

Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers

Artificial
Intelligence in
FinTech

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Abstract

Purpose – Considering the increasing impact of Artificial Intelligence (AI) on financial technology (FinTech), the purpose of this paper is to propose a research framework to better understand robo-advisor adoption by a wide range of potential customers. It also predicts that personal and sociodemographic variables (familiarity with robots, age, gender and country) moderate the main relationships.

Design/methodology/approach – Data from a web survey of 765 North American, British and Portuguese potential users of robo-advisor services confirm the validity of the measurement scales and provide the input for structural equation modeling and multisample analyses of the hypotheses.

Findings – Consumers' attitudes toward robo-advisors, together with mass media and interpersonal subjective norms, are found to be the key determinants of adoption. The influences of perceived usefulness and attitude are slightly higher for users with a higher level of familiarity with robots; in turn, subjective norms are significantly more relevant for users with a lower familiarity and for customers from Anglo-Saxon countries.

Practical implications – Banks and other firms in the finance industry should design robo-advisors to be used by a wide spectrum of consumers. Marketing tactics applied should consider the customer's level of familiarity with robots.

Originality/value – This research identifies the key drivers of robo-advisor adoption and the moderating effect of personal and sociodemographic variables. It contributes to understanding consumers' perceptions regarding the introduction of AI in FinTech.

Keywords Robo-advisors, Artificial Intelligence, Robots, Finance, Technology adoption

Paper type Research paper

1. Introduction

Robots and Artificial Intelligence (AI) are already transforming all kinds of industries, from manufacturing, to retail and service provision. This technological revolution is threatening established principles in economy and labor, since automated technology penetration has been growing at a rate of 20 percent per year (International Federation of Robotics, 2017) and may replace almost half of current jobs in the next 20 years (Acemoglu and Restrepo, 2017).

This is also the case in the finance industry, where financial technology (FinTech) is being revealed as a key element in the strategy of banks and financial start-up companies (Jung, Dorner, Weinhardt and Pusmaz, 2018). The concept of FinTech goes beyond e-banking and consumer digitalization and focuses on the development and successful introduction of innovative technology instruments to meet users' financial needs and demands. In this line, AI represents a clear opportunity to advance the transformation of the finance industry by providing users with greater value and increasing firms' revenues (Park *et al.*, 2016). For instance, more than a million customers of Bank of America use a chatbot named Erica to answer basic banking questions (Rosman, 2018). Another amazing example is the case of Nao, a small bank teller humanoid that attends customers side by side with employees in some branches of the Bank of Tokyo (Marinova *et al.*, 2017). However, despite these thought-provoking innovations, the most disruptive phenomenon within FinTech has been the automated or assisted management of investments by means of AI, popularly called robo-advisors.



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In contrast to traditional human advisory services, robo-advisors reduce fees and provide 24/7 access to finances (Faubion, 2016; Park *et al.*, 2016). Thus, these autonomous systems are expected to democratize the use of financial advisor services to a wider range of customers (Sironi, 2016). As a consequence, banks and other finance companies are launching robo-advisor services as a source of competitive advantage. Indeed, robo-advisors are currently managing more than \$880,000m in assets, and are growing at an annual rate over 30 percent (Statista, 2019).

Nonetheless, consumer adoption of robo-advisor services "has been slow so far" (Jung, Dorner, Weinhardt and Pusmaz, 2018, p. 367). As is typical of disruptive innovations in initial stages, only a small group of early adopters have been willing to rely on this new system that is replacing traditional practices in finance management services (Laukkanen and Pasanen, 2008). That is, after attracting early adopters, in order to achieve greater effectiveness and value companies have been aiming to introduce the service to a greater public that may be initially hesitant about the worth of such an innovation (Ryu, 2018). Thus, managers need some guidance on how to successfully implement robo-advisors in order to help retain existing, and attract potential, customers.

