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Benefit versus risk: a behavioral model for using robo-advisors

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Benefit versus risk: a behavioral model for using robo-advisors

This research aims to propose and analyze a novel behavioral model for using robo-advisors grounded on stimulus–organism–response and decision theory. Data (n=596) were collected from a panel of US participants. The findings contribute to the financial services arena by demonstrating the relevance of customers' perceptions of robo-advisors' benefits and risks, particularly fear of losing money and wasting time. Greater or lesser ease in learning to use the robo-advisor and the perception of safety are the stimuli for customers to cognitively assess the balance between the risks and benefits of using the robo-advisor. Younger customers are more likely than older customers to recommend the robo-advisor to others, and male users tend to have more confidence than female users in their use of the service. Thus, robo-advisors need to learn how to adapt to different customer profiles to customize the service and to increase the perception of security and ease of use.

Keywords: benefit; risk; loyalty; word-of-mouth; robo-advisor.

利益与风险：使用机器人顾问的行为模型

本研究旨在提出并分析一种基于刺激-有机物-反应理论的机器人顾问新型行为模型。研究从 596 个美国参与者中手机了样本数据。研究结果通过客户对机器人顾问的利益和风险的看法的相关性，尤其是对损失金钱和浪费时间的恐惧，对金融服务领域做出了贡献。学习使用机器人顾问的难易程度和安全感是刺激客户从认知上评估风险和利益平衡的因素。年轻的客户比年长的客户更倾向于向他人推荐使用机器人顾问，同时男性用户往往比女性用户更有信心使用该服务。因此，机器人顾问需要学习如何适应不同的客户群体来定制服务，以此来提高对机器人顾问安全性和易用性的看法。

关键词：利益；风险；忠诚度；口碑；机器人顾问。

Introduction

Cutting-edge technologies enabled by artificial intelligence (AI) are redefining service industries (Ameen et al., 2021a; Loureiro et al., 2021; Ostrom et al., 2019). The banking and finance industry is a paradigmatic example of how these technologies reshape service boundaries (Caron, 2019). This sector pioneered the introduction of automated teller machines and online banking. Thanks to current trends in process automation and the introduction of AI that relies on financial technologies (fintech), recent reports predict that financial services will be the first completely automated sector in 2029 (PwC, 2022). Within this fintech phenomenon, our research focuses on robo-advisors, that is, "technological agents which automate or assist in managing investments by replacing human advisory services and/or the customer's own management" (Flavián et al., 2022, p. 294). These are a novel fintech instrument unquestionably enabled by AI capabilities. Due to their numerous advantages (Jung et al., 2019), robo-advisor services are growing year by year. In 2021, robo-advisors managed around US$ 1.21 trillion in assets, an amount that is expected to grow to US$ 2.50 by 2026 (Statista, 2022), with the leading robo-advisor firm currently managing US$ 206.6 billion (Forbes, 2022). In other words, robo-advisors have become a prominent alternative to conventional human advisors (Alsabah et al., 2021).

The importance of AI to the financial industry contrasts with the lack of relevant empirical research from the academy. Despite the interest that robo-advisors have drawn from both scholars and practitioners, studies investigating this phenomenon are scarce. In general, most insights into the impact of AI on service industries have been theoretical (Belanche et al., 2021c; Huang & Rust, 2021), with many studies focusing on performance-based analyses or legal debates (Jung et al., 2019; Tertilt & Scholz, 2018). Only some types of AI have been considered; for instance, previous studies have tended to focus on chatbots and robots, ignoring other common types of AI embedded in service industries such as finance (Castillo et al., 2021; Flavián et al., 2022). There is also an imbalance in terms of empirical evidence, with previous studies considering the supply side rather than the customer side of the phenomenon (Ivanov et al., 2019).

These gaps in the literature indicate a need for more empirical studies to investigate customer-based factors related to AI (Solakis et al., 2022). The few studies that have approached robo-advisors from the customer perspective (see Table 1) have used adoption models and customer traits to identify customers' motivations for adoption

(Flavián et al., 2022; Hodge et al., 2021; Isaia & Oggero, 2022). The factors that inhibit customer adoption of these innovative services have yet to be considered. This research gap is particularly serious since unsatisfactory introduction of AI innovations can lead to value co-destruction (Castillo et al., 2021) and even to service sabotage (Ma & Ye, 2022). In addition, adoption rates of robo-advisors have fallen short of initial predictions (Flavián et al., 2022), which suggests that further research is needed to understand the customer barriers to their successful introduction.

The lack of empirical research in relation to low market penetration is all the more to be regretted given that robo-advisors represent a particularly interesting case in which to study how customers embrace or avoid AI-enabled services (Flavián et al., 2022). Following the type of service encounters (de Keyser et al., 2019; Ostrom et al., 2019), a robo-advisor is an AI-performed service in which the frontline employee is replaced by technology that interacts with the customer and is able to adapt to customer needs and demands. In this financial service, AI-supported decisions are not taken by the company or the human employee (Mariani et al., 2022), but the AI itself takes the decisions autonomously during the service delivery (e.g., rebalancing the portfolio of investment during holidays according to customers' preferences but without a direct instruction). In addition, robo-advisors are a prototypical example of the latest advances of analytical or thinking AI, according to the categorization of AI levels of development (Huang & Rust, 2021). That is, this technology learns and adapts from data by using analytical and intuitive processes (Alsabah et al., 2021; Huang & Rust, 2021), representing a higher degree of sophistication than more usual mechanical AI (Buhalis et al., 2019; Schepers et al., 2022). Indeed, they exceed human ability in their analytical skills (e.g., amount of data processed, speed, availability).

Apart from their innovativeness, robo-advisors' popularity is based on the superior value provided at a lower cost (Trecet, 2019). In this regard, previous literature has assumed that, to gain competitive advantage, new financial services should combine both an increase in productivity and a successful introduction in the market (Hofmeister et al., 2022). Indeed, recent studies of robo-advisors suggest that this technological service may represent a competitive advantage for companies in the fintech industry and that gaining customers in the short term could be crucial to lead a "winners-take-it-all" market (Flavián et al., 2022; Wirtz et al., 2018).

Our research proposes a framework for understanding the factors in customers' decision-making in relation to the robo-advisor phenomenon. Avoiding the positivistic and deterministic approach of overused technology adoption models (cf. Bagozzi, 2007), we propose a novel framework integrating the stimulus–organism–response (SOR) model (Mehrabian & Russell, 1974), widely applied in service research (e.g., Kabadayi et al., 2022), and decision theory (Savage, 1954). The SOR model assumes that customers' decision-making follows three sequential stages (Barta et al., 2023; Roschk et al., 2017). First, customers evaluate the stimuli, that is, the most relevant observable features of robo-advisors. Following literature on online finance adoption (de Luna et al., 2019; Loureiro & Sarmento, 2018; Singh & Srivastava, 2020), ease of use and security are proposed as the main features of robo-advisors processed by customers when evaluating this innovative service. Second, as a novel research contribution and based on decision theory, our framework proposes that customers evaluate not only the benefits but also the risks of relying on robo-advisory services to manage their investments. The benefits include better investment opportunities and savings on fees, whereas the risks include performance, finance, social, and time concerns (Lee, 2009). Our proposal considers consumer decision-making regarding online investment to be complex, and assumes that consumers evaluate both the pros and the cons of robo-advisors. Moreover, following the COVID-19 pandemic, the role of risk in customer decision-making has been strengthened, because people have had to deal with greater levels of panic, uncertainty, and fear, not always related to the virus (Li et al., 2021). Finally, in the last stage of the SOR model, customers respond toward robo-advisors in terms of loyalty and WOM intentions. Both these dependent variables are complementary factors for the success of robo-advisors (Mainolfi et al., 2022; Oehler et al., 2021), and they should be analyzed independently for a better comprehension of their causes and implications from a marketing approach.

