that shape customers' attitudes towards robo-advice.

Therefore, the aim of our study is to analyse consumers' intention to use robo-advisors that support their investment decisions. To this end, we have taken a model developed by Liew et al., (2023) that was originally used to study the adoption of chatbots and extended its application to robo-advisors.

We see our study as contributing to research on robo-advisors in two ways. Firstly, it extends the literature on robo-advice and consumer behaviour by examining the factors that contribute to the adoption of robo-advice. Furthermore, our findings can also be applied in practice – particularly by credit institutions and fintech firms – to inform service development and deepen understanding of consumer adoption.

2 REVIEW OF THE LITERATURE

The use of IT innovations is not new in credit institutions, as banking operations and credit rating are now unimaginable without computer programs. Moreover, AI-based algorithms are increasingly appearing in asset and wealth management, as well as investment advisory services (Müller–Kerényi, 2021). There are many similar, overlapping and partly complementary definitions regarding robo-advisors. Platforms, considered one of the latest innovations in the financial sector, can substitute or even replace human labour in the management of investments (Goldstein et al., 2019). Investing through robo-advisors is simple and practical, as after a short registration process – during which, among other factors, the client's risk tolerance and return expectations are assessed (Polak et al., 2020) – robo-advisors can provide personalized investment advice. The artificial intelligence system behind the platform then creates a personal investment portfolio and makes recommendations and/or automatic adjustments based on the risk profile and return expectations (Belanche et al., 2019b; Szobonya, 2020). These advisors belong to a group of fintech solutions that can provide a higher quality and more user-friendly, personalised investment service that is more responsive to clients' needs (Horváth, 2020), aiming to "*maintain the personal experience while shifting the focus from human to machine assistance*" (Kovács–Vallyon, 2022, p. 102). We can talk about pure or hybrid robo-advisors: while the first category does not allow clients to discuss their financial situation and goals with a flesh-and-blood advisor, hybrid solutions "*offer automated portfolio management with human interaction*", where a personal financial advisor is also assigned to the client (Puhle, 2016). Several studies have shown that robo-advice-driven investing can be preferable to passive portfolio management even in crises (D'Hondt et al., 2020; Oehler & Horn, 2024). Like flesh-and-blood advisors, robo-advisors provide investment advice based on investment preferences and objectives using market information, meaning that they are not physical robots but "*algorithms that use artificial intelligence in part*" (Ződi, 2020, p. 109). Individual preferences also manifest in the selection of the preferred asset class, as so-called green robo-advisors enable investors to allocate funds to green asset classes (Horváth, 2022). In this study, we define a robo-advisor as a digital platform that provides automated, algorithm-driven financial planning and investment services with minimal or no human oversight. A typical robo-advisor asks questions about the client's financial situation and future goals through an online survey. It then uses the data to advise and automatically invest on behalf of the individual.

The widespread introduction and use of robo-advisors is still in its early stages. The COVID-19 pandemic simultaneously provided a significant impetus to the development of this form of advice – the opportunity for in-person, human advice was curtailed – and the pandemic constituted its first genuine test, since markets had hitherto followed a continuous upward trajectory, making it relatively straightforward to deliver strong results (Au et al., 2021). The proliferation of robo-advisors is a challenge for the banking and financial sector, but they can also be a great opportunity for credit institutions and Fintech companies to broaden their existing service portfolio (Nain–Rajan, 2024). Zogning and Turcotte (2025), examining the practices of French and Canadian banks, conclude that the revenue from robo-advisory services has a marginal impact on the earnings of credit institutions, and it is employed primarily to diversify income streams; but they also find that these institutions achieved higher non-interest income. Based on the findings of Brenner and Meyll (2020), in the long term, fears of widespread adoption of this form of advice are justified for those banks, brokers and insurance companies the business model of which rely exclusively on personal financial advisors.