However, despite the opportunities derived from the launching of FinTech AI applications, research on robo-advisor introduction is very limited. Most studies in the area have focused on technical or legal issues (Glaser *et al.*, 2019; Ji, 2017), ignoring the customer perspective, though this would help to extend these services to a greater number of customers. The scant research on robo-advisory designs (Jung, Dorner, Weinhardt and Pusmaz, 2018) has highlighted a need to increase the usability of these systems to facilitate users' interaction with them. Nevertheless, given the potential broad expansion of robo-advisors in the finance industry, there is a need to develop a comprehensive model that better explains the key perceptions and motivations driving robo-advisor adoption by a wide range of customers.

To do so, and based on well-established technology adoption theories, the authors propose a framework wherein perceptions about a robo-advisor's usefulness and ease of use, together with consumer attitudes, impact the intention to adopt this service. Complementarily, acknowledging the disruptive change that robo-advisors entail, the study's research model also predicts that subjective norms (i.e. social influence) motivate customers to start using robo-advisors.

As an additional contribution of this work, some moderating variables are considered that would be particularly relevant in the adoption of these kinds of AI-driven innovations. Considering that customers vary in their level of familiarity with AI and robot-based systems (e.g. some users already have experience with AI through services such as Alexa and products such as Roomba), the study's framework proposes that users' familiarity with such technology may play a moderating role. Specifically, it is suggested that customers with higher familiarity will tend to assign higher value to their own attitudes and usefulness perceptions, whereas customers with lower familiarity with robots will base their decision on subjective norms to a greater extent. Following previous research on technology adoption (Sun and Zhang, 2006), age and gender are also included as control variables. Finally, to increase the scope of the research to a broader range of customers, a *post hoc* analysis deepens understanding of cultural differences by contrasting the distinctions between the three countries considered in the empirical study: Portugal, the UK and the USA.

In sum, in order to adapt to the transformation of the finance industry, firms should seek to better understand customers' needs and demands so as to succeed in the introduction of robo-advisors. Given the lack of empirical work explaining robo-advisor adoption, the research contributes to the literature by:

- analyzing the relevance of key determinants (i.e. utilitarian and social motivations) of customers' decision to adopt robo-advisor systems;

- evaluating possible differences in the adoption process depending on customers' characteristics (i.e. familiarity with robots, age, gender, culture), which may moderate the relationships in the framework; and
- improving understanding and discussing consumers' perceptions about robo-advisor services in order to guide successful infusion of AI-driven innovations, which will benefit both companies and the general public.

The remainder of this paper is structured as follows. The next section presents the research framework, which is followed by the hypotheses formulation. The international empirical study, data collection process and methodology are then explained. Then results and main findings are described, and finally, implications of the research for managers and customers, together with its limitations, and lines for further research are discussed.

2. Literature review

2.1 *The challenge of introducing AI in frontline services*

The phenomenon of unprecedented growth of AI and robot-based systems across industries is having a critical impact on the economic, social and labor domains (Acemoglu and Restrepo, 2017). From a theoretical perspective, Huang and Rust (2018) described AI as a major source of innovation that will gradually replace human jobs in the future. More precisely, they predicted that automated technology will develop mechanical intelligence first, then analytical capacity (e.g. robo-advisors) and, after some time, intuitive and even empathetic intelligence; this will require workers to become specialized in tasks that can be less easily accomplished via automation (Huang and Rust, 2018).

In a similar vein, an emerging field of research is focusing on the challenge of introducing service innovations involving robots, droids or AI (Singh *et al.*, 2017; Han and Yang, 2018), with particular attention to those technologies that directly interact with customers in frontline operations (e.g. physically, online) (Van Doorn *et al.*, 2017). For instance, Singh *et al.* (2017) affirmed that customer interaction with organizations is being profoundly disrupted by intelligent interfaces. Similarly, Grewal *et al.* (2017) predicted that AI systems (e.g. Alexa, Cortana, Siri) would directly impact consumer shopping behaviors. Complementarily, Van Doorn *et al.* (2017) indicated that technology infusion within service interactions would depend on the level of human and automated social presence; that is, on the capacity of frontline robots to engage customers at a social level.