Thus, our research contributes to the discipline in three major domains. First, this study investigates the impact of cutting-edge technologies on service revolution. Specifically, we analyze users' decision process when interacting with robo-advisors (i.e., substituting human advisors) in advanced analytical AI-performing financial services. Second, we propose a novel approach for understanding customers' responses to robo-advisors. Complementing the leading stream in the literature that focuses on customers' motivations to use, this research considers inhibitors to adoption (Ben-David & Sade, 2018). More precisely—as proposed by decision theory—we assume that before taking decisions about this innovative service, customers consider both the pros (benefits) and cons (risks) of relying on robo-advisors for financial management. Third, we provide deeper insight into the kinds of risks that represent a barrier to entry to this new technology, either as direct or as moderating factors. In doing so, we address two important questions: How do the perceptions of security and ease of use of the robo-advisor operate as stimuli in the analysis of benefits and risks by customers? How does the benefit versus risk assessment mechanism work to drive customers to use the robo-advisor and recommend it to others?

Our research is based two priorities to better approach this technological revolution: (i) rethinking customer behavior models, assessing customers' interactions with automated services, and investigating customers' security concerns (Ameen et al., 2021a; Buhalis et al., 2019), and (ii) focusing on the finance sector, an industry less explored by scholars but leading automation processes in recent decades (Flavián et al., 2022). Thus, this study suggests practical guidelines for managers to succeed in new fintech initiatives addressed to the market, a subsector with a high level of competition that is suffering a technology race. From this practical approach, the study proposes to understand the decision process of two relevant behavioral intentions—loyalty and WOM (e.g., Amirtha and Sivakumar, 2022). The latter is a relevant but frequently ignored factor for the spread and consolidation of new technology-based services, such as robo-advisors, in the medium term (Belanche et al., 2012).

The remainder of this article is structured as follows. The next section presents a literature review summarizing previous scientific knowledge of robo-advisors. Then, the theoretical rationale for the proposed framework leads to the development of the hypotheses justifying the relationship between variables. Next, the method section details the data collection procedure, the scales of the questionnaire employed, and the validity of the measurement instrument. The results section presents the main findings resulting from the hypotheses testing. The study concludes with a discussion of these findings in relation to previous research, which is followed by the implications for management and the limitations that suggest further research lines to continue advancing this emerging research topic.

Literature review

Previous knowledge of robo-advisors

A robo-advisor is an automated investment robot that advises and executes investment operations, helping the customer to manage their investments, which is conveniently supported by portfolio redistribution techniques (Sironi, 2016). Table 1 summarizes the empirical literature on customer acceptance of robo-advisors.

INSERT TABLE 1 ABOUT HERE

Several studies have made progress investigating the factors motivating robo-advisor adoption, some of them focused on well-known technology adoption models (Belanche et al., 2019; Yeh et al., 2022). In complementary research, Wexler and Oberlander (2020) presented how robo-advisors may provide a higher value due to the use of advanced algorithms. Oehler et al. (2021) analyzed investors' characteristics influencing the decision to use robo-advisors. In this regard, Brunen and Laubach (2021) examined how robo-advisors may fulfill customers' preferences regarding socially responsible investments.

From a different stream of research—more directly related to AI-based services—Hildebrand and Bergner (2020) focused on anthropomorphic characteristics and measured how a static or dynamic robo-advisor may affect the evaluation of the service and the customer's final decision-making. Similarly, Flavián et al. (2022) and Hodge et al. (2021) examined the impact of a robo-advisor's name (e.g., calling it an AI-advisor, humanizing the name) on investors' judgments. Zhang et al. (2021) compared customers' expectations and hiring intentions between human financial advisors with high or low expertise and robo-advisors.

In a different approach, other studies have focused on demographic variables. Isaia and Oggero (2022) investigated the potential demand for robo-advisors among millennials and members of generation Z. They found that people who have a higher level of financial knowledge were more willing to use this service. In this vein, Flavián et al. (2022) found that service awareness was also very relevant to start using robo-advisors. Finally, in a cross-cultural study, Belanche et al. (2019) found that robo-advisor users from Anglo-Saxon countries were more affected by social norms than users from other countries.

In essence, as Table 1 shows, most studies have relied on technology adoption models or similar positivistic and deterministic frameworks. This kind of approach has been widely criticized for ignoring a number of key aspects of decision-making, such as the goals and barriers that affect behaviors (Bagozzi, 2007). The research framework proposed in this study is designed to overcome these limitations.

Theoretical underpinning

As stated above, our work seeks to integrate the SOR model and decision theory to better explain customers' decisions regarding the use and recommendation of robo-advisors. The SOR model sets out the sequential process by which customers perceive relevant stimuli in order to evaluate the innovative service and react to it accordingly; decision theory focuses on customer assimilation of both the benefits and the risks of the innovation before decision-making.

The SOR model (Mehrabian & Russell, 1974) proposes that customers' decision-making follows three ordered stages (Roschk et al., 2017). First, the customer analyzes the perceptions related to the features of the stimuli (S). Second, the customer integrates these perceptions (the organism, O) to evaluate the behavior in question. Finally, this evaluation leads to a decision that evokes subsequent behavioral responses (R).

In the case of robo-advisor adoption and diffusion, our research focuses on customers' perceptions of ease of use and security as two crucial features (stimuli) of customers' evaluation of online services in general and fintech services in particular (de Luna et al., 2019; Liébana-Cabanillas et al., 2018). Previous studies have established that ease of use and security are crucial features of technology-based applications in the banking industry, as confirmed in contexts such as e-banking (Casaló et al., 2007b), mobile banking (Singh & Srivastava, 2020), and green banking initiatives (Herath & Herath, 2022). These characteristics are particularly important in the early stages of development of financial innovations, because customers identify them as basic observable cues to be evaluated before progressing with the decision-making process (Casaló et al., 2007; Liébana-Cabanillas et al., 2018).

In a second stage, to describe how the organism (i.e., the customer) performs the decision-making process we rely on decision theory, a framework widely employed in investment decision-making. This process is adapted to the robo-advisor context to better explain customers' responses (i.e., whether to use and recommend the use of this new fintech service). Decision theory (Savage, 1954) is based on the assumptions of rationality and normative decision-making in situations of uncertainty but focusing on decisions made in real life, rather than theoretical situations. Savage proposed that individuals' decision-making is ruled by comparative beliefs and personal preferences leading to the maximization of expected utility, following the cost–benefit paradigm. Applying decision theory to individual investment, a person facing an investment decision expects a fair price for their investment, such that the expected benefits should compensate for the assumed risks (Mariani et al., 2022; O'Neill, 1977). In other words, the decision is taken based on the balance between benefits and risks, considering that these evaluations are based on individuals' previous perceptions and beliefs.

Decision theory—which also contributes to the philosophical and mathematical fields—has been applied to classical customers' decisions in social sciences when they involve benefits and damage (e.g., car insurance, fire management, taking someone to court) (O'Neill, 1977; Rodgers, 1980). In a purely financial approach, literature on decision theory has been linked to financial risk management, often from a probabilistic calculation of performance (i.e., profit) versus the risk of not matching that performance in a portfolio investment (e.g., French, 2001). However, the application of mathematical language to the cost–benefit calculation should not obfuscate the true dimensions of current decision-making, which also involves social and moral aspects (Pieper, 2022). Drawing on risk analysis in innovative services (e.g. Airbnb renting decisions; Yi et al., 2020), our research proposes that the benefits and risks of robo-advisor use are not exclusively financial (profit or loss) but entail more complex utility related sociotechnical aspects, such as non-financial benefits (e.g., time saving) or non-financial risks (e.g., social risks).