Piotrowski and Orzeszko (2023) categorise the literature on robo-advisory services into the following broad categories:

- The most frequently examined determinants were related to the technological and operational aspects of robo-advising.
- Several works have addressed the issue of trust in the companies providing robo-advisory services and the technology used in the service itself.
- Some studies have examined demographic and socio-economic factors as key determinants of the adoption of robo-advisory services.
- Another group of literature compared advisory services using artificial intelligence algorithms and traditional advice.

The present study does not aim to examine this area from a technological or legal perspective, but rather focuses on customers and consumers, which is why this literature review emphasises the results obtained so far on consumer attitudes and acceptance. This question is all the more interesting because extensive research in different countries shows that the adoption of financial robo-advisors is far from homogeneous (Fatima–Chakraborty, 2024). Piotrowski and Orzeszko (2023) investigated in their research the factors that determine the willingness of end-users to use the services of robo-advisors. One of their important findings was that the experience or lack of experience of bank customers with traditional banking services and traditional advice has no impact on the willingness of bank customers to accept the services of robo-advisors. The willingness to adopt robo-advice depends more on curiosity, openness to technological innovation, a belief in the benefits of AI, and experience with the use of AI in banking. The acceptance of this form of advice is also strongly influenced by the assumptions customers have about banks' handling of their personal data; the more they assume ethical behaviour, the more likely they are to accept the robo-advice provided by the bank. Similar results have been obtained by other researchers (Morana et al., 2020), who have recognised that the anthropomorphic design of advisors also determines the behaviour of users, i.e. their acceptance of AI-based solutions. Cheng et al., (2019) concluded that endowing robo-advisors with human attributes (voice, tone of voice, even the ability to perceive emotions) improves their acceptance by consumers by contributing to increased trust in the service, which has been confirmed by further research (Aw et al., 2024). Roh et al., (2023) investigated knowledge of technological innovation and the impact of trust. They concluded that companies should develop innovations that are relevant to consumers – that is, those that deliver tangible benefits – and endeavour to ensure that clients can clearly recognise the positive aspects of existing AI-based innovations. Their empirical results have shown that when services are linked to new technologies, consumer attitudes and eventual use of services are significantly influenced by trust. Flavián et al., (2022) analysed how clients' technological readiness and service choice awareness influence their intention to use robo-advisors. They found that those who have more knowledge about this service, know how robo-advisors work, their capabilities and limitations, are more likely to use them. Potential clients for credit institutions could be those who are interested in investing but have been deterred from investing by the time-consuming tasks involved in active investing (managing complex software or even dealing with advisors). As Isaia and Oggero (2022) have shown, financial literacy plays a key role in the uptake of robo-advice services by Generation Z. Individuals with higher levels of financial literacy are more likely to adopt robo-advisors, whereas lower financial literacy does not exhibit significant explanatory power. Looking at young people's overall online activity, they found that activities involving online financial transactions, online shopping and digital payments predict potential interest in financial advice provided through digital platforms. Similarly, the generational difference has been highlighted by other authors, including Figà–Talamanca é et al., (2022) and Nourallah (2023), who argue that Generation Y and Z are early adopters, but that those with greater wealth and older generations prefer traditional human advisors. Singh and Karamcheti (2025) investigated the interaction of factors that determine the perceived benefits and perceived risks of robo-advice. Their empirical results are consistent with previous research showing that perceived benefits significantly influence use. And perceived benefits are positively influenced by anthropomorphism, social influence and trust. In contrast to previous research, their study concludes that financial literacy has a significant impact on trust, but no direct effect on perceived benefits.

3 HYPOTHESES AND OUR OWN MODEL

Based on the literature reviewed in the previous chapters, the following hypotheses were formulated.

H1. Perceived intelligence ...