All in all, there is an increasing awareness of the need for firms to introduce AI advances to progress their management practices and product offerings (Han and Yang, 2018). By doing so, companies can achieve competitive advantage to better adapt to a market transformation taking place in the short and medium term. Nevertheless, these theoretical insights require empirical evidence to guide both customers and managers in the successful introduction of AI-related services.

2.2 *Previous knowledge on robo-advisors and its adoption by customers*

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, Dorner, Glaser and Morana, 2018, p. 81). The use of robo-advisors by regular customers is relatively simple. First, this technology-based service assesses the profile of the customer via an initial questionnaire (i.e. goal, risk, return expectations). It then starts to make specific recommendations or actions about investment or portfolio rebalancing, as would a human financial advisor, but it does so autonomously and based on AI.

Robo-advisors present numerous advantages compared to traditional human advisors, such as improving the temporal and ubiquitous accessibility to financial services, significantly reducing management fees and providing wider investment options based on systematic and quantitative analyses without ulterior motivations (Faubion, 2016; Park *et al.*, 2016). As a result, the amount of assets under management by robo-advisors, which, as noted above, has already surpassed \$880,000m, is expected to obtain an annual growth of 31.45 percent in the period 2019–2022 (Statista, 2019). In other words, banks and financial firms are launching these services to gain competitive advantage and expand their business to a wider public.

Despite the increasing interest on this phenomenon, literature on robo-advisor introduction is currently scarce and has frequently focused on the legal complexities (Ji, 2017) and risk-management aspects (Glaser *et al.*, 2019). The few recent studies on robo-advisors from a customer approach have described some of the problems related to widespread adoption of this service by customers. For instance, Jung, Dorner, Weinhardt and Pusmaz (2018) pointed out that banks are more enthusiastic about FinTech and robo-advisors than are customers, who often are reluctant to entrust their money to these kinds of AI-driven platforms. The results of Jung, Dorner, Weinhardt and Pusmaz's (2018), experiment which was conducted in a controlled lab setting, suggest that greater effort is needed to improve robo-advisor design (especially in terms of layout and usability) in order to boost adoption of this innovation by customers. From a more technical perspective, Faloon and Scherer (2017) identified personalization as the distinctive feature of robo-advisors compared to traditional human advisory services. In turn, Heinrich and Schwabe (2018) concluded that IT-supported advice-giving processes increase customers' learning, enabling them to make more informed decision related to financial products.

Therefore, due to the novelty of robo-advisory services, there is currently a lack of knowledge about the key determinants of their adoption by regular customers. As the innovation attempts to democratize advisory services to a wider public (Sironi, 2016), the current research seeks to close this gap by proposing a broad, comprehensive model that includes the main global drivers of customer adoption of robo-advisors.

3. Hypothesis formulation

3.1 An extension of the technology acceptance model to understand robo-advisor adoption

Or proposed model is based on the technology acceptance model (TAM) (Davis, 1989; Davis *et al.*, 1989). TAM is one of the best frameworks by which to understand users' reactions toward technological innovations because it is able to explain, to a great extent, consumer adoption of many innovations. As a result, this model has been widely used in previous literature in both finance and online settings (Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003).

However, the simplicity of TAM has been frequently criticized (e.g. Bagozzi, 2007) for failing to consider other relevant aspects, such as the influence of social processes, which suggests that attitudes should be complemented with subjective norms, as proposed by the theory of reasoned action (Fishbein and Ajzen, 1975). Therefore, and similar to the proposals of Venkatesh and Davis (2000) regarding software introduction, this study broadens TAM by integrating the influence of subjective norms (i.e. individuals' perceptions about the opinions of others) which could be crucial in the adoption of financial robo-advisors by potential users.

