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Intention to use analytical Artificial Intelligence in services. The effect of technology readiness and awareness

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Purpose: The automation of services is rapidly growing, led by sectors such as banking and financial investment. The growing number of investments managed by artificial intelligence (AI) suggests that this technology-based service will become increasingly popular. This study examines how customers' technology readiness and service awareness affect their intention to use analytical-AI investment services.

Design/methodology/approach: Hypotheses were tested with a data set of 404 North American-based potential customers of robo-advisors. In addition to technology readiness dimensions, the potential customers' characteristics were included in the framework as moderating factors (age, gender and previous experience with financial investment services). A post-hoc analysis examined the roles of service awareness and the financial advisor's name (i.e., robo-advisor vs. AI-advisor).

Findings: The results indicated that customers' technological optimism increases, and insecurity decreases, their intention to use robo-advisors. Surprisingly, feelings of technological discomfort positively influenced robo-advisor adoption. This interesting finding challenges previous insights into technology adoption and value co-creation, as analytical-AI puts customers into a very passive role and reduces barriers to technology adoption. The research also analyzes how consumers become aware of robo-advisors, and how this influences their acceptance.

Originality: This is the first study to analyze the role of customers' technology readiness in the adoption of analytical-AI. We link our findings to previous technology adoption and automated services' literature and provide specific managerial implications and avenues for further research.

Keywords: artificial intelligence, technology readiness, optimism, innovativeness, discomfort, insecurity, awareness, intention to use, robot, robo-advisor, financial services, FinTech.

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1. Introduction

Technological advances in robotics and artificial intelligence (AI) are radically changing service provision (Belanche *et al.*, 2020a; Lu *et al.*, 2020; Robinson *et al.*, 2020). Huang and Rust (2018) predicted that automated technology will gradually replace workers in task requiring mechanical, analytical, intuitive and even empathetic intelligence. Wirtz *et* al. (2018) proposed that AI software that works autonomously, and learns over time, can be distinguished from service robots depending on manifestation (virtual or physical), level of anthropomorphism (from none to high) and task orientation. For companies, AI data and knowledge are likely to become important sources of competitive advantage, based on economies of scale and scope, leading to "winners-take-all" markets (Wirtz *et al.*, 2018).

The banking and finance industries has become prototypical examples of the AI technological revolution worldwide as a sector leading internal and customer-oriented automation processes (Caron, 2019). In this regard, financial technology (FinTech) has revolutionized the finance industry by increasing user value and firms' revenues in the last decade (Huang and Rust, 2021; Kumar *et al.*, 2019; Goldstein *et al.*, 2019).

Within the scope of AI-based financial services, this study focuses on robo-advisor agents, that is, agents which automate or assist in managing investments by replacing human advisory services and/or the customer's own management, a recent innovation in the finance industry (Goldstein *et al.*, 2019). The assets under robo-advisor management are expected to grow annually by 27.0%, reaching US$2,552 billion in 2023, while the number of robo-advisor users is expected to grow by 75.4% year-on-year until 2023 (Statista, 2019). As distinct from most mechanical-based automation (e.g., robots), these innovative services are based on analytical-AI, which has been defined as the ability to process, and learn from, information for problem-solving purposes (Huang and Rust, 2018). Nonetheless, the penetration rate of robo-advisors among customers is still relatively low (Jung *et al.*, 2018b; Belanche *et al.*, 2020a). To address this challenge there is a need to better understand how to integrate AI into service offerings. To this end, several experts in the AI adoption domain (e.g., Mende *et al.*, 2019; van Doorn *et al.*, 2017; Belanche *et al.*, 2020a) have suggested that the technology readiness index (TRI) is a suitable framework, hitherto unexplored, in this novel context.

To address this research gap, we apply the TRI to examine the role of technology readiness in explaining intention to use robo-advisors, prototypical examples of analytical-AI services already accessible to a wide spectrum of customers. Unlike technology acceptance models based on customer motivations, the TRI (Parasuraman, 2000) captures consumers' positive (i.e., optimism and innovativeness) and negative (i.e., discomfort and insecurity) mental readiness regarding technologies. The TRI dimensions assess crucial consumer perceptions in the financial sector, such as their enthusiasm (optimism), perceived control (or discomfort) and service reliability (or insecurity); these often determine the initial investment decisions that can lead to successful long-term relational exchanges (Clark-Murphy and Soutar, 2004). The framework also categorizes users based on their propensity to embrace technologies, as it links personality and technology use (Walczuch *et al.*, 2007) and facilitates the design of segmentation variables (Victorino *et al.*, 2009). Therefore, as robo-advisors represent a disruptive technological advance, the TRI seems particularly suited to understanding customer willingness to use AI-based services.

As a complement to this framework, we propose that customers with higher awareness of robo-advisors may be more willing to use these innovative services. Service awareness, an important variable in other service domains (e.g., Andersen *et al.*, 2000; Crist *et al.*, 2007), has been neglected in previous research based on the assumption that customers are fully aware of the available technologies (Venkatesh *et al.*, 2003); however, these assumptions may be misplaced as these innovations are just starting to penetrate the market. In addition, to increase the practical implications of our research, we propose that renaming "robo-advisors" as "AI-advisors", a more accurate and sophisticated description, unrelated to robots, may increase their acceptance by potential adopters. Finally, previous studies have found that individual characteristics are key in explaining technology usage and proposed them as moderating variables (Sun and Zhang, 2006; Blut and Wang, 2019). Therefore, we include age, gender and previous investment experience in the model as moderating variables (Venkatesh et al., 2003).

The present study's contribution is threefold. First, we empirically investigate the adoption of a prototypical analytical-AI service, financial robo-advisors. Most of the previous research into automation has been conceptual in nature, and the growing number of empirical studies in the field focus on mechanical-AI (e.g., service robots). However, analytical AI represents a more advanced stage in the development of intelligent automation skills (Huang and Rust, 2018), with distinctive features that make it ideal for service personalization and optimal productivity (e.g., it learns from, and adapts to, data, Belanche *et al.*, 2020b, Huang and Rust, 2021). Due to the disruptive nature of analytical-AI and its multiple social and economic implications, there is an urgent need for more research and analysis in this fast-growing area.

Second, by drawing on the TRI framework we assess to what extent regular customers are ready to embrace an autonomous technology that performs analytical tasks traditionally carried out by humans (i.e., investing customers' money). This is the first study to apply the TRI framework to identify if analytical-AI adoption differs from the adoption of previous technological innovations, research which has been repeatedly called for by scholars in the field (e.g., Mende *et al.*, 2019; van Doorn *et al.*, 2017; Belanche *et al.*, 2020a). In contrast to previous new technology adoption literature, our study revealed that technological discomfort does not harm, instead it promotes, the adoption of robo-advisors. That is, customers who feel overwhelmed by technology are more likely to use analytical-AI as it is a simple system that requires minimal user participation. This important finding suggests, in the case of analytical-AI, there is a need to reconsider previous theoretical technology adoption and value co-creation axioms, as users may not, in the future, play such active roles in value creation and decision-making.

Third, our research identified consumer awareness as a critical, but frequently ignored, factor in adoption; thus, to identify how consumers become aware of robo-advisors, a post-hoc analysis was conducted. In summary, this research advances the understanding of customers' decisions about the use of analytical-AI services and can help managers design better strategies for the successful introduction of these innovations.

The remainder of this work is structured as follows. First, we review the previous robo-advisor literature. Second, we develop the research model's hypotheses to explain customers' intention to use analytical-AI services. Third, we describe the data collection procedure and the measurement validation. Next, we present the results of the empirical and the post-hoc analyses.

Finally, we discuss the main conclusions, the theoretical and practical implications, the study's limitations and further research lines.

2. Literature review

AI has been defined as "machines exhibiting facets of human intelligence" (Huang and Rust, 2018, p. 155). Previous research in the service domain has posited that customers approach AI-related services differently to how they approach traditional services (Grewal *et al.*, 2017). Unlike other technologies (e.g., self-service technologies), AI-based systems operate autonomously or with few instructions, often replacing humans (Belanche *et al.*, 2020b; De Keyser *et al.*, 2019). Thus, companies must understand how to introduce AI technologies to reduce barriers to their use by customers (Mazurek and Małagocka, 2019) to improve management practices and product offerings (Kumar *et al.*, 2019).