Finally, the last step in the SOR model focuses on customers responses. Our framework analyzes two behavioral responses on the part of customers: loyalty and WOM intention. Loyalty is fundamental for the growth and continuation of robo-advisors as an alternative to traditional financial advisory services (Flavián et al., 2022; Oehler et al., 2021). However, WOM is also crucial for the success of services in the early stages of the diffusion process (Eisingerich et al., 2015; Mainolfi et al., 2022). We assume that loyalty and WOM are two distinctive and complementary factors in the expansion of the use of robo-advisors. These factors should be analyzed independently because they may have differential causes and implications; for example, customers may personally accept certain risks in the use of robo-advisors, but these risks may nevertheless discourage them from recommending robo-advisors to others.

Research hypotheses

Figure 1 depicts the proposed research framework, which integrates decision theory (Savage, 1954) into the SOR model (Mehrabian & Russell, 1974) to explain the decision-making process of the organism (the customer), and which considers demographic characteristics (age, gender, and income) as control variables.

INSERT FIGURE 1 ABOUT HERE

Perceived ease of use is defined as "the degree to which the prospective user expects the target system to be free of effort" (Davis et al., 1989, p. 985). Digital services that are easy to use are typically graded better and are seen as a more useful, helpful, and desirable tool increasing performance expectancies (Featherman & Pavlou, 2003; Teo et al., 2003). In this regard, previous research on online services indicated that when users perceive that the system is easy to use, then they tend to consider that its benefits are higher (e.g., efficiency, enjoyable experience) (Rodrigues et al., 2016; Templeton & Byrd, 2003).
Security refers to the technological safeguards that ensure compliance with regulatory obligations and best practices regarding privacy (Casaló et al., 2007b). In the context of online systems, security has been defined as "the extent to which a consumer believes that making payments online is secure" (Vijayasarathy, 2004, p. 751). Security is a key factor when discussing technology because technological uncertainty generates a threat "in the form of destruction, disclosure, alteration of data, denial of service and/or fraud, waste, and abuse" (Kalakota & Whinston, 1997, p. 853); thus, security breaches may have negative consequences for service companies (e.g., Zhang et al., 2022). In the online banking context, systems perceived as more secure are considered to provide greater value because they ensure that the transaction is free from safety failures (e.g., attacks to the data transactions) (Lee, 2009). Security in online banking is a challenging issue to ensure customers' evaluation of the system as sufficiently beneficial for them to be willing to rely on such a platform (Bestavros, 2000; Lee, 2009).

Amalgamating all of these issues and adapting the reasoning to the robo-advisor context, we propose that both features (ease of use and security) will have a positive influence on the perceived benefits of using robo-advisors:

H1: Perceived ease of use (a) and security (b) have a positive influence on the perceived benefits of using robo-advisors.

Furthermore, customers' evaluation of risks is a very important factor in the decision-making process in the online environment. Peter and Ryan (1976) defined perceived risk as the prediction of losses linked to a purchase, which inhibits purchasing behavior. Lee (2009) defined perceived risk in online banking as the subjective perception of loss when considering a particular online transaction made by the user. Risk is particularly relevant when it deals with important decisions such as managing personal investments (Koller, 1988).

Cunningham (1967) distinguished between performance and psychosocial risks and identified six risk dimensions: performance, financial, opportunity/time, safety, social, and psychological risks. However, not all of these risk categories can be applied to every context (Sharifpour et al., 2014; Wangenheim & Bayon, 2004). Since online banking platforms do not incur any danger to human life (Lee, 2009) and security should be considered as the customer's perception about a characteristic of the system rather than a psychological risk (Ameen et al., 2021b; Robbins & Stylianou, 2003), these dimensions are excluded in our context following previous research recommendations (Birinci et al., 2011; Lee, 2009; Sharifpour et al., 2014). Consequently, our research focuses on the following dimensions of risk: performance, financial, social, and time. Conceptually, each type of risk could be considered to be a different dimension. For example, performance risk is directly linked to the outcomes obtained by the platform, not performing as it was supposed to and failing to fulfill what was expected (Grewal et al., 1994). In the case of financial risk, it is defined as the possibility of financial loss owing to transaction error or bank account abuse (Featherman & Pavlou, 2003). Social risk refers to the disapproval of the people who surround us, such as friends, family, and colleagues (Featherman & Pavlou, 2003). Opportunity or time risk refers to the loss of time and inconvenience caused as a result of payment delays or difficulties in the navigation process. This risk is related to the length of time taken to learn how to use the platform, searching on the website, or if the program is too slow (Forsythe & Shi, 2003).

Perceived risks are a significant barrier to customer acceptance of e-services (Featherman & Pavlou, 2003) particularly in online financial services (Lee, 2009). Systems that are perceived as easy to use are considered to be less complex, less problematic, with fewer usage uncertainties, and having fewer performance problems. Therefore, ease of use has usually been proposed to reduce the risks of an online system (Featherman & Pavlou, 2003). At the same time, as the platform is perceived to be more secure, it is expected that the customer will have a lower perception of risk. In a longitudinal study of online services, Ha and Pan (2018) found that if a customer receives positive security information regarding a system, the perceived risks of that system are lower for such a customer the next time they use it. Also, in mobile payment services, customers prefer more secure platforms to avoid potential risks (Link et al., 2011). Thus, adapting this reasoning to the robo-advisor context, we propose that:

H2: Perceived ease of use (a) and security (b) have a negative influence on perceived risk of using robo-advisors.

Loyalty refers to a stable customer behavior expressed over time to establish a fruitful user–brand relationship (Casaló et al., 2008). Loyalty leads to higher purchasing intentions (Casaló et al., 2007a), so it is essential in business. Thus, managers are always searching for methods to gain customers' loyalty (Andreassen, 1999). Having loyal customers has many advantages and represents an essential factor for company success and sustainability (Flavián et al., 2006; Keating et al., 2003).

Another key variable in relational marketing is WOM. This can be defined as informal communication between people with regard to the evaluation of services (Dichter, 1966). It is considered to be one of the strongest forces in the marketplace (Bansal & Voyer, 2000). The power of this variable relies on the fact that customers' opinions expressed through WOM influence other customers to behave accordingly in the future (Lutz & Reilly, 1973). Moreover, customers tend to believe informal and personal communication sources rather than formal ones that could be perceived as biased due to companies' commercial purposes. As the person providing WOM information has nothing to gain, this communication channel is effective and is considered to be a more objective information source (Kozinets, 2002).

As mentioned above, robo-advisory services present numerous benefits that could attract customers to this form of financial innovation (Isaia & Oggero, 2022). In comparison to human advisory services, robo-advisors reduce costs, improve accessibility (through ubiquity due to the relatively small initial investment), and provide transparency in transactions (Flavián et al., 2022; Isaia & Oggero, 2022). Robo-advisors increase customers' investment possibilities, such as by investing in different products simultaneously, by planning a schedule for new investments, or by investing in other markets around the world. Previous studies suggest that higher perception of benefits leads to higher behavioral intention by customers (Lee & Heo, 2020). For instance, customers who see the benefits of online systems want to take advantage by using those systems (Kang & Shin, 2016). They may also want to share these advantages with others to place themselves in a positive light (Uslu & Karabulut, 2018), so that a greater benefits' perception can also lead to higher WOM intentions. For these reasons, we propose that:

H3: Perceived benefits of using robo-advisors have a positive influence on loyalty (a) and WOM intentions (b) of using robo-advisors.