In addition, to better understand this adoption process, the current study considers the moderating role of individual characteristics. In particular, although robo-advisors represent a new service linked to more familiar or experienced AI and robot technology (e.g. Alexa), the level of familiarity may vary among customers (Young *et al.*, 2009). Thus, it is proposed that

customers' familiarity with robot technology may moderate the main effects of the study's framework. According to previous literature (Sun and Zhang, 2006), the influence of the antecedents of behavioral intentions may vary due to heterogeneity across users depending on personal characteristics such as age or gender; thus, these two variables are also included as control variables in the model.

The research model is summarized in Figure 1.

3.2 TAM-related hypotheses

Consistent with TAM formulations (Davis, 1989; Davis *et al.*, 1989), its proposed relationships are first adapted to the context of adoption of financial robo-advisors in order to explain customers' behavioral intentions (i.e. "the strength of a person's willingness to perform a certain behavior" Belanche *et al.*, 2012).

Specifically, this model proposes that behavioral intentions mainly depend on attitude (i.e. "the degree to which a person has a favorable or unfavorable evaluation of the behavior in question" Ajzen, 1991, p. 188) and perceived usefulness (i.e. "the degree to which a person believes that using a particular system would enhance his or her performance" Davis, 1989, p. 320). In turn, following a cost-benefit paradigm, attitude is affected by perceived usefulness and perceived ease of use ("the degree to which a person believes that using a particular system would be free of effort" Davis, 1989, p. 320). Finally, perceived ease of use also plays an instrumental role, and positively influences perceived usefulness as performance may be increased due to the effort saved (Davis *et al.*, 1989). Adapting these well-established TAM relationships to the present research context, the following hypotheses are proposed:

- H1a. Perceived ease of use of financial robo-advisors has a positive effect on their perceived usefulness.
- H1b. Perceived ease of use of financial robo-advisors has a positive effect on attitudes toward them.
- H1c. Perceived usefulness of financial robo-advisors has a positive effect on attitudes toward them.

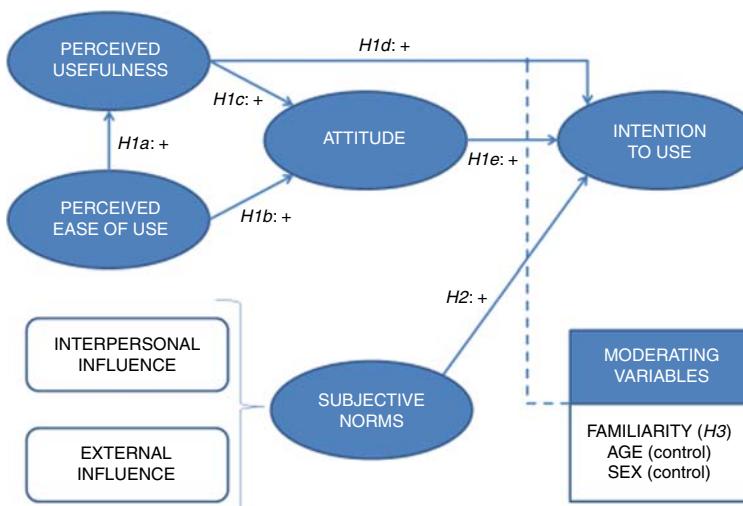


Figure 1.
Research model

H1d. Perceived usefulness of financial robo-advisors has a positive effect on the intention to use them.

H1e. Attitude toward financial robo-advisors has a positive effect on the intention to use them.

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3.3 *The influence of subjective norms*

Normative influences have been described in social psychology as “a person’s perception that most people who are important to her/him think she/he should or should not perform the behavior in question” (Fishbein and Ajzen, 1975, p. 302). Literature has clearly established that these norms rely on social information as a kind of social pressure to perform a particular behavior based on the personal perception of others’ opinions (Taylor and Todd, 1995; Fishbein and Ajzen, 1975).

The influence of social norms could be of particular interest with reference to customers facing a disruptive change with limited information (Taylor and Todd, 1995), as in the case of robo-advisors. In the absence of their own experience or well-formed beliefs, individuals are influenced by social norms by means of three psychological mechanisms (Belanche *et al.*, 2012): internalization of messages from expert sources, need to identify with relevant others by accepting their opinions and compliance with others to achieve social rewards or avoid social punishments.