2.1 Previous robo-advisor knowledge

Robo-advisors have been defined as "digital platforms comprising interactive and intelligent user assistance components that use information technology to guide customers through an automated investment advisory process" (Jung *et al.*, 2018a, p. 81). Financial robo-advisors are based on narrow analytical-AI that technically exceeds human abilities (memory, faster information processing, etc.) (Kaplan and Haenlein, 2019). Robo-advisors provide financial advice with minimal human intervention. From the customer perspective, investing via robo-advisors is simple and practical; they need only around 10 minutes to register and start investing (Belanche *et al.*, 2019). The clients first complete a short online form that evaluates their risk tolerance and return expectations. The AI system then creates a personal investment portfolio and offers recommendations and/or makes automated adjustments based on the consumer's risk profile and objectives. The service is, thus, a prototypical example of an analytical-AI-based technology, widely available to the public.

The previous literature has indicated that the two main advantages of AI-based financial services are profitability and cost savings (Trecet, 2019). In addition, important factors such as transparency and temporal and ubiquitous accessibility to financial services are fundamental pillars of the diffusion of robo-advisors (Belanche *et al.*, 2019; Jung *et al.*, 2018b). Robo-advisors have been described also as instruments that will democratize the investing world by reducing entry barriers to financial advisory services for a wider public (Dayan, 2019); nevertheless, it has not yet been established whether regular customers are ready to embrace these technologies.

From the managerial perspective the scant literature on robo-advisors has focused on legal issues (Jung *et al.*, 2019). These authors suggested that critical robo-advisor weaknesses are lack of personal contact and the risk they will not fulfill regulatory fiduciary requirements. Ji (2017) proposed that companies should be more transparent about the decisions made by asset-allocation algorithms by, for example, revealing how they deal with conflicting interests and risk management. Furthermore, Tertilt and Scholz (2018) highlighted differences in the quality of investment advice offered, positing that robo-advisors usually ask relatively few questions during risk evaluations.

From a customer-oriented approach, Faloon and Scherer (2017) highlighted the value provided by system personalization. Similarly, Glaser *et al.* (2019) examined how the design of service interfaces might affect financial risk taking, particularly in the context of the need to present information differently to individuals making large investments. Focusing on technology adoption models, Belanche *et al.* (2019) found that perceived usefulness, ease of use and subjective norms (i.e., social influences) affected robo-advisor acceptance. Ben-David and Sade (2018) found that performance expectancy and distrust (anxiety) determined preferences for robo-advisors over human advisors.

However, despite the increasing interest in, and expected growth of, robo-advisors, some authors have argued that customers are less enthusiastic about robo-advisors than about banks (Jung *et al.*, 2018b), which may be because customers are not yet ready to rely on AI-driven systems (Belanche *et al.*, 2020a). van Doorn *et al.* (2017) and Mende *et al.*, (2019), focusing on the rise of automated agents, proposed segmenting consumers based on broad measures such as technology readiness (Parasuraman and Colby, 2015).

3. Hypotheses formulation

3.1 Technology readiness

Personality differences are regarded in management and marketing theories as important human behavior determinants. Prior new technology acceptance literature has argued that individual's reactions to technology are diverse (Mick and Fournier, 1998; Ratchford, 2020). This can be explained by the positive and negative feelings technology triggers in customers (Parasuraman and Colby, 2015). In this regard, Parasuraman (2000) developed the TRI, defining technology readiness as "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work" (p. 308). The TRI captures consumers' positive and negative mental readiness regarding technology; it has previously been employed to explain the adoption of innovations such self-service technology in airports (Liljander *et al.*, 2006), C2C platforms (Lu *et al.*, 2012) and mobile payment systems (Martens *et al.*, 2017). Technology readiness (later improved and renamed TRI 2.0 [Parasuraman and Colby, 2015]) is measured through four dimensions; two motivators, optimism and innovativeness, and two inhibitors, discomfort and insecurity. Prior research has underlined the independence of the four dimensions, as each measures the extent of a person's openness to technology differently (Lu *et al.*, 2012).

Technological optimism represents "a positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives" (Parasuraman and Colby, 2015, p. 60). This definition can be extended to AI, as people may perceive it as a "hell" or a "heaven" (Kaplan and Haenlein, 2020). Optimists accept situations and are more willing to use new technologies (Lu *et al.*, 2012), perceiving them as functional and trustworthy, overlooking possible negatives outcomes, than are pessimistic technology users (Walczuch *et al.*, 2007). Thus, optimistic customers are more positively predisposed toward new technologies (Godoe and Johansen, 2012). In the financial sector, more enthusiastic consumers tend to look for new investment opportunities (Clark-Murphy and Soutar, 2004), for example, robo-advisors. Thus, we propose that:

Hypothesis 1: *Customers' technological optimism has a positive effect on their intention to use financial robo-advisors*.

Technological innovativeness has been defined as "a tendency to be a technology pioneer and thought leader" (Parasuraman and Colby, 2015, p. 60). Innovators are willing to try new technologies (Martens *et al.*, 2017) and related services (Rodriguez-Ricardo *et al.*, 2018). Highly innovative people tend to be open-minded and exhibit greater willingness to use technologies, including innovative financial services, for example, mobile payment (Oliveira *et* *al.*, 2016). Furthermore, innovativeness is an antecedent of adoption intentions; innovative customers generally have a positive impression of technology functionality even when its potential value is uncertain (Prodanova *et al.*, 2018). Thus, we propose:

Hypothesis 2: *Customers' technological innovativeness has a positive effect on their intention to use financial robo-advisors*.

Technology discomfort has been defined as "a perceived lack of control over technology and a feeling of being overwhelmed by it" (Parasuraman and Colby, 2015, p. 60). People who experience discomfort with technologies perceive them as complicated and unable to satisfy their needs (Lu *et al.*, 2012). Customers experiencing high levels of discomfort in an unknown technology environment can feel averse toward using new technology-based products and services (Tsang *et al.*, 2004). The feeling of lacking control or the capability to deal with technologies can result in rejection of innovative systems. Customers who feel discomfort in surrendering control to an automated system may not want to use robo-advisor services. Thus, the following hypothesis is proposed:

Hypothesis 3: *Customers' technological discomfort has a negative effect on their intention to use financial robo-advisors.*

Finally, technology insecurity has been defined as "distrust of technology, stemming from skepticism about its ability to work properly and concerns about its potential harmful consequences" (Parasuraman and Colby, 2015, p. 60). Users need at least a rudimentary understanding of how AI systems function to have confidence in them (Kaplan & Haenlein, 2019). Customers with high levels of technology insecurity may avoid using them (Lu *et al.*, 2012). Prior studies have concluded that, in the finance industry, insecure customers tend to refuse to adopt new technology-based services (Oliveira *et al.*, 2016). Thus, we posit:

Hypothesis 4: *Customers' technological insecurity has a negative effect on their intention to use financial robo-advisors.*

3.2 Awareness

Service awareness has been defined as "being conscious of, having knowledge of, or being informed about a given service" (Crist *et al.*, 2007, p. 212). Awareness has not hitherto been closely examined in the technology acceptance literature, but it may be particularly important in the study of recently launched technological services such as robo-advisors. In advertising, awareness refers to product/brand recognition (Hellofs and Jacobson, 1999) and indicates that customers have paid attention to, and are conscious of, information provided about a new product or service.

The scarce literature on service awareness focuses on specific domains. In the elderly care sector, most studies understand awareness as the customers' knowledge about the existence of the service (Andersen *et al.*, 2000). In this sense, individuals with more knowledge about elderly care services are more aware of their options and use them to a greater extent than those hearing about the services for the first time (Crist *et al.*, 2007). Thus, individuals' awareness of services is related to the information they have received, researched and their experiences. Previous research in an organizational context has shown that when employees are aware of their company's corporate social responsibility activities this encourages them to contribute to the company's efforts (Raub and Blunschi, 2014). Applying this concept to this research domain, we propose that customers who are aware of robo-advisors will be more willing to use them. Accordingly, we propose:

Hypothesis 5: *Customers' awareness has a positive effect on their intention to use financial robo-advisors*.

3.3 Moderating effects

Previous research has suggested that individual characteristics may help explain the dynamics of technology acceptance (Sun and Zhang 2006). More specifically, age, gender and the user's previous experience have been proposed as key moderating factors (Venkatesh *et al.*, 2003; Sun and Zhang, 2006).