Perceived risk, however, has been shown to negatively influence the intention to perform any kind of transaction in the online context. Previous literature proposed that risk perceptions significantly influence consumer behavioral intentions (Bach et al., 2020; Yi et al., 2020). When a person is immersed in the process of deciding what product to buy or what service to use, they tend to avoid the alternatives that imply risk (Jarvenpaa et al., 2000). In this connection, Kesharwani and Bisht (2012) argued that perceived risks negatively influence behavioral intentions toward the use of electronic transactions, and Jarvenpaa et al. (2000) showed that reducing the perceived risks of online transactions improves the likelihood of a buyer making a purchase

Similarly, when a service is perceived as having low risk, people are willing to recommend it to their acquaintances. Hwang and Choe (2020) found that perceived risks damage service image, which in turn reduces customer intention to engage in positive WOM. If the service implies a higher risk, people have less intention of talking about it to their relatives and friends, in order to avoid others being harmed by that product or service (Lampert & Rosenberg, 1975). Following the same pattern, we argue that when the robo-advisor is perceived as riskier, people will be less loyal and less willing to spread WOM. Consequently, we propose the following hypothesis:

H4: Perceived risks of using robo-advisors have a negative influence on loyalty (a) and WOM intentions (b) of using robo-advisors.

As we suggested before, a more favorable customers' evaluation of the benefits of using a robo-advisor would lead them to increase their loyalty and WOM intentions. However, this influence can be challenged when customers perceive that the use of a service entails a high level of risk (Lin & Fang, 2006). Indeed, recent research on fintech identified perceived risk as a moderating variable, particularly in the early stages of the adoption process (Belanche et al., 2022). Previous literature on service innovation showed that, even when customers perceive an improvement in service due to the introduction of a new technology, the positive effect of these benefits on loyalty vanishes due to negative perceptions about the service provider (e.g., Nijssen et al., 2016).

The benefits of a new system can make the customer consider the platform worthy. However, a high level of risk would make customers reconsider that decision, that is, the initial wish for robo-advisor services would not be enacted due to the risks to be assumed. Consequently, it is expected that perceived risks will moderate the relationship between perceived benefits and loyalty in a negative way. The same moderation effect would affect the relationship between perceived benefits and WOM. Users who would be willing to speak positively about a service would repress these intentions due to perceived risk to avoid feeling regret or guilt resulting from harming others by giving bad advice (Lin & Fang, 2006). In this case, and following the previous reasoning, we propose our last hypothesis:

H5: Perceived risks of using robo-advisors negatively moderate the relationship between perceived benefits and loyalty intentions (a) and between perceived benefits and WOM intentions (b).

Control variables

Based on past research, demographic variables such as age, gender, and income might exercise an influence on the customers' decision process affecting two behavioral intentions: loyalty and WOM (e.g., Melnyk et al., 2009; Mittal & Kamakura, 2001). Thus, we consider these three variables as controls.

Method

Data collection

The data collection process was based on an online survey addressed to potential users of robo-advisors in the US. The participants were recruited through a market research company. Following the instructions of the ethical code for social sciences research approved by our University Management Team (6.8/2018), before completing the questionnaire, participants were provided with information on the scientific purpose of the study and data protection and they gave their explicit informed consent. Questionnaire respondents received an incentive payment, and response quality control measures (i.e. attention and item understanding checks) were applied. According to previous studies (e.g., Belanche et al., 2019), participants were required to have previous experience with online financial services. Following this method, we finally obtained a sample of 596 US participants with the following socio-demographic characteristics: gender (59.90% female), age (<25 years 12.25%, 25–34 years 32.72%, 35–44 years 28.02%, 45–54 years 17.28%, 55 or older 9.73%), and income (<$5,000 3.19%, $5,000–10,000 8.05%, $10,001–25,000 30.37%, $25,001–50,000 35,74%, $50,001–100,000 17.62%, >100,000 5.03%). Following Podsakoff et al. (2003), the questionnaire was designed to guarantee the anonymity of participants, ensure there were no right or wrong answers, and avoid item ambiguity, complicated syntax, and vague concepts.

Following Flavián et al. (2022), the research questionnaire started with a general description regarding financial robo-advisors including some images from specific robo-advisor applications, but without linking them to any specific brand name to avoid any reputation bias (e.g., MacKenzie et al., 1986). The scenario description is presented in Appendix 1. In addition, following Viglia et al. (2021), to improve realism—and hence the external validity and generalizability of the results—we presented participants with an investment situation in which they had to make choices (i.e., use and recommend robo-advisors). Thus, participants were asked to assume an investor role in the situation and react as if they were in that situation (Taylor et al., 2021; Viglia et al., 2021). Specifically, we described that they had some money for investment and explained that their banks offered them the possibility of investing using the robo-advisor.

After all the information was presented, the respondents answered the questionnaire, which included multi-item scales adapted from previous studies to measure the research variables: perceived security (Belanche et al., 2015; Kim et al., 2008;), perceived ease of use (Davis et al., 1989), perceived benefits (Lee, 2009; Yiu et al., 2007), perceived risk (performance risk, financial risk, social risk, and time risk [Featherman & Pavlou, 2003; Lee, 2009]), loyalty intention toward the robo-advisor (Bhattacherjee, 2000), and WOM intention (Belanche et al., 2021a). After the authors had adapted the original scales to the research context, a panel of 10 experts in service research and technology adoption evaluated each item's representativeness of the construct of interest (i.e. they evaluated each item as clearly, somewhat, or not representative). In line with previous proposals in the literature (Lichtenstein et al., 1990; Zaichkowsky, 1985), we retained the items that achieved a high level of consensus, namely those that were classified by at least 80% of the experts as clearly or somewhat representative of the construct. This method improves face validity, thereby ensuring a valid operationalization of the research constructs (Hardesty & Bearden, 2004). All scales (see Appendix 2) employed a seven-point Likert-type response format, from 1 ("completely disagree") to 7 ("completely agree").

Estimation procedure

Similar to recent studies in service research (e.g., Belanche et al., 2021b; Schepers et al., 2022; Anasori et al., 2023), data were analyzed using partial least squares (PLS) because of its ability to deal with higher-order constructs (Sarstedt et al., 2019) and simultaneously handle both reflective and formative factors (Chin, 1998)—perceived risk in our case. PLS is particularly suitable to develop prediction-based models that focus on identifying key driver constructs (Hair et al., 2011), and for exploratory research and when the phenomenon under research is relatively new (Roldán & Sánchez-Franco, 2012). This aligns with our research objectives. Specifically, we employed SmartPLS 3.0 statistical software (Ringle et al., 2015).

Given that customers' perceived risk is a higher-order reflective-formative construct, we estimated our model using a two-stage approach (Ringle et al., 2012). The first step served to obtain the latent variable scores of the first-order dimensions used to measure perceived risk (i.e., performance risk, financial risk, social risk, and time risk). In the second step, the latent variable scores obtained for each dimension were included as the measures of perceived risk in a formative way. Finally, a non-parametric bootstrapping procedure with 10,000 sub-samples, no sign change, was used to assess the significance of paths and indicators.

Measures' validation

Following the two-stage approach, we first evaluated the reliability and convergent validity of the first-order reflective constructs. In particular, the factor loadings of construct indicators are all above the threshold of 0.7 (Henseler et al., 2009), supporting their reliability. In addition—as can be seen in Table 2—Cronbach's alpha values are above 0.7 (Nunnally, 1978), composite reliability values are above 0.65 (Jöreskog, 1971), and the average variance extracted (AVE) is higher than the cut-off value of 0.5 suggested by Fornell and Larcker (1981), which supports convergent validity. We next evaluated the discriminant validity (see Table 2) by checking that the square root of the latent variables' AVE was higher than their correlations with other variables (Fornell & Larcker, 1981). We also assessed the heterotrait–monotrait (HTMT) ratio of the correlations, and all of them were lower than 0.9 (Henseler et al., 2015). Finally, we checked that each indicator's factor loadings were higher for its assigned construct than for other variables. These criteria support the discriminant validity of our variables (Table 2).