In the specific domain of e-finance, Bhattacherjee (2000) proposed that subjective norms are based on interpersonal sources (e.g. influence of peers and superiors) and external sources of information (e.g. influence of mass media). This view agrees with previous research on technology-based innovations, where the opinion of society affects individuals’ behavior by means of comments and behaviors of people and mass media news and reports related to the innovation (Belanche *et al.*, 2012). Thus, assuming that consumers need some basic social confirmation and account for social incentives related to the use of robo-advisors, the following hypothesis is proposed:

H2. Subjective norms about using financial robo-advisors have a positive effect on the intention to use them.

3.4 *Moderating effects*

The use of AI in finance represents a disrupting innovation not only from the internal firm perspective, but also in the eyes of consumers (Singh *et al.*, 2017). Specifically, robo-advisors are autonomous intelligent systems that provide advice about finance management – a task that is clearly replacing the job of human employees and that could involve interacting with AI systems with pseudo social presence (Van Doorn *et al.*, 2017). Thus, this transformation suggests that consumers need to adapt to the innovation in order to be willing to engage with the interactions it entails for the management of their finances. Indeed, there has been increasing attention toward robotic and AI systems that provide services (e.g. Roomba cleaner, Alexa assistant), and there is also a growing number of formative courses and materials dealing with the programming of robots and AI systems designed to directly interact with humans. Nevertheless, not all individuals have this knowledge or experience; thus, customers may differ in their level of familiarity with such innovations (Young *et al.*, 2009). Consequently, this study suggests that individuals’ differences in their level of familiarity with robotic systems may play a crucial role in the adoption of robo-advisors.

In this line, previous research has found that customers with low levels of familiarity with online banking require auxiliary features (e.g. information about investment topics)

compared to customers with higher familiarity, who tend to focus on utilitarian reasons (Mäenpää, *et al.*, 2008). Updating these findings to the current context, it is proposed that familiarity with AI and robots acts as a moderating variable. Users with a higher level of familiarity (i.e. previous interaction or training) with such innovations will have first-hand knowledge, will value such technology in terms of their usefulness, and will have better attitudes toward them because they have more knowledge about the practical value of these systems and have a solid personal predisposition about the targeted behavior (Castañeda *et al.*, 2007). Conversely, consumers with lower familiarity will be more affected by subjective norms (i.e. others' opinions) because they have vaguer and indirect knowledge about robo-advisors (Venkatesh and Davis, 2000). Consequently, the following moderating effect of familiarity is proposed:

H3. The effects of perceived usefulness and attitude on intention to use robo-advisors are strengthened for users with higher familiarity with robots, whereas the effect of subjective norms on intention to use robo-advisors is strengthened for users with lower familiarity with robots.

For the sake of completeness, this study also considers the moderating influence of two sociodemographic characteristics, age and gender. Following Sun and Zhang (2006), these individual characteristics may help better explain the dynamics of adoption processes. In this respect, previous literature has suggested that older people have more stable beliefs and are less susceptible to others' messages compared to younger people (e.g. Hess, 1994). Similarly, women are more willing than men to take others' opinions into account when deciding to use a new technology (e.g. Sun and Zhang, 2006; Venkatesh *et al.*, 2003). As a result, the influence of the antecedents of intention to use financial robo-advisors may vary according to these variables.

4. Method

4.1 Data collection

A web survey was used to collect the data for this study; specifically, participants comprised 765 customers recruited via Prolific, a market research company, which enabled us to obtain a diverse sample in terms of demographic characteristics such as gender (56.99 percent of participants are female), age (< 25 years 17.39 percent, 25–34 years 34.25 percent, 35–44 years 26.41 percent, 45–54 years 14.25 percent, 55 or more 7.71 percent), income (< \$5,000 5.89 percent, \$5,000–10,000 13.48 percent, \$10,001–25,000 32.98 percent, \$25,001–50,000 31.54 percent, > \$50,000 16.10 percent), employment situation (full-time job 57.89 percent, part-time job 15.58 percent, student 10.73 percent, unemployed 4.58 percent, retired or other 11.78 percent) and country of origin (28.76 percent of participants come from Portugal, 36.34 percent from the UK and 33.20 percent from the USA). The study was targeted to potential users of robo-advisors with at least some previous experience with online banking. To develop the web survey and make the most of this method, the study followed recommendations by Illum *et al.* (2010), such as keeping it short and guaranteeing the anonymity of participants.