It has been found that technology adoption decisions made by younger/older users may be based on different factors (e.g., Venkatesh *et al.*, 2003; Wang *et al.*, 2009; Chawla and Joshi, 2020). For example, younger users place more importance on extrinsic rewards, that is, positive outcomes (Venkatesh *et al.*, 2003), which are linked to technological optimism; thus, optimism will be a more important determinant of intention to use robo-advisors for younger than for older users Similarly, younger consumers easily become familiar with new technologies (Hauk *et al.*, 2018). They have grown up in a digital world with easy access to copious information (Brenner, 2020), thus, they are accustomed, and may attach more value, to being up to date. Therefore, optimism and innovativeness may be more important for younger than for older users in the adoption of financial robo-advisors. In contrast, while younger customers feel competent to use digital innovations (Hauk *et al.*, 2018), older customers are typically less skilled in using technological devices and services (Dietrich, 2016). Using new technologies requires fluid cognitive abilities, which decrease with age (Salthouse, 2004). Therefore, technological discomfort and insecurity may be more important barriers for older customers. Finally, as the mental ability to process information decreases with age (Cole and Balasubramanian 1993), older users may limit the amount of information they use in their decision-making, and mainly rely on their own, previously held beliefs (Belanche *et al.*, 2012). Thus, awareness may be more important for older consumers, as it involves being conscious of, and having information about, the new technology, which may help them form more stable and concrete beliefs about the technology. Based on these points, the following hypothesis is proposed:

Hypothesis 6: *Optimism (H6a) and innovativeness (H6b) influence consumers' intention to use financial robo-advisors more for younger than for older customers; in turn, discomfort (H6c), insecurity (H6d) and awareness (H6e) influence intention to use financial robo-advisors more for older than for younger customers.*

Another important moderating factor in the adoption and use of emergent technologies is gender (e.g., Sun and Zhang, 2006; Faqih, 2016; Wang et al., 2009; Chawla and Joshi, 2020). This may be due to the differences between men's and women's decision-making processes (Venkatesh and Morris, 2000), as they consider different factors as more important when evaluating behaviors. The consumer behavior literature has identified that men are more motivated by achievement needs than women (Hoffman, 1972); therefore, with identical levels of technological optimism, men may be more likely to adopt new technologies to achieve gains. Similarly, previous studies have suggested that, traditionally, men are more associated with innovative behaviors than are women (Luksyte *et al.*, 2018); thus, following role congruity (Eagly & Karau, 2002), innovativeness may be a more important factor for men than for women. On the other hand, women tend to exhibit higher anxiety and lower self-efficacy than men when dealing with new technologies (Sun and Zhang, 2006; He and Freeman, 2019), to the extent that they avoid technologies that cause them discomfort (Faqih, 2016). As a result, with identical levels of discomfort and insecurity, women may be less likely than men to adopt new technologies. Similarly, women may value awareness more than do men because it reduces their anxiety levels and increases their perceived self-efficacy. Indeed, as a means of increasing their confidence with a technology, women tend to acquire relevant knowledge, by consulting additional information sources, before making decisions (Burke, 2001), which suggests that awareness may be more important for women than for men (Sorce *et al.*, 2005). Accordingly, we propose:

Hypothesis 7: *Optimism (H7a) and innovativeness (H7b) influence consumer intention to use financial robo-advisors more for men than for women; discomfort (H7c), insecurity (H7d) and awareness (H7e) influence intention to use financial robo-advisors more for men than for women.*

Finally, previous studies have suggested that experienced and inexperienced users form their intentions in different ways (Sun and Zhang, 2006; Venkatesh *et al.*, 2003). The individual's prior experience with financial services may form his/her behavioral intentions, based on his/her habits and favorable predisposition toward investment services (Fishbein and Ajzen, 1975). Consequently, previous experience is another moderator variable that has been extensively examined in technology acceptance studies (Venkatesh *et al.*, 2003; Venkatesh, 2000). Experience also increases customers' perceptions of their ability and confidence to manage new information services (Meuter *et al.*, 2005). Conversely, feelings of insecurity or discomfort may be more important for new than for repeat customers (Constantinides, 2004). Thus, all other things being equal, where the consumer has more investment experience, this will enhance the positive effects of technological optimism and innovativeness, and reduce the negative effects of technological discomfort and insecurity, In turn, service awareness may be more important for less experienced customers than for more experienced customers, as the previous literature suggests that less experienced customers need more information about new products and services to adopt them (Breuer and Brettel, 2012). Thus, the following hypothesis is proposed:

Hypothesis 8: *Optimism (H8a) and innovativeness (H8b) influence intention to use financial robo-advisors more for experienced than they do for less experienced customers; in turn, discomfort (H8c), insecurity (H8d) and awareness (H8e) influence intention to use financial robo-advisors more for less experienced than they do for more experienced customers.*

3.4 Control variables

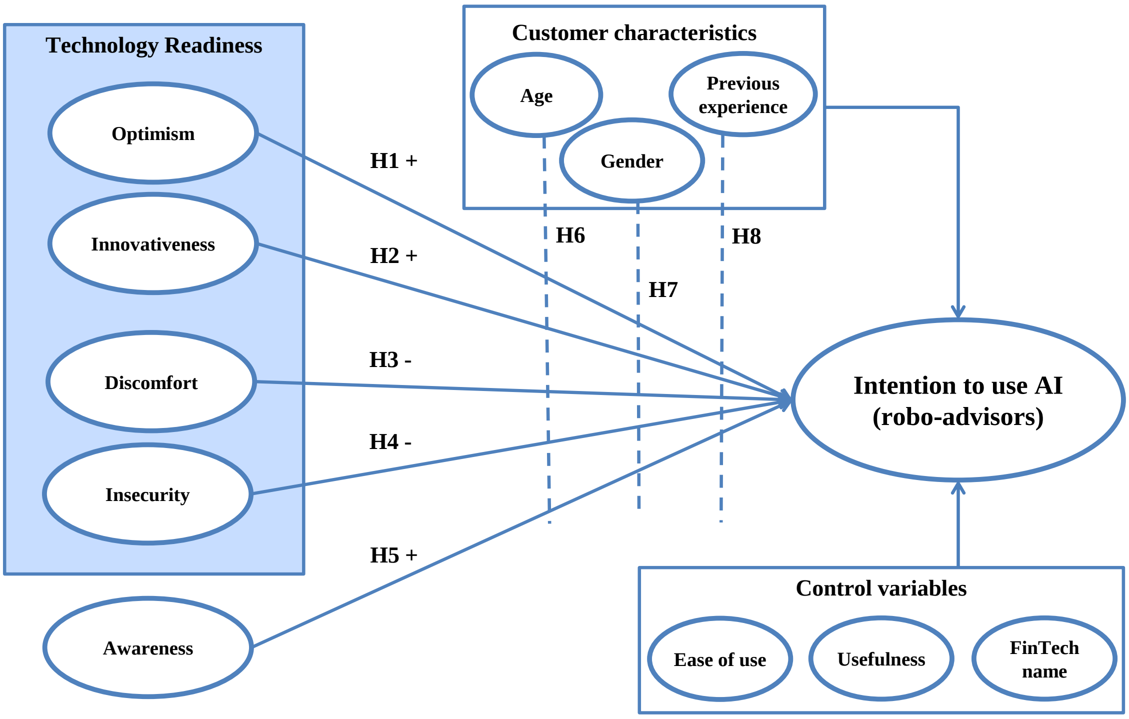
3.4.1. Technology acceptance model (TAM)

The technology acceptance model (TAM) (Davis, 1989; Davis *et al.*, 1989), due to its parsimony and predictive capability, has been widely employed to explain technology adoption in various sectors (Venkatesh *et al.*, 2003). Thus, to complete our framework, we introduce perceptions of ease of use and usefulness (the TAM's two independent variables) as control variables that may exert a positive effect on behavioral intentions toward robo-advisors. Davis defined ease of use as "the degree to which a person believes that using a particular system would be free of effort", and perceived usefulness as "the degree to which a person believes that using a particular system would enhance his or her performance" (Davis, 1989, p. 320).

3.4.2. Socio-demographics

Sociodemographic factors have been shown to be important in the adoption of technology and financial services; they may also exert a direct effect on behavioral intentions (Xiao and Kumar, 2019). In other words, robo-advisors may be more accepted by some customers groups than by others (Belanche *et al.*, 2020a). Thus, for the sake of completeness, the direct effects of age, gender and previous investment experience on intention to use robo-advisors are included in the model.