INSERT TABLE 2 AROUND HERE

After evaluating the measurement model of our first-order reflective constructs, the model was re-estimated by incorporating the latent scores of performance risk, financial risk, social risk, and time risk as indicators of risk in a formative way. The validity of this formative construct was confirmed by three different criteria related to limited multicollinearity (Diamantopoulos & Winklhofer, 2001), significance of weights (Chin, 1998), and theoretical content and expert opinion (Rossiter, 2002). As can be seen in Table 3, variance inflation factor (VIF) values were calculated, showing acceptable values < 3.3 (Ali et al., 2016), and indicators exhibit significant weights on the formative construct at the .05 level with the exception of performance risk. However, as Diamantopoulos and Winklhofer (2001, p. 273) noted, "indicator elimination—by whatever means—should not be divorced from conceptual consideration when a formative measurement model is involved". Thus, non-significant indicators in formative constructs should be retained as they may still capture some part of the construct and not considering them may alter the conceptual meaning of the construct and cause specification problems (Andreev et al., 2009). Therefore, we decided to maintain this item due to its theoretical relevance in forming risk (Featherman & Pavlou, 2003; Lee, 2009).

INSERT TABLE 3 AROUND HERE

Finally, following Kock (2015), the whole model is considered to be free of common method bias as all factor-level VIF are lower than 3.3.

Results

Once the measures were validated, we analyzed the structural effects proposed in the model and their significance. First, we assessed the global fit of the structural model through the standardized root mean residual, obtaining a value of .064, which indicates an adequate global fit as it is below the cut-off value of 0.08 (Hu & Bentler, 1998). The path estimates are shown in Figure 2.

INSERT FIGURE 2 ABOUT HERE

Regarding the research hypotheses, we first evaluated the influence of customers' perceptions about the robo-advisors' features on customers' evaluations (i.e., benefits and risks). As theoretically proposed, ease of use (β=.357; p<.01) and security (β=.461; p<.01) have a positive effect on robo-advisor benefits, supporting H1a and H1b. In contrast, ease of use (β=-.352; p<.01) and security (β=-.165; p<.01) have a significant negative impact on risk, which supports H2a and H2b. Following this pattern, while the benefits considered by users have a significant positive influence on loyalty (β=.573; p<.01) and WOM intentions (β=.561; p<.01), supporting H3a and H3b, the risks exert a negative influence on both loyalty (β=-.246; p<.01) and WOM intentions (β=-.193; p<.01), supporting H4a and H4b, too. Finally, the results of our study support risk as a moderating factor. In particular, perceived risk moderates the influence of benefit on both loyalty (β=-.092; p<.01) and WOM intentions (β=-.086; p<.01) in a negative way, in support of H5a and H5b, respectively. That is, the positive influence of perceived benefit on these variables is reduced as perceived risk increases.

To better illustrate this moderating effect by comparing by groups, we followed the procedure of Belanche et al. (2021b) and divided customers evaluating high and low levels of risk according to their mean scores of risk measures. The same process (divide customers based on the mean of the reported scores) was carried out to distinguish between customers evaluating the benefits as high or low. Following this process, we confirmed that the difference in loyalty and WOM intentions between those who perceived high levels of benefits and those who perceived low levels of benefits is greater when perceived risk is low. As an example, Figure 3 shows the interaction effect between risk and benefit on loyalty intentions.

INSERT FIGURE 3 ABOUT HERE

Regarding the control variables, we observed that compared to females, males exhibit greater loyalty and WOM intentions. Similarly, young people are more related to WOM intention, but we found no influence of age on loyalty intention. In turn, income does not exert any significant influence on our dependent variables. All these relationships allow us to partially explain our endogenous variables: benefit (R^2=.471), risk (R^2=.197), loyalty intention (R^2=.509), and WOM intention (R^2=.444). Specifically, these values imply a small fit for risk and a medium fit for benefit, loyalty, and WOM intentions (Chin, 1998).

Finally, according to our results, perceived benefit and risk can mediate the effect of robo-advisor characteristics (i.e., perceived ease of use and security) on customers' behavioral intentions (i.e., loyalty and WOM intentions). Therefore, we followed Chin (2010) and Zhao et al. (2010) and analyzed these potentially mediated relationships by calculating the bias-corrected and accelerated confidence intervals of such effects, using 10,000 sub-samples, no sign change. The indirect effects in each sample were used to build confidence intervals. These effects are significant when the intervals exclude the value 0. Table 4 shows the results of this mediation analysis. As can be seen, there are significant and positive indirect effects of perceived ease of use and security on both loyalty and WOM intentions, via benefit and risk. In particular, these indirect effects are stronger via benefit than via perceived risk, suggesting that robo-advisor features are crucial to increase the benefits considered by users when deciding to use and recommend them. Yet, these features play a less relevant role in reducing the risk considered to be a barrier by customers.

INSERT TABLE 4 AROUND HERE

Discussion

The findings presented in this study allow several conclusions to be drawn. First, in line with decision theory, according to which individuals are more rational in making decisions in uncertain environments, our results indicate that a reduction of risk in financial operations would boost customers' use of financial robo-advisor services. Risks are perceived negatively, and negative perceptions affect people's loyalty toward the service (Bhattacherjee, 2000) and their willingness to communicate about it to others (Belanche et al., 2021a). We found that this effect is particularly relevant in the case of the customer's decision-making on whether or not to use the service. Therefore, any mechanism that reduces the risk of using financial assistance services from robo-advisors would contribute to successful implementation of this innovation.

Second, although both security and ease of use contribute to increasing the perceived benefits of using robo-advisors, the effect of security on the perceived benefits appears to be stronger. Although ease of use is relevant to customers who adopt a financial advice service with robo-advisors, it is critical to improving their perception of the service as an advantageous option that they consider making payments and exchanges online to be secure (Vijayasarathy, 2004).

Third, this study confirms the findings of previous research that ease of use and security have a negative influence on the perception of risk (Mariani et al., 2022; O'Neill, 1977), although ease of use exercises a stronger negative effect on risk than does security. Robo-advisors can perform relevant support tasks, helping and advising customers and reducing the effort involved in using financial advice services. These aspects are essential to reduce the perception of risk and, consequently, to increase customer willingness to be loyal to the service and recommend it to others.

Fourth, perception of the benefits of using robo-advisor financial services is a factor in ensuring that customers use and recommend such services, as previous research has pointed out (e.g., Flavián & Casaló, 2021). However, risk can interfere with how customers internalize and interpret the benefits (Mariani et al., 2022; Nijssen et al., 2016). The current study demonstrates that when the perception of risk increases, the strength of the positive effect of the benefit on loyalty and WOM tends to decrease. Thus, risk and benefit do not operate independently in the customer decision-making process; when they internalize the stimuli that they receive through financial assistance with robo-advisors, customers tend to balance the two aspects.

Fifth, we find that in shaping customers' overall risk perception, financial and temporal risks (Featherman & Pavlou, 2003; Forsythe & Shi, 2003) are the most important. Thus, above all other risks, customers are worried about losing money due to the intervention of a robo-advisor instead of a human consultant, and about the loss of convenience and time involved in learning to use and adapt to the robo-advisor.