- *(a) ... has a positive impact on performance expectancy.*
- *(b) ... has a positive impact on effort expectancy.*
- *(c) ... has a positive impact on trust.*
- *(d) ... has a negative impact on perceived risk.*
- *(e) ... has a positive impact on anthropomorphism.*

Perceived intelligence has a positive impact on performance expectancy, given investors' trust in robo-advisors' more efficient portfolio performance, personalised recommendations and accurate market forecasts (Beccalli et al., 2020; Sarin–Sharma, 2023). Perceived intelligence has a positive impact on the effort required, as investors believe that intelligent robo-advisors provide a seamless and intuitive user experience that simplifies investment management. Perceived intelligence has a positive impact on trust, as investors perceive intelligent robo-advisors as reliable, objective and transparent in the financial advice they provide. There is a contradictory relationship between perceived risk and perceived intelligence. On the one hand, investors see intelligent robo-advisors as an efficient alternative to managing their investments, which reduces financial risks in general. However, there are also several concerns about data security and technology exposure.

H2. Anthropomorphism ...

- *(a) ... has a positive impact on performance expectancy.*
- *(b) ... has a positive impact on effort expectancy.*
- *(c) ... has a positive impact on trust.*
- *(d) ... has a negative impact on perceived risk.*

According to our hypothesis, anthropomorphism has a positive impact on performance expectancy; that is, the more human-like we perceive the robo-advisors, the more effective we consider the services they provide. In addition, we also assume that anthropomorphism also has a positive impact on effort expectancy, which in effect means that the more human we perceive the appearance of robo-advisors to be, the easier we perceive their use in our investment decisions to be. In addition, we find that anthropomorphism increases investor confidence, hence as the perceived human characteristics of robo-advisors evolve, so does the confidence placed in them. Finally, we argue that anthropomorphism negatively affects the perceived risk, or more precisely, the higher the perceived security risk, the more pronounced the anthropomorphic nature of the robo-advisors, given the critical role of the human factor in the use of IT technologies. The sub-hypotheses related to anthropomorphism were formulated based on Cai et al., (2022), Melián–González et al., (2021), and Pillai–Sivathanu (2020).

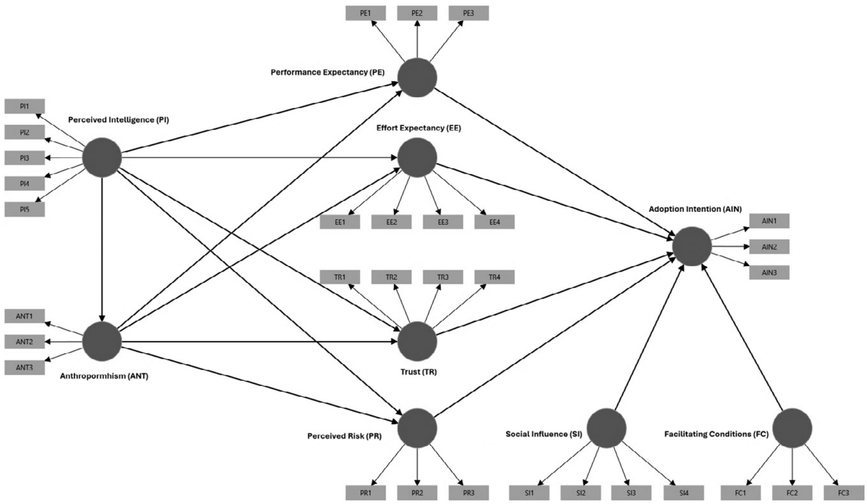
H3. The intention to use robo-advisors ...

- *(a) ... is positively influenced by the performance expectancy.*
- *(b) ... is positively influenced by the effort expectancy.*
- *(c) ... is positively influenced by trust.*
- *(d) ... is negatively influenced by the perceived risk.*
- *(e) ... is positively influenced by social influence.*
- *(f) ... is positively influenced by the facilitating conditions.*