Figure 1. Research model



Note: Solid lines represent direct effects; broken lines represent moderating effects.

3.4.3. FinTech name

Finally, to increase the contribution of this research, and enhance its managerial implications for this first stage of the adoption process, we manipulated the name given to this new automated financial advisory service. Currently, the term “robo-advisor” (i.e., the contracted form of robotic-advisor) is the academic and industry standard (Jung *et al.*, 2018a; McCann, 2020). However, it includes the word “robot”; robots have been defined as “mechanical devices programed to perform specific physical tasks” (Belanche *et al.*, 2020a, p 205). Thus, the term robo-advisor may mistakenly suggest that this service is provided by a physical machine or humanoid agent. It is proposed that the term “AI-advisor” is much more appropriate, because the tasks are performed through AI, that is, “technologies that mimic or even surpass human intelligence” (Huang *et al.*, 2019, p. 44), not by robots. Indeed, analytical-AI learns from, and adapts to, data input, which represents a higher level of advancement than mechanical technologies (Huang and Rust, 2018; Belanche *et al.*, 2020b). Therefore, despite the increasing popularity of the name “robo-advisor”, we propose that the more accurate and sophisticated term, “AI-advisor”, may directly increase consumers’ intention to use the system.

Nevertheless, this influence may be particularly important for some customers (e.g. those more reluctant to use the technology). Indeed, previous research found that preference for service and brand names often depends on other factors such as consumer socio-demographics (e.g. Klink, 2009), which suggests possible moderation effects on this control variable that we include in our model for the sake of completeness.

Figure 1 summarizes the proposed research framework.

4. Method

4.1 Data collection

The study data were collected through an online survey designed and hosted by SurveyMonkey. An invitation and link to the questionnaire was sent to US-based English-speaking consumers between 20 and 85 years. This sampling process was conducted using a reputable consumer panel comprising over 70,000 consumers unrelated to any specific banking provider. The participants were paid US$1.20. Only those respondents who completed the whole questionnaire in a reasonable timeframe were rewarded/considered for analysis. After removing 14 records due to incomplete responses, the final sample was 404. The sample was very similar in socio-demographic terms to North American consumers aged between 20 and 85 (US Census Bureau Office, 2020). Table 1 shows the participants' and US population's demographics.

The invitation link asked the panelists to participate in a study about financial services. Replicating other experimental design manipulation procedures, for around half of the sample the advisor was referred to as a "robo-advisor", whereas for the other half it was referred to as an "AI-advisor". Some 207 participants were randomly assigned to the AI-advisor scenario, and 197 to the robo-advisor scenario. The name given to the service was the only difference between the scenarios. Both subgroups were similar in terms of gender and age distribution. Specifically, χ^2 tests confirms that there is no significant difference in gender ($\chi^2 = 0.329$, 1 d.f., $p > 0.1$) and age ($\chi^2 = 10.105$, 12 d.f., $p > 0.1$) distributions between both groups. The questionnaires were adapted to the different financial service names. The study's website gave the participants the kind of information normally presented to consumers considering using robo-advisors. First, they were provided with a basic general description of financial robo-advisors (or AI-advisor); this explained that they were new autonomous financial advisors that evaluated the market through analytical-AI, and adapted their advice to the customers' profiles. As robo-advisors have no anthropomorphic appearance, the description included four illustrative screenshots of a real financial advisor interface, showing graphs and rates adapted to avoid brand familiarity bias (i.e., colors, fonts and figures were altered, and company names omitted). The questionnaire included TRI-related scales of optimism, innovativeness, discomfort and insecurity; it also asked the respondents about their level of awareness of these financial services. They were also asked to indicate the perceived ease of use and usefulness of, and their intention to use, robo-advisors/AI-advisors. The final questions covered socio-demographics (age, gender) and previous investment experience.

Table 1. Demographic characteristics

		Survey respondents Percentage	U.S. Census Bureau Percentage*
Gender	Female	47.03	50.97
	Male	52.23	49.03
	Prefer not to say	0.74	
Age (years)	20–24	9.41	8.97
	25–29	10.89	9.83
	30–34	9.41	9.26
	35–39	10.40	9.05
	40–44	6.19	8.27
	45–49	7.43	8.59
	50–54	7.92	8.59
	55–59	11.14	8.94
	60–64	11.39	8.69
	65–69	8.91	7.33
	70–74	4.21	5.97
	75–79	1.73	3.95
	80–84	0.25	2.55
	Not reported	0.74	
Educational level	Primary	1.98	14.82
	High/secondary	14.36	27.01
	University	82.43	58.17
	Not reported	1.24	
Annual Personal Income (US$)	<5,000	6.44	0.46
	5,000–9,999	3.71	0.66
	10,000–14,999	7.67	2.01
	15,000–19,999	5.94	3.57
	20,000–24,900	6.93	6.57
	25,000–34,999	8.91	14.81
	35,000–49,999	14.85	20.34
	50,000–74,900	20.30	23.85
	75,000–99,999	9.41	11.45
	100,000 and over	15.10	16.28
	Not reported	0.74	
Previous investment experience?	Yes	56.93	Not reported
	No	43.07	Not reported

* Source: U.S. Census Bureau Office (2020) for people aged between 20 and 84.

4.2 Measurement instrument

All scales used in the study were adapted from previous literature. Appendix I shows the scale items employed for the robo-advisors (as aforementioned, the scales were also adapted to the “AI-advisor” name). Specifically, we incorporated Parasuraman and Colby’s (2015) TRI; this uses 16 items (four per construct) to measure customers’ levels of optimism, innovativeness, discomfort and insecurity (Parasuraman and Colby, 2015). The consumers’ awareness of robo-advisor services was measured using a three-item scale adapted from Raub and Blunschi (2014) and Collins (2006). Following previous research, awareness was measured using the following question: “How did you know about robo-advisors?” (Kangis and Passa, 1997). Perceptions of ease of use and usefulness were measured using scales developed by Davis et al. (1989) and Bhattacherjee (2000), four items per variable. The participants’ intention to use robo-advisors was measured using three items adapted from Bhattacherjee (2000). All scales used self-reported measures based on 7-point Likert-type response formats, from 1 (“completely disagree”) to 7 (“completely agree”). The demographic questions covered age (1 = 20-24 years, 2 = 25–29, 3 = 30-34, 4 = 35-39, 5 = 40-44, 6 = 45-49, 7 = 50-54; 8 = 55-59, 9 = 60-64, 10=65-69, 11= 70-74, 12 = 75-79, 13= 80-84) and gender (1 = woman, 0 = man); and the participants were asked about previous investment experience (1 = yes, 0 = no).

4.3 Analytical procedure and measure validation

Partial least squares structural equation modeling (PLS-SEM), with SmartPLS 3.0 statistical software, was used to analyze the research model and test the hypotheses. PLS was selected as the estimation method because the main goal of this research is predictive (i.e., to predict intention to use robo-advisors). PLS is appropriate because, as a variance-based (VB) SEM (compared to the covariance-based [CB] SEM), it provides optimal predictive power (e.g., Fornell and Bookstein 1982; Bagozzi, 1994). In addition, PLS modeling is particularly useful for testing exploratory models formed by numerous variables under normality and non-normality data distribution assumptions (Hair *et al.*, 2016; Roldán and Sánchez-Franco, 2012). Similarly, previous literature (e.g., Anderson and Gerbing 1988; Baumgartner and Homburg 1996) has suggested that, to identify a model in CB SEM, a minimum of three indicators per construct must be used. Therefore, as we consider socio-demographics (age, gender and previous investment experience) using only one indicator per construct, and develop a complex model which includes several simultaneous direct and moderating effects, PLS is more appropriate (Davcik, 2014). Finally, this analytical method has been frequently used in well-established service journals (Hogreve *et al.*, 2019; Bacile, 2020).

Table 2. Convergent validity

Variable	Cronbach’s α	CR	AVE
Optimism	0.909	0.936	0.786
Innovativeness	0.902	0.931	0.773
Discomfort	0.838	0.855	0.600
Insecurity	0.771	0.811	0.596
Awareness	0.913	0.945	0.851
Intention to use	0.948	0.966	0.906
Ease of use	0.956	0.968	0.883
Usefulness	0.966	0.975	0.907

Notes: CR = composite reliability, AVE = average variance extracted.