Finally, age negatively affects the willingness to recommend robo-advisors' financial assistance services. Indeed, it is to be expected that older customers are less likely to use this type of service where there is no human intervention on the provider's side. Younger customers tend to be more open to novelties, especially those associated with technology (Castillo et al., 2021; Flavián et al., 2022; Mainolfi et al., 2022). In addition, men tend to be more loyal and recommend these services more often than women. Although this is contrary to common findings (Mittal & Kamakura, 2001), this result is usual when dealing with new technology-based services (Belanche et al., 2020).

Theoretical implications

The main theoretical contribution of this research is the combination of the SOR model with decision theory to propose a new model of customers' responses to robo-advisors, a cutting-edge technology reshaping service industries (Ameen et al., 2021a; Belanche et al., 2020). The proposed model presents ease of use and security as stimuli for the experience of using financial advice services with robo-advisors. These stimuli are internalized and interpreted by customers in the form of benefits and risks (organism). Thus, benefits and risks operate as the inner cognitive assessment that a customer carries out based on the information received through the stimuli provided by ease of use and security. The balance of benefit and risk leads to the customer responses of loyalty and WOM. When the cognitive assessment (the customer's internal analysis of the risks and benefits) is positive, then the response will be to use and recommend the robo-advisor for managing investments. In contrast, when the balance between risks and benefits is negative (that is, the risks outweigh the benefits in the customer's mind), then the response will be not to use or recommend the robo-advisor for managing investments.
Furthermore, the proposed model demonstrates the relevance of ease of use and security in the perception of benefit and risk by customers when using robo-advisors in advanced analytical AI-performing financial services. While the benefit has a similar influence on loyalty and WOM of these innovative services, the risks—especially financial and time—primarily affect customer loyalty. This study combines decision theory and the SOR model through customers perceptions about benefits and risks (organism). Specifically, the cognitive assessment evaluation process, with customers balancing the risks and benefits of relying on robo-advisory services to manage their investments, is based on decision theory.

A further research implication is that perceived risk can act as moderator in the relationship between benefit and loyalty and benefit and WOM. Risk can interfere negatively with the strength of these relationships. During the experience of using a robo-advisor financial service, as customers perceive the risk associated with it (Ben-David & Sade, 2018), the smaller the positive effect of its benefit on customer loyalty and WOM tends to be. Thus, this study adds to the organism component of the SOR model by introducing two new elements and their relationship (the balance between risks and benefits) to the customer inner cognitive process assessment.

Managerial implications

The findings have four managerial implications. First, it is of paramount importance that robo-advisors have mechanisms to ensure the safe transmission of customers' information and to make safe investments. Only a robo-advisor that is perceived as safe in executing its tasks can create a perception of benefit for its human customers. That perception makes customers willing to interact with the robo-advisor in another service encounter and, at the same time, drives them to recommend the robo-advisor's services to others. Therefore, companies offering robo-advisors should develop plans to ensure security and to communicate this crucial feature of robo-advisors to users.

Second, it is not only important for the robo-advisor to be perceived as safe when transmitting the customer's information and making secure investments; the robo-advisor must also be able to reduce the perception of risk. The two types of risks that are the most relevant in the customer's mind are financial and time risks. In terms of financial risk, managers and robot designers should seek to reduce the possibility of customers losing money because of mistakes made by the robo-advisor. Banks and other fintech services could also assume the risk by compensating customers for any mistakes made by the robot (although this measure might be very costly). In terms of time risk, the fact that customers are unwilling to spend significant amounts of time learning how to operate in the system through the robo-advisor reinforces the importance of ensuring that the whole system is easy to understand and to use.

Third, managers should be aware that younger customers are more likely than older customers to adopt robo-advisor services. This finding suggests that robo-advisors could be preferentially targeted to a younger audience, encouraging this group of customers to start using AI rather than human advisory services and to spread WOM among their peers.

Finally, as male users are more willing than female users to become loyal in using robo-advisors, we recommend that managers focus more on understanding the features of the robo-advisor that can improve female users' perception of safety and risk reduction. In this connection, managers could organize customer workshops to demonstrate how safe robo-advisors can be. Nevertheless, to increase the perception of safety and ease of use, it remains essential for the robo-advisor to adapt to the customer's profile.

Limitations and further research lines

As in any research, the findings of this study should be interpreted carefully due to its limitations. The survey respondents were from the United States, and the US market has particular characteristics (e.g. a proliferation of regional/state banks and online intensive users). US citizens are also likely to have different concerns about personal data and security compared to European citizens, and these differences may affect their responses. Thus, the proposed model should be replicated and analyzed with data from other countries with different cultural contexts (Belanche et al., 2019). Experimental designs focused on different segments of the market would help to assess the effectiveness of communication campaigns that could contribute to the diffusion of robo-advisors (e.g., how to approach older customers).

Although our research identifies risk as the principal barrier for using and recommending robo-advisors, previous studies on the introduction of AI in non-financial settings found alternative concepts to capture this technology avoidance, such as perceived sacrifices (Ameen et al., 2021b), negative emotions (Schepers et al., 2022), or even “creepiness” (particularly when they have a physical appearance, Ostrom et al., 2019). Further research should focus on establishing how the adaptation of such negative influences in each industry may be compared or integrated in a more general conceptualization of avoidance.

Although robo-advisors represent a higher level of analytical AI development, they do not create affective bonds and research on feelings about AI are still scarce (Huang & Rust, 2021). Future research should explore how these innovative services could incorporate social bonds with customers as some other technologies, such as social robots, have begun to accomplish (Schepers et al., 2022).

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APPENDIX 1 – SCENARIO DESCRIPTION

This research has been designed by University of Zaragoza for academic purposes.

In recent years, many banks and financial service providers have introduced automated advisories that help customers to manage their investments.

A robo-advisor is a banking automated service specifically created to manage a portfolio of investments. This service is based on technology and uses a computer algorithm, which is a set of rules for choosing appropriate investments based on personal risk tolerance and time horizon. Robo-advisors will also automatically rebalance a customer's investments when the time is right and use tax harvesting strategies to reduce tax liability. This service is expected to reduce the cost of financial advisor fees.

Robo-advisors offer websites and mobile apps to provide automated, professionally based recommendations and management. Suppose that you have some money to invest and that your bank gives you the option to use a robo-advisor as an additional investment choice.

This questionnaire has been designed to assess customers' opinions and decisions about these services.