We find that performance expectations have a positive effect on the intention to use robo-advisors, i.e. the more useful we consider the services provided by robo-advisors to be, the more open we are to using them. This was confirmed by Chow et al., (2023) who argued in their study for a positive correlation between performance expectancy and consumer adoption of AI-based services. A study conducted in Malaysia by Khoo et al., (2024) found that the correlation between effort expectancy associated with the use of robo-advisors and the intention to use robo-advisory services was not significant. However, in another Malaysian study Nguyen et al., (2023) found that intention to use robo-advisors was positively influenced by effort expectancy, hence we base our hypothesis above on this finding. We assume that trust in robo-advisors has a positive effect on the intention to use them. This is supported by the study of Bruckes et al., (2019) and Nourallah et al., (2023), in which a strong correlational relationship between initial trust in robo-advisors and the corresponding intention to use was identified. According to a study on investors' openness to using robo-advisory services and artificial intelligence, perceived risk is a construct that influences investors' intention to use artificial intelligence to manage their investments. Ashrafi's (2023) dissertation provides insights into the psychological mechanisms behind the intention to use as shaped by social factors. We therefore believe that social influence has a positive effect on the intention to use. There is evidence that facilitating conditions such as algorithm interpretability, structural safety and interactivity have a positive impact on users' investment intentions when using robo-advisors (Hong et al., 2023).

To summarise the hypotheses detailed above, we have developed the following theoretical model (*Figure 1*), which also illustrates the measurement models included in the study and the relationships between the constructs.

Figure 1
Extended UTAUT model of consumer adoption of financial robo-advisors (theoretical model)



Source: Own editing

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

4 METHODOLOGY

4.1 Research method and sample

During the research, we conducted a cross-sectional study among respondents who had previously heard of robo-advisors (several such services are already available in Hungary). Respondents were invited to participate in the survey in the various social media platforms and investment thematic groups. Between March and April 2024 (over a two-month period), 309 people filled out the questionnaire, and after data cleaning, only 249 relevant respondents remained. Statistical analyses were carried out in SPSS and the hypotheses of the research were tested using the covariance-based structural equations method (CB-SEM) in SmartPLS. SEM is generally used to explain several statistical relationships simultaneously through visualisation and model validation. With this technique, complex models can easily be handled and explained. SEM is an extension of traditional linear modelling techniques, such as multiple regression analysis and analysis of variance (ANOVA) (Dash–Paul, 2021). Our methodological choice is fundamentally explained by the large sample size, the multivariate normal distribution, the factor-based modelling, and the focus on theory testing. In essence, it is based on these factors that we decided to use CB-SEM. According to the recommendation of Marsh et al. (1988), the minimum sample size for CB-SEM studies is 200 records, a requirement that is met by our final sample size of 249.

The demographic characteristics of respondents can be summarised as follows. Distribution by gender: 60.2% of respondents were male, 39.8% female. Distribution by age: 36.1% were in the 18-29 age group, 33.7% in the 30-39 age group, 13.3% in the 40-49 age group, 9.6% in the 50-59 age group and 7.2% in the 59+ age group. In terms of educational attainment, 20.5% of the respondents had a secondary education and 79.5% had a tertiary education. Respondents rated their own subjective financial situation as average on a seven-point scale (M=4.49; SD=0.885), where (1) is "significantly below average", (4) is "about average" and (7) is "significantly above average". Only 7.2% of respondents had used a robo-advisor before, the rest (92.8%) only knew about the concept by hearsay. Accordingly, actual use was excluded from the survey and only intention to use was analysed.

4.2 The measurement method

Table 1 shows the constructs included in the study and the relevant indicators. The measurement indicators were defined by the authors with reference to the original elements of the SRH Chatbot adoption intention model created by Liew et al., (2023), endeavouring to harmonise them with the objective of measuring intention to use robo-advisors. The data collection consisted of a 32-variable questionnaire on the use of robo-advisors. Respondents were asked to rate each of the indicators in *Table 1* on a seven-point Likert scale, with the two extremes of the scale being the response alternatives *"strongly disagree"* (1) and *"strongly agree"* (7).