To assess the validity of the measurement model we first confirmed the constructs’ convergent validity. All item loadings exceeded the recommended value of 0.7 (Henseler *et al.*, 2009), except for the first insecurity item ($\lambda = 0.499$), which was removed from the model. As Table 2 shows, both the Cronbach’s α and the composite reliability of the latent constructs exceeded the 0.7 thresholds (Nunnally and Bernstein, 1994). Furthermore, the average variance extracted (AVE) of each construct exceeded the recommended threshold of 0.5 (Hair *et al.*, 2013).

To test for discriminant validity (see Table 3) we verified that the square roots of the AVEs for each construct were greater than the inter-construct correlations (Fornell and Larcker, 1981). Furthermore, the heterotrait-monotrait ratio (HTMT), which evaluates the average of the HTMT correlations, was, in each case, below the 0.85 threshold (Henseler *et al.*, 2015).

Table 3. Discriminant validity

Fornell–Larcker criterion												
	1	2	3	4	5	6	7	8	9	10	11	12
1. Optimism	0.887											
2. Innovativeness	0.431	0.879										
3. Discomfort	-0.162	-0.033	0.774									
4. Insecurity	-0.307	-0.264	0.329	0.772								
5. Awareness	0.193	0.334	0.170	0.011	0.923							
6. Intention to use	0.418	0.308	0.087	-0.217	0.456	0.952						
7. Ease of use	0.345	0.315	-0.092	-0.203	0.300	0.501	0.940					
8. Usefulness	0.333	0.161	0.048	-0.151	0.259	0.644	0.557	0.952				
9. Age	-0.187	-0.327	0.002	0.149	-0.109	-0.213	-0.110	-0.144	1.000			
10. Gender	-0.053	-0.013	0.010	-0.099	-0.121	-0.069	-0.101	-0.052	0.096	1.000		
11. Previous investment experience	0.182	0.272	0.060	-0.082	0.442	0.262	0.277	0.151	-0.019	-0.070	1.000	
12. FinTech name	-0.018	-0.010	0.058	0.069	0.060	0.045	-0.014	0.022	-0.020	-0.029	-0.018	1.000
Heterotrait–Monotrait Ratio (HTMT)												
	1	2	3	4	5	6	7	8	9	10	11	12
1. Optimism												
2. Innovativeness	0.475											
3. Discomfort	0.214	0.171										
4. Insecurity	0.379	0.252	0.544									
5. Awareness	0.213	0.358	0.180	0.078								
6. Intention to use	0.449	0.326	0.065	0.172	0.489							
7. Ease of use	0.368	0.344	0.127	0.142	0.321	0.523						
8. Usefulness	0.354	0.168	0.042	0.116	0.275	0.672	0.576					
9. Age	0.195	0.346	0.114	0.114	0.113	0.217	0.112	0.147				
10. Gender	0.055	0.045	0.019	0.144	0.127	0.070	0.103	0.053	0.096			
11. Previous investment experience	0.192	0.278	0.060	0.075	0.463	0.268	0.283	0.154	0.019	0.070		
12. FinTech name	0.027	0.011	0.076	0.068	0.064	0.046	0.014	0.023	0.020	0.029	0.018	

Finally, we tested for available global model fit measures using PLS-SEM. The normed fit index (NFI) was 0.85, which is close to the recommended 0.90 (Hu and Bentler, 1998). The standardized root-mean-square residual (SRMR) of the research model was 0.05, which is lower than 0.08, indicating good model fit (Hu and Bentler, 1998).

5. Results

5.1. Structural Model

To test the hypotheses and the structural model, the SmartPLS algorithm, followed by bootstrapping with 5,000 subsamples, was used (Hair *et al.*, 2011). The results are presented in Table 4. As to the technology readiness-related hypotheses, the results indicated that customers' optimism significantly influenced their intention to use robo-advisors ($\beta = 0.187$, $p < 0.01$), supporting Hypothesis 1. In turn, customers' level of innovativeness did not have a significant effect on use intentions ($\beta = -0.015$, $p > 0.10$); thus, Hypothesis 2 is not supported. Contrary to expectations, customers' discomfort with technologies had a significant positive influence on behavioral intentions ($\beta = 0.079$, $p < 0.10$); thus, Hypothesis 3, which proposed a negative effect, is not supported. Conversely, customers' feelings of insecurity with the technology had a significant negative impact on their intentions to use robo-advisor financial services ($\beta = -0.094$, $p < 0.05$), supporting Hypothesis 4. In addition, the consumers' awareness of robo-advisors had a significant positive effect on their intention to use these services ($\beta = 0.221$, $p < 0.01$), supporting Hypothesis 5.

Most of the influences exerted by the control variables were consistent with the previous literature. That is, customers' perceptions of both robo-advisors' ease of use ($\beta = 0.125$, $p < 0.05$) and usefulness ($\beta = 0.413$, $p < 0.01$) had a significant positive impact on their decisions to use them. Older customers showed lower intentions to use the service ($\beta = -0.076$, $p < 0.05$). Nevertheless, gender did not have a direct influence on intentions to use robo-advisors ($\beta = 0.001$, $p > 0.10$). Similarly, the customers' previous investment experience did not significantly influence their behavioral intentions ($\beta = 0.025$, $p > 0.10$). Finally, the FinTech name used (AI-advisor vs. robo-advisor) did not have a direct influence on use intentions ($\beta = 0.033$, $p > 0.10$).

The results of the analysis of the moderating effects produced some interesting findings. Age did not moderate the effect of the TRI variables on intention to use. Thus, optimism, innovativeness, discomfort and insecurity affected customers similarly, irrespective of age. However, age moderated the effect of awareness on intention to use ($\beta = -0.083$, $p < 0.10$); being aware of robo-advisors was more important for younger than for older customers. Awareness was also moderated by gender ($\beta = 0.090$, $p < 0.05$), that is, being aware of robo-advisors is more important for women than it is for men. Gender also moderated the effect of innovativeness ($\beta = -0.090$, $p < 0.05$), that is, the influence of innovativeness on intention to use robo-advisors was higher for men than for women. Nevertheless, gender did not moderate the effect of the other two TRI variables. Conversely, investment experience moderated the influence of insecurity on intention to use ($\beta = -0.100$, $p < 0.05$), that is, insecurity acts as an inhibitor of adoption for less experienced customers. Nevertheless, investment experience did not moderate the influence of optimism, innovativeness, discomfort and awareness on behavioral intentions. Finally, the name given to the service, "AI-advisor" or "robo-advisor", did not influence use intentions, or moderate the influence of the other independent variables.

These relationships help explain the dependent variable, behavioral intention to use robo-advisors ($R^2 = 0.566$). This value can be considered to have a high level of explained variance in comparison to previous studies examining behavioral intentions toward technology-based services (Venkatesh and Davis, 2000). As an additional assessment of the model's capability to predict the endogenous variable, we examined the Stone–Geisser Q^2 using the blindfolding technique (Tenenhaus *et al.*, 2005). This indicator showed a value well above zero

(Q^2 = 0.512), thus the observed values of intention to use can be reconstructed as evidence of the model's predictive relevance (Henseler *et al.*, 2009).