Specifically, all participants were invited to read a general description regarding financial robo-advisors. In order to avoid bias due to brand reputation (MacKenzie *et al.*, 1986), the robo-advisor was not linked to any specific firm, but the phrase "consider that you have some money for investment and your bank gives you the possibility to use a robo-advisor" was added. Next, respondents answered the questionnaire, including a portion on their perceptions of robo-advisors (i.e. perceived usefulness, perceived ease of use), subjective norms (i.e. social influence and external influence), attitude toward the use of robo-advisors, their behavioral intention to use them and previous familiarity with the use of robots. All scales (see Table AI in the Appendix) were based on

self-reported measures and used seven-point Likert-type response formats, from 1 ("completely disagree") to 7 ("completely agree").

4.2 Measurement validation

The initial set of items proposed to measure the latent constructs came from an in-depth review of relevant literature pertaining to online banking, e-commerce and the adoption of new technologies. The measures were adapted from previous scales assessing perceived usefulness and perceived ease of use (e.g. Davis *et al.*, 1989; Bhattacherjee, 2000), interpersonal influence and external influence (e.g. Belanche *et al.*, 2012; Bhattacherjee, 2000), attitude (e.g. Taylor and Todd, 1995; Bhattacherjee, 2000), intention to use (e.g. Mathieson, 1991; Bhattacherjee, 2000) and familiarity (e.g. Flavián *et al.*, 2006; Casaló *et al.*, 2008). The extensive review helped to ensure the content validity of the scales. Following Zaichkowsky (1985), the authors also asked a panel of experts about the degree to which they judged that the items were clearly representative of the targeted construct, in order to test for face validity. Items that prompted a high level of consensus among the experts were retained (Lichtenstein *et al.*, 1990).

To confirm the dimensional structure of the scales, this study used confirmatory factor analysis and employed the statistical software EQS 6.1. First, the factor loadings of the confirmatory model were verified regarding whether they were statistically significant (at 0.01) and higher than 0.5 (Steenkamp and Van Trijp, 1991; Jöreskog and Sörbom, 1993). No item needed to be eliminated, and acceptable levels of convergence, R^2 values, and model fit were obtained ($\chi^2 = 404.864$, 155 df, $p < 0.000$; Satorra-Bentler scaled $\chi^2 = 263.251$, 155 df, $p = 0.05672$; NFI = 0.979; NNFI = 0.989; CFI = 0.991; IFI = 0.991; RMSEA = 0.030; 90% confidence interval (0.024, 0.036)). To assess construct reliability, this study also checked that values of the composite reliability indicator (Jöreskog, 1971) were above the suggested minimum of 0.65 (Steenkamp and Geyskens, 2006), as can be seen in Table I. To further ensure convergent validity, it was verified that average variance extracted (AVE) values were greater than 0.5 (see Table I) and converged on only one construct (Fornell and Larcker, 1981). Finally, regarding discriminant validity, Table I shows that each construct shared more variance with its own measures than with the other constructs in the model (Fornell and Larcker, 1981); that is, for each construct, the square root of the AVE is greater than correlations among constructs.