Table 1
Constructs and measurement indicators

Construct	Measurement indicator	Code
Performance Expectancy (PE)	I find the use of robo-advisors useful when making investment decisions.	PE1
	Robo-advisors allow me to make a better informed, substantiated decision about my investments.	PE2
	By using robo-advisors, I can expand my knowledge of investing.	PE3
Effort Expectancy (EE)	The interaction with the robo-advisor is simple and straightforward for me.	EE1
	It's easy for me to learn how to use robo-advisors and become proficient in using them.	EE2
	I find the use of robo-advisors simple.	EE3
	Learning how to use robo-advisors is not a problem for me.	EE4
Social Influence (SI)	People who influence my financial decisions think I should use robo-advisors.	SI1
	People who are important to me think I should use a robo-advisor.	SI2
	The community at large will support the use of robo-advisors.	SI3
	By using robo-advisors, I am also meeting societal expectations.	SI4
Facilitating Conditions (FC)	I have the resources necessary for using robo-advisors.	FC1
	I have the knowledge to use robo-advisors.	FC2
	The robo-advisors are compatible with the tools I use.	FC3
Anthropomorphism (ANT)	I feel like I'm having a conversation with a human when I use the robo-advisor.	ANT1
	My interactions with the robo-advisors I use feel completely natural.	ANT2
	My dialogues with robo-advisors do not seem artificial.	ANT3

Construct	Measurement indicator	Code
Trust (TR)	I consider the investment information provided by robo-advisors to be fair and credible.	TR1
	I find the services provided by the robo-advisors transparent.	TR2
	I consider robo-advisors to be reliable.	TR3
	I believe that robo-advisors have the skills needed to provide accurate investment information.	TR4
Perceived Intelligence (PI)	I consider robo-advisors to be competent.	PI1
	I consider robo-advisors to be well informed.	PI2
	I consider robo-advisors to be intelligent.	PI3
	I consider robo-advisors to be responsible.	PI4
	I consider robo-advisors to be sensitive.	PI5
Perceived Risk (PR)	The security systems built into robo-advisors may not be strong enough to protect my account.	PR1
	My decision to use a robo-advisor represents a high risk.	PR2
	If I use a robo-advisor, internet hackers may access my account.	PR3
Adoption Intention (AIN)	I will use a robo-advisor for investment information in the future.	AIN1
	I think I will use a robo-advisor when making investment decisions in the future.	AIN2
	I will continue to use a robo-advisor when I need investment information.	AIN3

Source: own editing

5 RESEARCH RESULTS

5.1 Convergent and discriminant validity

We have performed both convergent and discriminant validation of our model. According to the Fornell-Larcker criterion (Fornell–Larcker, 1981), convergent validation requires that the average variance extracted (AVE) exceeds 0.5 points. However, in order to establish convergent validity, as suggested by Hair (2006), AVE and standardised factor weights greater than 0.5 and composite reliability (CR) greater than 0.7 are required. As shown in *Table 2*, our model meets all these criteria.

Table 2
Summary table of means, standard deviations, validity and reliability indicators

Construct	Indicator	M	SD	Factor weight	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			
Anthropomorphism (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			
	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			

Source: Own editing

Our model has satisfactory discriminant validity, given that none of the correlation values exceeded the threshold of 0.85, which, based on Henseler et al., (2015), would suggest weak discriminant validity. The observed correlations are illustrated *in Table 3*.

Table 3
Heterotrait-monotrait (HTMT) ratio 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	

Source: Own editing

5.2 Reliability

The accuracy and consistency of our model was assessed using three reliability tests: (1) Cronbach's alpha (α), (2) average variance extracted (AVE), (3) composite reliability (CR). A measurement model is considered acceptable if all three factors are significant, α is greater than 0.5 or ideally 0.7, AVE is greater than 0.5 for all constructs (Fornell–Larcker, 1981), and CR is greater than 0.7 in all cases (Malkanthie, 2015). As illustrated in *Table 2*, all constructs produced Cronbach's α values of 0.68 or higher, AVE scores are consistently above 0.56, and composite reliability (CR) is greater than 0.71 in all cases. All these results suggest optimal reliability of the measurement model.

5.3 Model fitting

In addition to the above, we also assessed both absolute and relative model fit, on the basis of which it can be stated that all absolute indices are statistically significant. Specifically, the chi-square test yielded a value of 203.605 (DF=128) with a probability level of 0.000. Furthermore, the CMIN/DF ratio was 1.591, while the GFI stood at 0.792, the AGFI at 0.722, the RMSEA at 0.085, and the SRMR at 0.0773.