Table 4. Results, estimated coefficients and significance

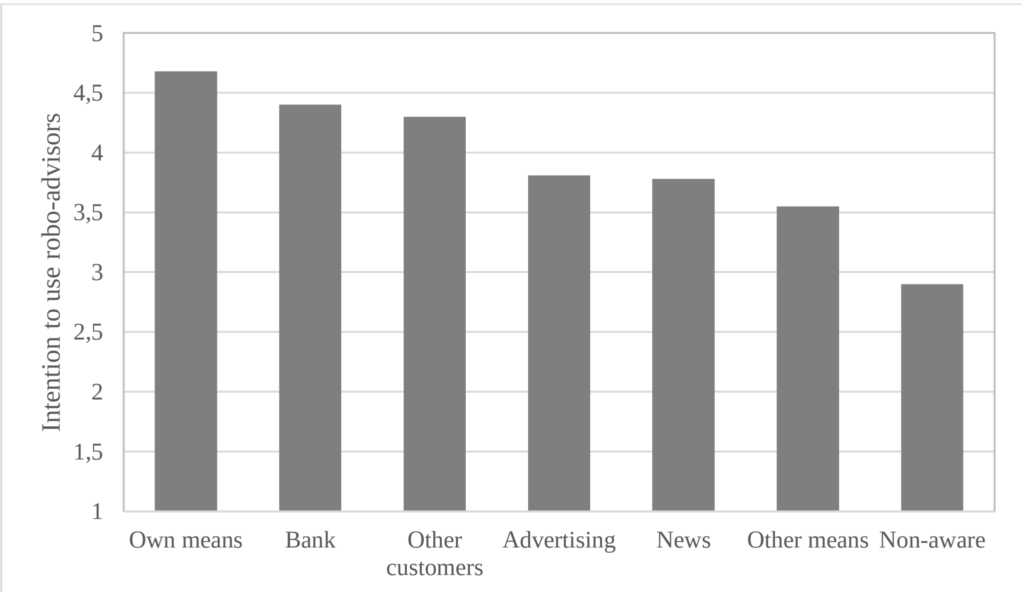
Hypotheses	β	*p-value*	*Supported*
TRI variables			
- Optimism (H1)	0.187***	0.000	Supported
- Innovativeness (H2)	-0.015	0.775	Not Supported
- Discomfort (H3)	0.079*	0.094	Not Supported[a]
- Insecurity (H4)	-0.094**	0.036	Supported
Awareness (H5)	0.221***	0.000	Supported
Moderating effects			
- Age x Optimism (H6a)	-0.042	0.334	Not Supported
- Age x Innovativeness (H6b)	0.025	0.619	Not Supported
- Age x Discomfort (H6c)	-0.027	0.586	Not Supported
- Age x Insecurity (H6d)	-0.043	0.367	Not Supported
- Age x Awareness (H6e)	-0.083*	0.074	Not Supported[a]
- Gender x Optimism (H7a)	0.058	0.135	Not Supported
- Gender x Innovativeness (H7b)	-0.090**	0.043	Supported
- Gender x Discomfort (H7c)	-0.008	0.877	Not Supported
- Gender x Insecurity (H7d)	-0.033	0.468	Not Supported
- Gender x Awareness (H7e)	0.090**	0.024	Supported
- Experience x Optimism (H8a)	-0.008	0.845	Not Supported
- Experience x Innovativeness (H8b)	-0.048	0.288	Not Supported
- Experience x Discomfort (H8c)	0.054	0.258	Not Supported
- Experience x Insecurity (H8d)	-0.100**	0.040	Supported
- Experience x Awareness (H8e)	0.082	0.151	Not Supported
Control variables			
TAM variables			
- Usefulness	0.413***	0.000	
- Ease of use	0.125**	0.011	
Socio-demographics			
- Age	-0.076**	0.050	
- Gender	-0.001	0.976	
- Previous investment experience	0.025	0556	
FinTech name (Direct effect)			
- Fintech name (AI vs. robo-advisor)	0.033	0.334	
FinTech name (Moderating effects)			
- Fintech name x Optimism	0.026	0.492	
- Fintech name x Innovativeness	-0.025	0.597	
- Fintech name x Discomfort	-0.027	0.571	
- Fintech name x Insecurity	0.064	0.174	
- Fintech name x Awareness	0.066	0.127	
- Fintech name x Age	0.001	0.973	
- Fintech name x Gender	0.000	0.993	
- Fintech name x Experience	0.043	0.262	

[a] Significant effect, contrary to expected

5.2 Post-hoc analysis: the roles of awareness and financial advisor name

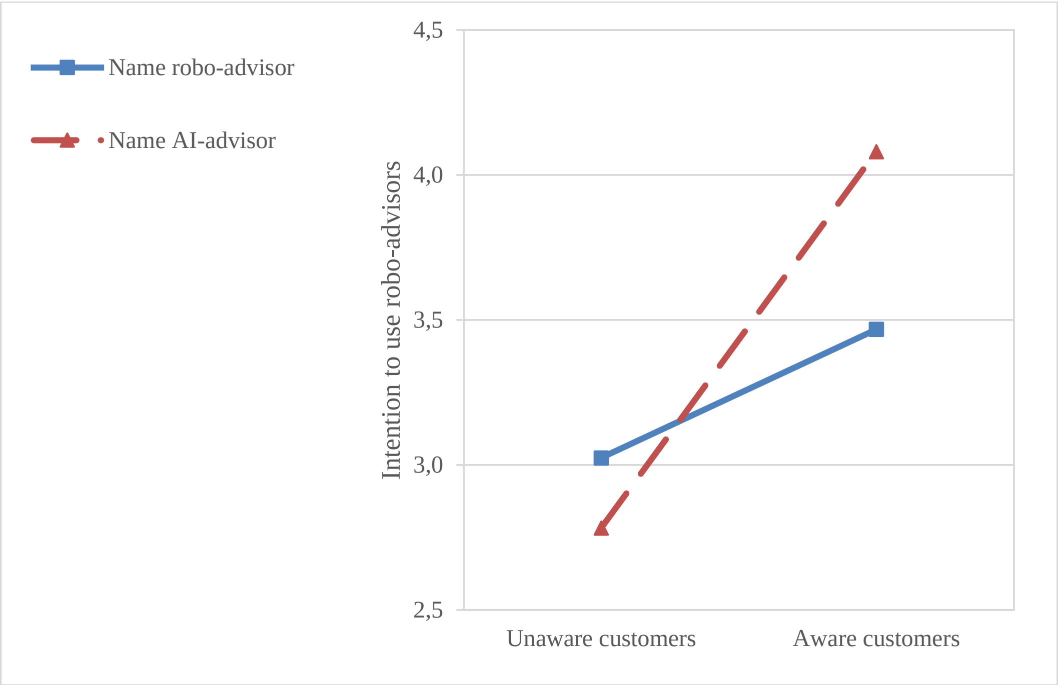
To better understand consumer awareness we carried out a post-hoc analysis. As normal in research into service awareness in other fields (e.g., Kangis and Passa, 1997), the questionnaire asked the respondents if they had previously been aware of robo-advisor services. Some 54.95% of the sample reported that they had not been very aware of robo-advisors, and 45.05% that they had learned about robo-advisors through the following means: 32.11% from press and news reports; 26.42% from financial services ads; 12.20% because their bank had directly offered them the service; 11.38% through their own means (i.e. through online searches and their own experiences); 8.94% from other customers; and 8.94% through other means (e.g., specialized investment magazines and blogs). We analyzed to what extent robo-advisor adoption was affected by how consumers became aware of them. As the categories were not exclusive, independent t-tests were conducted; taking one example, we compared intention to use robo-advisors by the customer group who learned about them through advertising with those who did not learn about them through advertising. The results showed that awareness of robo-advisors by almost any means increased intention to use, supporting Hypothesis 5. The analyses showed that customers with higher intention to use robo-advisors had learned about the services through their own means (M = 4.64, $t = 4.35$, $p < 0.01$), followed by customers who received information directly from their banks (M = 4.40, $t = 3.72$, $p < 0.01$) and from other customers (M = 4.30, $t = 2.74$, $p < 0.01$); participants who had been exposed to robo-advisor advertisements (M = 3.81, $t = 2.51$, $p < 0.05$) and related news items (M = 3.78, $t = 2.70$, $p < 0.01$) also had increased intentions to use the services, but to a lesser extent. Being aware of robo-advisors by other means did not significantly influence use intention (M = 3.55, $t = 0.66$, $p > 0.10$). Figure 2 illustrates use intentions based on how customers became aware of the services.

Figure 2. Mean values of intention to use robo-advisors based on how potential customers became aware of them



In addition, we used the participants' responses to test whether the financial advisor's name had a differential effect on behavioral intentions among those aware and unaware of the service. We performed a 2 (aware vs. unaware) × 2 (AI-advisor vs. robo-advisor) analysis of variance (ANOVA) to assess the interaction effect between both factors on intention to use. The results of the ANOVA confirmed that consumer awareness significantly increased intention to use (F = 25.82; $p < 0.01$), whereas the financial advisor's name did not (F = 1.17; $p > 0.01$). The interaction effect between both variables on intention to use was also significant (F = 25.82; $p < 0.01$), as Figure 3 shows. Specifically, the FinTech name did not significantly affect customers unaware of the service ($M_{AI\text{-}advisor} = 2.78$, $M_{Robo\text{-}advisor} = 3.02$, t = 1.07, $p > 0.10$). However, the financial service's name was important for customers aware of the service; they presented higher use intentions for AI-advisors than for robo-advisors ($M_{AI\text{-}advisor} = 4.08$, $M_{Robo\text{-}advisor} = 3.47$, t= 2.37, $p < 0.05$).