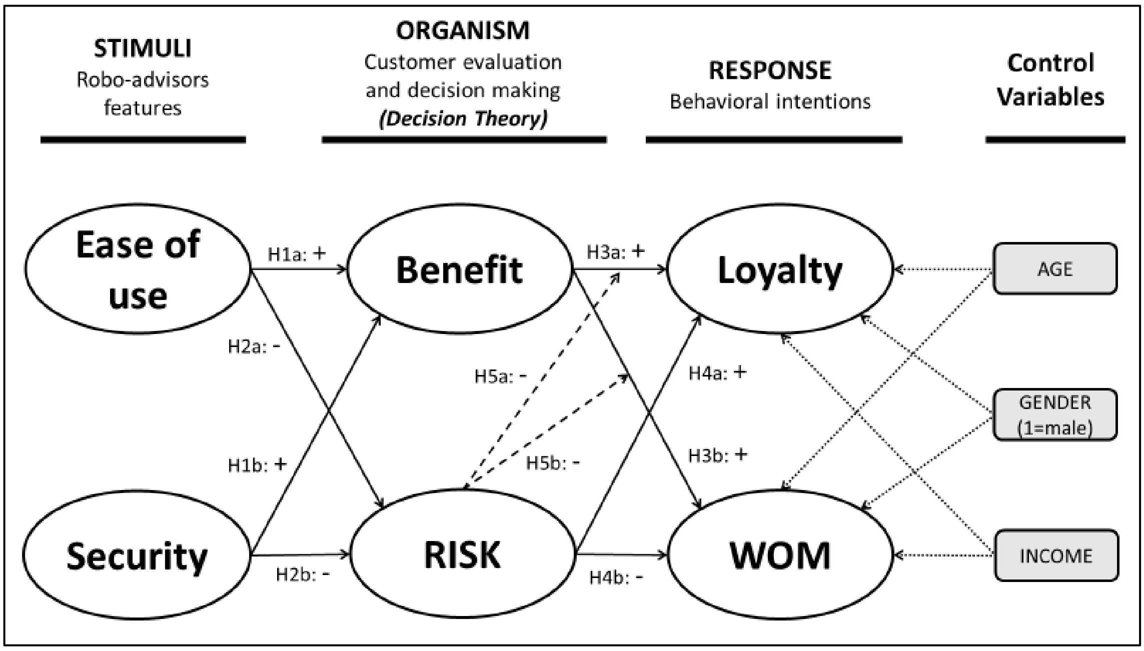
(The description included four illustrative screenshots of real financial advisor interfaces, displaying graphs and rates. The screenshots were adapted to avoid brand familiarity bias; i.e., colors, fonts, and figures were altered, and company names were omitted.)

APPENDIX 2 – MEASUREMENT SCALES

Ease of use (adapted from: Davis et al., 1989)
Learning to use robo-advisors would be easy for me
I would find it easy to manage investments using robo-advisors
It would be easy for me to become skillful at using robo-advisors
I would find robo-advisors easy to use
Security (adapted from: Belanche et al., 2015; Kim et al., 2008)
I think robo-advisors would have mechanisms to ensure the safe transmission of their customers' information
Robo-advisors would make investments with security
I would feel safe using robo-advisors for making investments
Benefit (adapted from: Lee, 2009; Yiu et al., 2007)
I think that using robo-advisors can save the management fees in investments
I think that using robo-advisors can save my time in performing investments
I think that using robo-advisors can offer valuable investment opportunities
Risk
Performance risk (adapted from: Featherman & Pavlou, 2003; Lee, 2009)
Robo-advisors may perform wrongly because of slow download speeds, the servers being down, or because the system is undergoing maintenance
Robo-advisors may process investment and operations incorrectly
Financial risk (adapted from: Featherman & Pavlou, 2003; Lee, 2009)

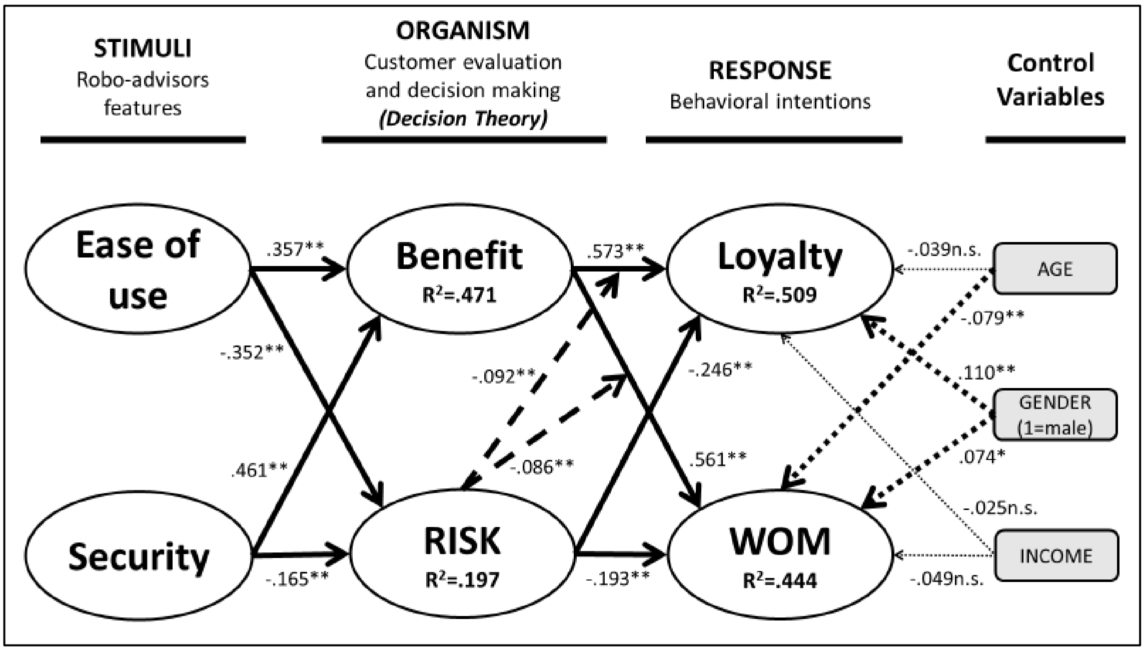
When making investments, I am afraid that I will lose money due to mistakes by the robo-advisor
When a robo-advisor error may occur, I worry that I cannot get compensation from the bank/company
Social risk (adapted from: Featherman & Pavlou, 2003; Lee, 2009)
I'm sure that if I decided to use robo-advisors and something went wrong, my friends, family, and colleagues would think less of me
If my investment incurs fraud or a hacker invades, I would have loss of status in one's social group
Time risk (adapted from: Featherman & Pavlou, 2003; Lee, 2009)
Using robo-advisors would lead to a loss of convenience for me because I would have to waste a lot of time setting up the system and my preferences
It would take me lots of time to learn how to use and manage robo-advisors
Loyalty intention (adapted from: Bhattacherjee, 2000)
I would intend to use robo-advisors for managing investments
Using robo-advisors for managing investments is something I would do
My intention is to use robo-advisors rather than any human financial advisor
WOM intention (adapted from: Belanche et al., 2021)
I would recommend robo-advisors to my friends or others
I would say positive things about robo-advisors to others
I would encourage others to use robo-advisors

Figure 1. Research model



Note: Solid lines represent direct effects; dashed lines represent moderating effects; dotted lines represent control effects.

Figure 2. Path estimates and significance



Note: * significant at the .05 level, ** significant at the .01 level, n.s.- non-significant. Solid lines represent direct effects; dashed lines represent moderating effects; dotted lines represent control effects. Bold lines represent significant effects.