For the evaluation of relative model fit, we considered the TLI/NNFI, NFI, IFI, and CFI indices, all of which indicated either acceptable or excellent fit (TLI/NNFI = 0.936; NFI = 0.870; IFI = 0.948; CFI = 0.947). Following the guidelines proposed by Bentler and Bonett (1980), values above 0.90 indicate acceptable model fit, while those exceeding 0.95 suggest good model fit. Both the absolute and relative fit indices confirmed that our structurally embedded model is suitable for the analysis and interpretation of parameter estimates.

5.4 Hypothesis testing and estimations

The structural model was used to test our hypotheses and to gain a deeper understanding of the intention to use robo-advisors. The results of the hypothesis test, together with the unstandardised and standardised regression weights measured in the model, are presented in *Table 4.*

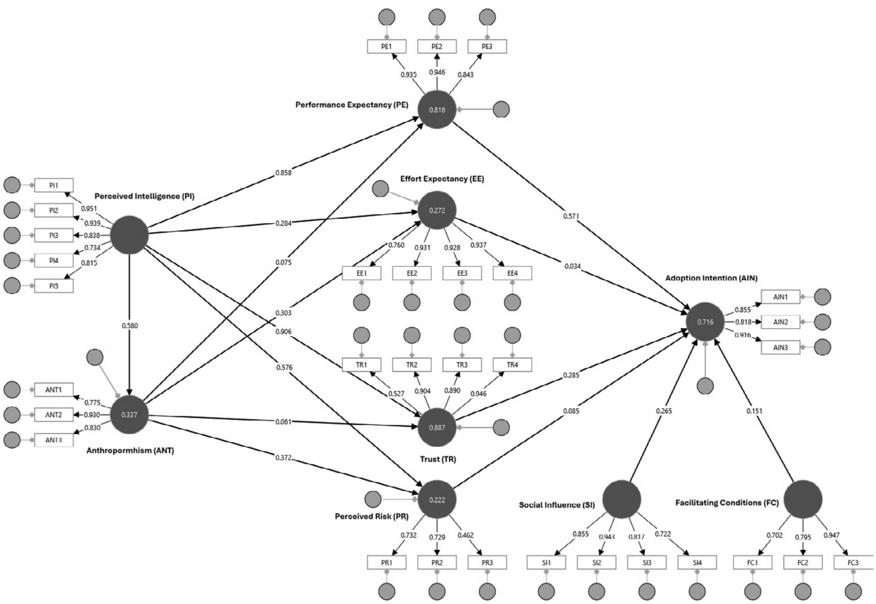
Table 4
Non-standardised and standardised regression weights and hypothesis testing

Hypothesis	Correlation	Regression weights				Standardised regression weights	Result
		Est.	S.E.	T	P		
H1a	PI → PE	0.858	0.086	10.013	0.000	0,858	accepted
H1b	PI → EE	0.202	0.092	2.195	0.031	0,284	accepted
H1c	PI → TR	0.467	0.090	5.170	0.000	0,906	accepted
H1d	PI → PR	−0.418	0.122	3.425	0.001	−0,576	accepted
H1e	PI → ANT	0.446	0.091	4.920	0.000	0,580	accepted
H2a	*ANT → PE*	*0.097*	*0.101*	*0.965*	*0.338*	*0,075*	*rejected*
H2b	ANT → EE	0.279	0.125	2.233	0.028	0,303	accepted
H2c	*ANT → TR*	*0.041*	*0.048*	*0.848*	*0.399*	*0,061*	*rejected*
H2d	ANT → PR	0.352	0.172	2.047	0.044	0,372	accepted
H3a	PE → AIN	0.461	0.156	2.947	0.004	0,571	accepted
H3b	*EE → AIN*	*−0.038*	*0.107*	*0.357*	*0.722*	*−0,034*	*rejected*
H3c	*TR → AIN*	*0.446*	*0.308*	*1.447*	*0.152*	*0,285*	*rejected*
H3d	*PR → AIN*	*0.094*	*0.114*	*0.824*	*0.413*	*0,085*	*rejected*
H3e	SI → AIN	0.257	0.086	3.006	0.004	0,265	accepted
H3f	*FC → AIN*	*0.172*	*0.102*	*1.691*	*0.095*	*0,151*	*rejected*

Source: own editing

Figure 2 shows the standardised estimates and factor weights, and also illustrates the relationships between the constructs and the observed indicators. If the statistically significant relationship ($p<0.05$) in the predicted direction was confirmed, the corresponding hypothesis was accepted.