Figure 3. Service awareness and FinTech name interaction effect on intention to use



6. Discussion

6.1 Theoretical implications

Robo-advisor services represent a prototypical example of analytical-AI, which is already shaking the financial services industry. However, some customers may be reluctant to start using such a disruptive technology. To understand more about this underexplored field, we investigated whether customers are ready to embrace robo-advisors. To that end we analyzed the extent to which the direct effect of technology readiness factors and awareness, and the moderation effects of age, gender, previous experience and the FinTech advisor's name influenced customers' decisions to use analytical-AI to manage their investments. This is the first study to test the effects of technology readiness on consumers' preferences for analytical-AI, which had been identified as a research gap (Belanche *et al.*, 2020a; Mende *et al.*, 2019;

van Doorn *et al.*, 2017).

As a novel, important finding, technological discomfort, that is, the lack of control and overwhelming complexity of technologies experienced by some customers, had a positive and significant effect on intention to use robo-advisors. This result is particularly interesting because technological discomfort was originally proposed as a TRI factor that inhibited adoption (Parasuraman, 2000; Parasuraman and Colby, 2005). Indeed, discomfort has been shown to reduce the adoption of investment software among employees (Walczuch *et al.*, 2007). AI systems are based on automation, thus the user does not need to deal with the demanding, and often problematic, tasks of understanding and operating the technology, tasks that must be undertaken when using other systems; analytical-AI carries out the tasks for the user (Belanche *et al.*, 2020b). Therefore, paradoxically, AI systems may be particularly embraced by customers who suffer higher levels of technological discomfort because automation removes the need for learning and dealing with awkward technological processes. This finding provides a thought-provoking insight into AI adoption literature as customers may no longer need to play active roles in the service process. A theoretical contribution of the present study is the finding that technological discomfort, previously regarded as a key barrier to technology adoption, might act as a driver of acceptance. In turn, several important drivers of adoption, such as the user's self-efficacy, or perceived control, may act in the future as barriers to AI adoption (i.e., more skillful users might avoid using AI). Furthermore, this finding questions some service-dominant logic value co-creation axioms such as "The customer is always a co-creator of value", and that "Value is always uniquely and phenomenologically determined by the beneficiary" (Vargo and Lusch, 2016, p. 8). In the context of analytical-AI robo-advisors, the customer no longer plays an active role, that is, the technology creates the value. When frontline employees are replaced by automated agents interacting socially with customers (e.g. assistive robots), the participation of the different actors often leads to value co-creation (Čaić *et al.*, 2018). However, when automated agents replace the customers' role because of their greater skills and performance, value is created because of the customer's reduced participation. In other words, lower customer participation and co-creation results in higher service value.

Turning to the other TRI variables (Parasuraman and Colby, 2015), as hypothesized, customers' optimism had a positive impact, and insecurity a negative impact, on robo-advisor adoption. In general, higher technology optimistic customers will be more likely to use robo-advisors as they believe they will help them better perform their tasks and increase their quality of life. Thus, our results suggested that having an overall positive opinion about the benefits of technology encourages customers to embrace innovations, as was the case with previous technologies when first launched onto the market (Liljander *et al.*, 2006). In addition, optimism may be increasingly important in the post-COVID-19 era, during which individuals perceived that robot and AI-based technologies increased their quality of life (González-Jiménez, 2020).

In turn, insecurity concerns reduced consumers' behavioral intentions to use robo-advisors. Thus, customers who worry about the harmful consequences of technologies, such as increased technology dependence or reduced personal interaction quality, may avoid using AI-based financial services. This finding is in line with recent research that has indicated there is a need to explore people's fear of service robots and AI, especially when these innovations have human skills or appearances (Mende *et al.*, 2019; Ransbotham *et al.*, 2018). Indeed, it seems that anxiety felt toward AI and robots will become a field of increasing interest among scholars and should be added to the already wide body of knowledge about customers' awareness of the harmful consequences of technology (e.g., smartphone or social media addiction [Jiang *et al.*, 2018; Sanz-Blas *et al.*, 2019]). An interesting moderating effect observed was that insecurity inhibited behavioral intentions to use robo-advisors more among customers without investment experience than among those with investment experience. This finding suggests that investment experience lowers the barriers to acceptance of this new technology; thus, experienced customers, who will be less troubled by technology threats, may be a good target sector for robo-advisors. This finding is in line with previous research that found that consumers must have confidence in both the vendor (firm) and the technology to adopt new technology-based services (Belanche *et al.*, 2014) such as robo-advisors (Cheng *et al.*, 2019).

In contrast, innovativeness did not have a significant direct effect on behavioral intentions. That is, in general, customers' technology innovativeness is not a critical driver of robo-advisor adoption. Perhaps, in such an evolving market, the more innovative consumers are looking for even more creative investment alternatives such as cryptocurrencies and/or crowdfunding. To the extent that robo-advisors reduce the active role of customers through technology, they may also attract less innovative customers. Nevertheless, the influence of innovativeness is significant among men, and exerts a positive effect on their intentions to use robo-advisors. This finding is consistent with previous studies that have suggested that innovative men are more likely to use new service technologies (Kalinić *et al.*, 2019). Therefore, innovative men may be a particularly fertile target segment for robo-advisor service adoption.

In an additional theoretical contribution we identified that customer awareness positively influenced intention to use robo-advisors, shedding light on a factor ignored in the previous technology adoption literature. Our study found that service awareness (i.e., being conscious of, and having knowledge of) significantly increased the acceptance of new and disruptive services among many customer groups. The moderating effects observed revealed that awareness is particularly important for younger customers and women. These findings align with previous research; as women report lower levels of self-efficacy when dealing with new technologies (Sun and Zhang, 2006), awareness may be especially important for them as it increases confidence in technologies. On the other hand, awareness is more important for younger than for older customers. This may be because younger users are more autonomous in their decision-making (Sun and Zhang, 2006) and, thus, may rely to a greater extent on their acquired knowledge, that is, awareness, to decide whether to adopt this new technology. This finding is consistent with previous research into social communications which has suggested that younger people and women tend to incorporate available social information into their decision-making processes (Sorce *et al.*, 2005; Burke, 2001). The study's post-hoc analysis increased the understanding of how customers become aware of the existence of robo-advisors, and to what extent this information affects use intentions. These findings contribute to the existing knowledge in the field, as previous studies have found that subjective norms (i.e., other's opinions) affect robo-advisor adoption (Belanche *et al.*, 2019); however, we identified that when customers become aware of robo-advisors through their own means, or directly from their banks, they are more likely to adopt the service. In addition, the results of the post-hoc analysis revealed that for customers' who were previously aware of these services, the name "AI-advisor" created higher use intention than did the name "robo-advisor". Thus, although the standard industry name, robo-advisor, may be effective with first-time users, those with previous knowledge of these FinTech initiatives were more attracted by the term "AI-advisor".

The control variables included in the model also affected customers' intentions to use robo-advisors. As proposed in technology adoption models (e.g., the TAM; Davis, 1989), customers' perceptions of robo-advisors as easy to use and useful increased their behavioral intentions. Customers tend to use technologies that perform well and do not require too much effort to operate. These effects are consistent with those observed in previous research (Bhattacherjee, 2000; Belanche *et al.*, 2019), and can be understood in economic terms, as customers' decisions in financial markets are often based on the cost–benefit paradigm, including non-monetary and psychological costs (Lee and Cunningham, 2001). As to the direct effects of demographic factors, older customers had lower use intention. This finding is consistent with previous research that indicated that older customers have more negative attitudes toward online-based services and service robots (Hudson *et al.*, 2017; Onorato, 2018). Thus, our study confirms that robo-advisors are more likely to be popular among younger users, and that older consumers may prefer traditional financial advice channels (Woodyard and Grable, 2018). Our results also suggested that men and women are equally inclined to use robo-advisors. Although previous literature has found that women have more negative attitudes than men toward technological services (Chen and Huang, 2016), this was not the case in this analysis of a representative sample of North American men and women. Finally, we found that prior investment experience did not affect customers' intention to use automated financial advisors. Perhaps customers with previous experience feel they do not need to switch to FinTech alternatives. In any case, these findings reinforced the proposals that robo-advisors democratize access to financial investment services (Belanche *et al.*, 2020a), and that FinTech services should be oriented toward both men and women, with or without previous investment experience.