Figure 3. Moderation effect of risk on loyalty intentions

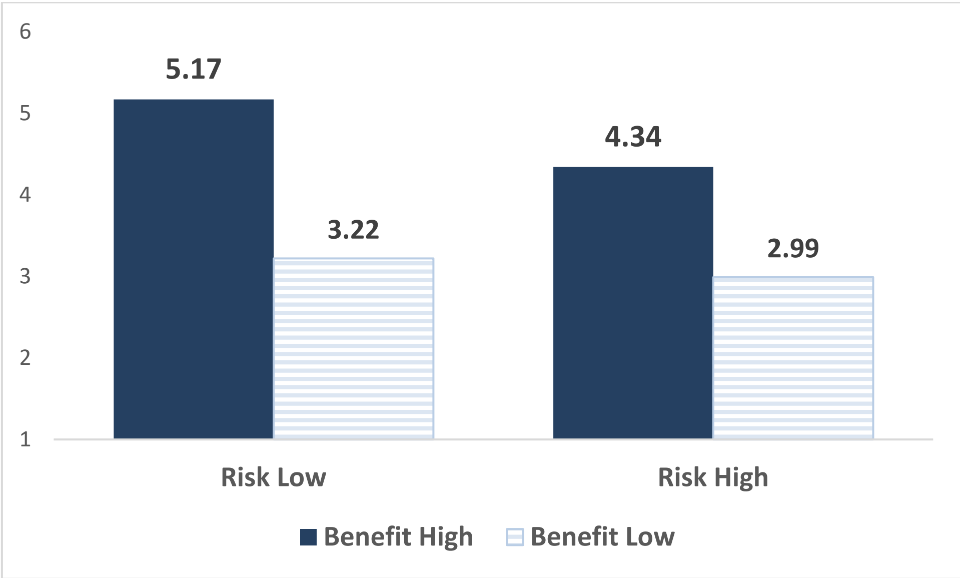


Table 1. Empirical studies of customer acceptance of robo-advisor services

Source	Theoretical framework	Main findings
Belanche, Casaló, & Flavián (2019)	TAM and TRA	Consumer attitude toward robo-advisors, together with mass media and subjective interpersonal norms, determines adoption. Subjective interpersonal norms are particularly influential for users with a lower level of familiarity with robots and for users from Anglo-Saxon countries.
Fan & Swarn (2020)	Diffusion of innovations	The desire to free up time, higher levels of risk tolerance, subjective financial expertise, and a greater quantity of investable assets motivates use of robo-advisors. Customers under 65 with higher risk tolerance and stronger perceived financial expertise are more inclined to employ robo-advisors.
Hildebrand & Bergner (2021)	Interpersonal psychology	Conversational robo-advisors elicit greater affective trust and a more favorable evaluation of a financial services firm than non-conversational robo-advisors. Affective trust increases asset allocation on robo-advisors and investors' recommendation of this innovative service.
Hodge, Mendoza, & Sinha (2021)	Naming effects of technology	Investors are more inclined to rely on the investing recommendations of an unnamed robo-advisor than of a robo-advisor with a human name. This effect is particularly relevant when the advisor is perceived to be performing a relatively complex task; a robo-advisor is preferred for simpler tasks.
Oehler, Horn, & Wendt (2021)	Big Five personality factors, locus of control, PANAS, and trust	Extraversion, optimism, and pessimism (adversely) influence the intention to use a robo-advisor. Participants with a lower locus of control and who are less risk averse are more inclined to use a robo-advisor. Investors who employ robo-advisors and invest in hazardous assets independently have superior financial knowledge and expertise.
Wexler & Oberlander (2021)	Algorithmic authority	The introduction of a robo-advisor is more successful when the algorithmic authority in the programmed services is minimally disruptive, trustworthy, and expands the client base while maintaining industry control over the knowledge domain of the profession.
Zhang, Pentina, & Fan (2021)	Self-service technology adoption	Consumers prefer human financial advisors with extensive knowledge to robo-advisors. There are no major differences between robo-advisors and inexperienced financial advisors in terms of expected performance and hiring intention.
Brunen & Laubach (2022)	Theory of moral licensing and theory of consisting behavior	Consumers make sustainable investment decisions if they care about sustainability but will also carry out activities that are consistent with sustainable values. The findings provide more evidence that evaluating sustainability in terms of real choices is essential.
Flavián, Pérez-Rueda, Belanche, & Casaló (2022)	Technology readiness	Technological optimism increases the intention to use robo-advisors, whereas insecurity decreases that intention. Surprisingly, technical discomfort positively boosts acceptance of robo-advisors, because AI frees customers from complex investment tasks. Customer awareness of robo-advisors positively influences adoption, whereas AI name does not affect adoption.

Isaia & Oggero (2022)	Estimation strategy	People with an advanced degree of financial understanding are more likely to be the target of robo-advisors. Online behaviors with a financial component (e.g., online shopping or digital payments) increase the interest in robo-advisors.
Yeh, Yu, Liu, & Huang (2022)	UTAUT	Technological facilitating conditions directly influence the intention to use a robo-advisor. Performance expectation, effort expectancy, and social influence have an indirect influence through attitude. Investment to income ratio moderates the relationship between performance expectation, effort expectancy, and social influence on attitude.
Current research	SOR and decision theory	Security and ease of use when using robo-advisors influence the perception of benefit and contribute to reducing the perception of risk. Perceived benefit positively influences willingness to use the service and to recommend it to others. Perceived risk, particularly fear of losing money and wasting time, negatively affects the strength of the relationship between benefit and behavioral intentions.

Table 2. Construct reliability, convergent validity, and discriminant validity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	α	CR	AVE
Ease of use (1)	**.921**	*.429*	*.594*	*.303*	*.196*	*.133*	*.560*	*.495*	*.445*	*.010*	*.152*	*.180*	.940	.958	.848
Security (2)	.401	**.883**	*.675*	*.321*	*.240*	*.104*	*.304*	*.644*	*.596*	*.036*	*.106*	*.077*	.863	.914	.780
Benefits (3)	.541	.605	**.899**	*.225*	*.202*	*.149*	*.391*	*.706*	*.663*	*.043*	*.097*	*.076*	.882	.927	.808
Financial Risk (4)	-.267	-.296	-.200	**.912**	*.815*	*.240*	*.469*	*.462*	*.410*	*.049*	*.128*	*.140*	.799	.908	.831
Performance Risk (5)	-.171	-.226	-.188	.651	**.896**	*.125*	*.371*	*.386*	*.326*	*.041*	*.199*	*.136*	.767	.891	.804
Social Risk (6)	-.122	-.089	-.133	.200	.103	**.926**	*.509*	*.046*	*.058*	*.102*	*.125*	*.088*	.837	.923	.858
Time Risk (7)	-.487	-.257	-.320	.374	.292	.409	**.906**	*.272*	*.202*	*.063*	*.043*	*.099*	.783	.901	.820
Loyalty (8)	.467	.609	.650	-.405	-.341	.033	-.231	**.945**	*.883*	*.065*	*.198*	*.036*	.940	.962	.893
WOM (9)	.425	.572	.620	-.361	-.293	.048	-.174	.839	**.964**	*.104*	*.149*	*.003*	.962	.975	.929
Age (10)	-.010	.027	-.019	.020	.017	-.092	.054	-.063	-.102	-	*.016*	*.057*	-	-	-
Gender (11)	.147	.109	.095	-.115	-.170	.111	-.041	.192	.146	.016	-	*.024*	-	-	-
Income (12)	.175	.075	.070	-.127	-.114	-.082	-.090	.035	.003	.057	.024	-	-	-	-

Note: Bold numbers on the diagonal show the square root of the AVE; numbers below the diagonal represent construct correlations; italic numbers above the diagonal represent HTMT values.

Table 3. Items, weights, and VIF of the formative construct

Items in the formative construct: Risk	**Weight**	**t-value**	**VIF**
Financial risk	.589**	5.786	1.660
Performance risk	.145	1.442	1.573
Social risk	.296**	3.032	1.196
Time risk	.593**	5.580	1.333

Note: ** significant at the .01 level.

Table 4. Specific indirect effects

Effects	Estimates	95% bias-corrected and accelerated confidence interval
EOU→BENEFIT→LOYALTY	.205**	(.154; .254)
EOU→RISK→LOYALTY	.086**	(.056; .119)
EOU→BENEFIT→WOM	.201**	(.150; .250)
EOU→RISK→WOM	.068**	(.039; .100)
SEC→BENEFIT→LOYALTY	.259**	(.208; .313)
SEC→RISK→LOYALTY	.040*	(.015; .076)
SEC→BENEFIT→WOM	.264**	(.213; .314)
SEC→RISK→WOM	.032*	(.011; .064)

Note: EOU = perceived ease of use; SEC = perceived security; WOM = word-of-mouth. ** significant at the .01 level; * significant at the .05 level.

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