Figure 2
Test results of the extended UTAUT model of consumer adoption of financial robo-advisors



Source: Own editing

First of all, our hypothesis was that perceived intelligence would have a positive effect on performance expectancy (H1a), effort expectancy (H1b), trust (H1c) and anthropomorphism (H1e), but a negative effect on perceived risk (H1d). All five hypotheses were confirmed. Our results demonstrate that perceived intelligence about robo-advisors positively affects performance expectancy ($\beta=0.86$, $p<0.001$), effort expectancy ($\beta=0.28$, $p=0.03$), trust ($\beta=0.91$, $p<0.001$), and anthropomorphism ($\beta=0.58$, $p=0.001$), while perceived risk is negatively affected ($\beta=-0.58$, $p<0.001$). In essence, the more intelligent we consider a robo-advisor to be, the more useful, simple, reliable and human-like we consider their services to be, but at the same time the more risky we consider their use to be.

Second, our hypothesis on anthropomorphism was broken down into four sub-hypotheses: anthropomorphism positively affects performance expectancy (H2a), effort expectancy (H2b), trust (H2c), but has a negative effect on perceived risk (H2d). Of these, hypotheses H2a and H2c were rejected, while hypotheses H2b and H2d were accepted. Our results show that the human-like nature of robo-advisors has a positive effect on effort expectancy ($\beta=0.30$, $p=0.03$) and perceived risk ($\beta=0.37$, $p=0.04$), but no significant effect on either performance expectancy or trust. Consequently, the more human-like we perceive a robo-advisor to be, the easier and riskier we consider it to be to use.

Our third hypothesis (H3) concerned the impact of factors influencing the intention to use robo-advisors. We assumed that performance expectancy has a positive effect on the intention to use. Our model test confirmed this sub-hypothesis ($\beta=0.57$, $p=0.004$). In other words, the more useful we find a robo-advisor, the more likely we are to use it in our investment decisions. In our next sub-hypothesis, we hypothesized a positive effect between effort expectancy and intention to use, which was not supported by our results. Our third sub-hypothesis assumed a positive effect between trust and intention to use. This sub-hypothesis was also not supported by the model test results. Our next sub-hypothesis assumed a negative relationship between perceived risk and intention to use, which was also not supported by our calculations. In our fifth sub-hypothesis, we assumed that social influence has a positive effect on intention to use. We confirmed this sub-hypothesis ($\beta=0.27$, $p=0.004$), suggesting that reference groups such as family, friends, acquaintances or financial influencers positively influence an individual's intention to use robo-advisors. Finally, in our last sub-hypothesis, we assumed a positive relationship between facilitating conditions and intention to use. This sub-hypothesis was rejected.

In summary, it can be concluded that among the influencing factors included in the original UTAUT model, performance expectancy and social influence proved to have a significant effect on the intention to use robo-advisors. At the same time, performance expectancy is well explained by perceived intelligence, a factor not included in the original UTAUT model. This result alone confirms the need to extend the UTAUT model.