6.2 Managerial implications

Banks and financial service providers are introducing robo-advisors to achieve competitive advantage based on economies of scale and scope (Wirtz *et al.*, 2018). Our findings to a significant extent explain customers' intention to use robo-advisors and have interesting practical implications, not only for financial services' managers but also for companies seeking to introduce AI technologies into their service offerings. Potential customers need to perceive robo-advisors as easy to use and useful for their financial management. Providing clear instructions and user-friendly apps to help customers start using these innovations could increase ease-of-use perceptions. Undertaking trial programs and providing statistics about robo-advisors' performance may also enhance perceived usefulness.

Technology readiness plays a crucial role, but managers should pay more attention to customer characteristics that have been shown to form intention to use robo-advisors. Specifically, banks and other financial firms should focus on customers with higher levels of technological optimism as potential users of robo-advisor services. To identify customers with this profile companies should identify individuals who are enthusiastic about the use of technological services. They could do this through normal market research techniques, for example, customer surveys, CRM and big data analytics (e.g., linked to customers' activity on social media). Communication campaigns using celebrities and/or influencers with multiple followers based on their technology optimism (e.g., YouTube gaming influencers) could help attract customers through social media.

Customers with higher technology discomfort may be more likely to adopt robo-advisor services. Banks and finance companies should focus on customers who are interested in making investments, but who do not want to undertake the complicated task of managing their own investments using complex software and/or who want to avoid the fees and time involved in interacting with human financial advisors. In this instance, robo-advisors would fulfill the tasks of analytical-AI, that is, helping and supporting less skilled customers using the newest technological advances in the sector (Huang and Rust, 2018). These customers might be identified by seeking out those who abandon managing their investments (e.g., due to complexity) and/or who informally complain about the difficulties of operating other technological banking systems. Robo-advisor communication campaigns should favorably contrast the service to human financial advisory services (e.g., "to avoid high fees") and to customer self-management (e.g., "let AI do the work").

The moderation results of the study indicated that customer innovativeness may be particularly significant in terms of robo-advisor use by men. Segmentation strategies based on online navigation cookies, programmatic advertising and internal CRM software should be combined to focus on innovative male customers. Managers might also use cross-selling techniques in collaboration with leading, groundbreaking technological brands (e.g., Apple, Amazon Alexa) and with companies focused on innovative users (e.g., IBM, Uber) to target this customer group.

Managers should also focus on customers' perceptions of technology insecurity as a key inhibitor of robo-advisor use intention, specifically among less experienced investors. Robo-advisors could be offered preferentially to customers with lower levels of technological insecurity; these might be identified through surveys or other market research techniques. Alternatively, finance industry companies should try to reduce insecurity by better explaining how robo-advisors work, why they are reliable (e.g., AI ensures privacy and data protection [Mazurek and Małagocka, 2019]) and how financial risks might be limited. Training programs that offer small monetary investments and sign-on bonuses may reduce the initial wariness about robo-advisors among inexperienced investors.

As to awareness, the industry should make greater efforts to spread knowledge about robo-advisors, how they function and their benefits. Banks and other financial firms should use direct communications to promote these services, as these have been shown to be more effective than advertising and mass media communication. In addition, they should encourage customers to increase their knowledge about robo-advisors through their own means (e.g., detailed information on the web, trial programs). As a complementary, effective marketing action, managers should develop "bring a friend" campaigns to encourage more experienced users of robo-advisors to recommend them to other customers.

Finally, our study revealed that younger customers are more willing to use robo-advisors. It should be easy for companies to address this customer segment, as age is basic information contained in CRM systems. In particular, employees such as bank tellers and financial advisors should recommend robo-advisors to younger customers in their discussions about the bank's services, for example, about which channels to use. Nevertheless, although in this initial stage robo-advisors may be preferred by the young, analytical-AI and automated forms of financial management must be taken up by a wide spectrum of customers if companies are to take advantage of economies of scale and scope (Kumar *et al.*, 2019; Wirtz *et al.*, 2018).

6.3 Limitations and further research

The present study has several limitations. To test the effect of technology readiness on use intentions we used the TRI (Parasuraman, 2000; Parasuraman and Colby, 2005). Although the TRI is the most accepted framework through which to analyze consumers' technology readiness, alternative models with slightly different components might be tested (e.g., compatibility [Moore and Benbasat, 1991]; trust [Robinson *et al.*, 2020]; and creepiness [Ostrom *et al.*, 2019]). Although the TRI factors may overlap with some of these variables (Liljander *et al.*, 2006), alternative measures directly related to the financial market could be employed (Lee and Cunningham 2001). Similarly, further research is needed to clarify the influence of customers' technological readiness on AI adoption in other sectors (e.g., health, education, tourism) (Yoganathan, et al, 2021). The important role of awareness in adoption may vary as time passes. In particular, as robo-advisor use increases, customers will develop greater knowledge, which will increase awareness among their peers (e.g., word-of-mouth, consumer recommendations). Therefore, longitudinal studies may help explain how the role of awareness evolves over time.

Another limitation is that our study is based on a sample of North Americans, who tend to score lower in uncertainty avoidance (Hofstede, 2011) than most European and Asian consumers. Thus, the research should be replicated in other countries to assess how cultural dimensions may affect robo-advisor adoption (Belanche *et al.*, 2019). Although the term robo-advisor seems to be the more popular worldwide, further research should be conducted to assess whether another name (e.g., AI-advisor, or an alternative), or even a specific brand-related name, may enhance customers' perceptions of these analytical-AI services. Similarly, increasing the customer's perception of humanness, for example, by representing the robo-advisor as a humanoid (Yoganathan *et al.*, 2021; Belanche et al., 2021), might have a significant impact on acceptance; this merits further research.

The robo-advisor phenomenon should be analyzed within the broader scope of AI, its ethical limits and the need for regulation of such innovative systems (Robinson *et al.*, 2020). The moderating effects we found suggest that individuals' optimism may be crucial for motivating usage. Nevertheless, people's concerns with technology (i.e., insecurity) and, in particular, feelings of anxiety in relation to automated forms of interaction (particularly among less experienced customers), deserve further research attention. Finally, the study revealed that, paradoxically, customers with higher technological discomfort are more willing to embrace AI-based services. Contrary to co-creation axioms that suggest that technologies require higher user participation and ability, AI could be specifically designed for less skilled users. Thus, AI would fulfill its original purpose, that is, to use technological capacities to help humans, especially those who lack skills and/or are less efficient (Huang and Rust, 2018; Belanche *et al.*, 2020a). Investigating discomfort, and other human limitations, that have previously been regarded as barriers to technology adoption, but which may now be contributing to adoption, is a promising future research avenue.

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Appendix 1. Scale items

Technology Readiness [a]

Optimism
- New technologies contribute to a better quality of life
- Technology gives me more freedom of mobility
- Technology gives people more control over their daily lives
- Technology makes me more productive in my personal life

Innovativeness
- Other people come to me for advice on new technologies
- In general, I am among the first in my circle of friends to acquire new technology when it appears
- I can usually figure out new high-tech products and services without help from others
- I keep up with the latest technological developments in my areas of interest

Discomfort
- When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do
- Technical support lines are not helpful because they don't explain things in terms that I understand
- Sometimes, I think that technology systems are not designed for use by ordinary people
- There is no such thing as a manual for a high-tech product or service that's written in plain language

Insecurity
- People are too dependent on technology to do things for them
- Too much technology distracts people to a point that is harmful
- Technology lowers the quality of relationships by reducing personal interaction
- I do not feel confident doing business with a service that can only be reached online

Service Awareness

Before reading the description, …
- I was very aware of robo-advisor services
- I had a great deal of knowledge about robo-advisors
- I could quickly recall previous information I had received about robot-advisors

Perceived Ease of Use
- 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

Perceived Usefulness
- Using robo-advisors would improve my performance in managing investments
- Using robo-advisors would improve my productivity in managing investments
- Using robo-advisors would enhance my effectiveness in managing investments
- I would find robo-advisors useful in managing investments

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