6 DISCUSSION

Our analysis confirms that perceived intelligence significantly increases performance expectancy, effort expectancy, trust, and anthropomorphism, while reducing perceived risk. The results indicate that the more intelligent users perceive robo-advisors to be, the more useful and easier to use they consider these tools. In addition, perceived intelligence enhances trust and anthropomorphism, while paradoxically also increasing perceived risk. These results are consistent with the findings of Aw et al., (2024) who showed that perceived intelligence is the most important determinant of the acceptance of robo-advisory services. Contrary to our expectations and previous research (Aw et al., 2024), anthropomorphism has a positive effect on effort expectancy, but does not significantly affect either performance expectancy or trust. Moreover, anthropomorphism unexpectedly increases perceived risk, suggesting that there is a complex relationship between human-like characteristics and risk perception in the context of robo-advisors. Our hypotheses regarding performance expectancy and social influence have been confirmed, as both factors positively influence the intention to use robo-advisors, as supported by the results of Roh et al., (2023). At the same time, effort expectancy did not have a significant effect on intention to use. The presumed negative effect of perceived risk on usage intention was not confirmed either.

The positive effect of perceived intelligence on performance expectancy, effort expectancy, trust and anthropomorphism highlights the critical role of cognitive perceptions in technology adoption (Flavián et al., 2022). Users are more likely to adopt robo-advisors that demonstrate high levels of perceived intelligence, as they are perceived as more competent, reliable and easier to use (Piotrowski–Orzeszko, 2023). However, a concomitant increase in perceived risk can be a barrier to adoption, suggesting that users may associate intelligence with greater complexity and vulnerability. The unexpected effects of anthropomorphism – its limited influence on performance expectancy and trust, and the increase in perceived risk – suggest that while human-like characteristics can simplify interaction, they can also raise concerns about reliability and safety. This dichotomy suggests that anthropomorphism alone is not sufficient to build trust and reduce perceived risk, but must be complemented by other factors such as transparency and security guarantees.

7 CONCLUSION

Our study provides compelling evidence that perceived intelligence is a key factor in user acceptance of robo-advisors, as it has a significant impact on both functional and relational factors. The complexity introduced by anthropomorphism, however, requires a balanced approach to the design of robo-advisors. Developers need to focus on increasing perceived intelligence while mitigating perceived risks with robust security features and clear communication about the capabilities and limitations of AI tools. In summary, understanding the interplay between perceived intelligence, anthropomorphism and other influencing factors provides valuable insights for improving the design and adoption of robo-advisors. Addressing perceptions such as utility, ease of use, trust and risk enables developers to consciously shape technology solutions in line with users' expectations, thereby supporting their wider adoption in financial decision-making processes.

From a theoretical point of view, the study contributes to a deeper understanding of individual decision-making processes in the fintech sector, in particular by examining the adoption of robo-advisors. The addition of trust, perceived risk, perceived intelligence and anthropomorphism to the UTAUT model provides a robust theoretical framework to help understand individuals' intention to use robo-advisors. These platforms offer automated, algorithm-driven financial planning and investment services with minimal human supervision.

The article also contributes to scientific knowledge on individual decision-making by providing new insights into the decision-making processes of technology-oriented clients. The novelty of the research lies in the fact that it addresses a gap in the literature: while a number of studies have examined consumer adoption of technology in e-commerce, online banking and mobile banking in recent years, no research has yet been conducted on the adoption of automated investment advisors in emerging markets in the European Union.

From a management perspective, the study provides valuable customer insights for the fintech industry. Understanding the critical factors that influence the choice between automated investment management solutions and traditional investment advisors is key for fintech marketing managers to develop effective strategies to retain and grow their client base.

The study has several limitations that need to be taken into account when interpreting the results. First, the data was collected using an online questionnaire based on self-reporting, so there is a possibility of respondent bias. Second, the cross-sectional nature of the research means that it cannot take into account changes over time, and thus cannot examine long-term trends in the adoption of robo-advisors. Finally, although the extended UTAUT model includes several relevant factors, the inclusion of additional psychological and behavioural variables could further deepen the analysis.

In future research, it may be worthwhile to conduct longitudinal studies, which would allow for mapping the dynamic changes in the acceptance of robo-advisors. In addition, the use of qualitative methods such as in-depth interviews or focus group discussions could help to gain a deeper understanding of individual perceptions. Another possible direction would be to study patterns of technology use and actual behaviour, for example through a pilot study on a fintech platform. Finally, to further refine the model, it may be worthwhile to include new factors such as the quality of customer service interactions or the impact of the regulatory environment.

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