4.3 Multidimensionality of subjective norms

Previous literature has suggested that subjective norms may be formed by different social influences (e.g. Belanche *et al.*, 2012), and has mainly differentiated between interpersonal and external influences (e.g. Bhattacherjee, 2000). In order to understand whether these two influences form a multidimensional structure, two alternative models were compared

Construct	(1)	(2)	(3)	(4)	(5)	(6)	CR	AVE
Perceived ease of use (1)	<i>0.901</i>						0.945	0.812
Perceived usefulness (2)	0.590	<i>0.906</i>					0.948	0.821
Interpersonal influence (3)	0.410	0.538	<i>0.866</i>				0.900	0.750
External influence (4)	0.340	0.440	0.671	<i>0.868</i>			0.902	0.754
Attitude (5)	0.535	0.701	0.593	0.489	<i>0.934</i>		0.954	0.873
Intention to use (6)	0.600	0.826	0.548	0.456	0.834	<i>0.924</i>	0.946	0.854

Notes: Diagonal elements (italic) are the square root of the AVE (variance shared between the constructs and their measures). Off-diagonal elements are the correlations among constructs

Table I.
Construct reliability,
convergent
validity and
discriminant validity

following a rival model strategy (Anderson and Gerbing, 1988). On the one hand, a first-order model in which the dimensions were not differentiated was developed (all items formed a first-order factor). On the other hand, a second-order model (Steenkamp and Van Trijp, 1991) with two dimensions measuring subjective norms (i.e. interpersonal and external influence) was evaluated. A χ^2 difference test with one degree of freedom was performed to determine which model had a better fit (Bagozzi and Dholakia, 2006). The result of this test confirmed the multidimensionality of subjective norms, since the χ^2 difference was significant (χ^2_d (1) = 738.359; $p < 0.01$). In addition, the remaining fit indicators were much higher in the second-order model (see Table II) than in the first-order model, again suggesting the multidimensionality of the construct subjective norms.

5. Results

5.1 Hypotheses test

To test the TAM-related hypotheses ($H1a-H1e$) and the influence of subjective norms on the intention to use financial robo-advisors ($H2$), a structural equation model was developed. The model fit showed acceptable values ($\chi^2 = 697.652$, 163 df, $p < 0.000$; Satorra-Bentler scaled $\chi^2 = 462.847$, 163 df, $p < 0.000$; NFI = 0.962; NNFI = 0.971; CFI = 0.975; IFI = 0.975; RMSEA = 0.049; 90% confidence interval (0.044, 0.054)). First, regarding TAM-related relationships, it was observed that perceived ease of use has a positive influence on both perceived usefulness ($\gamma = 0.590$, $p < 0.01$) and attitude ($\gamma = 0.177$, $p < 0.01$), supporting $H1a$ and $H1b$, respectively. In turn, perceived usefulness positively affects attitude ($\beta = 0.721$, $p < 0.01$), which supports $H1c$, but its direct influence on intention to use is not significant ($\beta = -0.006$, $p > 0.1$); therefore, $H1d$ is not supported. Finally, intention to use is affected by attitude ($\beta = 0.800$, $p < 0.01$), supporting $H1e$. In sum, the results confirm all the proposed TAM-related hypotheses at the 0.01 level, except for $H1d$ (direct influence of usefulness on intention), which is not supported. Similarly, intention to use is affected by subjective norms ($\gamma = 0.230$, $p < 0.01$), supporting $H2$.

In addition, the proposed framework implies some indirect effects of perceived ease of use and usefulness. On the one hand, perceived ease of use exerts significant indirect effects on attitude (0.425, $p < 0.01$) via usefulness and intention to use (0.478, $p < 0.01$) via usefulness and attitude. On the other hand, perceived usefulness exerts a significant indirect effect on intention to use (0.577, $p < 0.01$) via attitude. These relationships can largely explain the dependent variables, perceived usefulness ($R^2 = 0.348$), attitude ($\bar{R}^2 = 0.702$) and intention to use ($R^2 = 0.684$). The values found are considerably high, as TAM models usually predict between 0.44 and 0.57 of the variance in usage intentions (Venkatesh and Davis, 2000).

$H3$ proposes a moderating role of familiarity, such that the effects of perceived usefulness and attitude on intention to use robo-advisors are strengthened for users with higher familiarity with robots, whereas the effect of subjective norms on intention to use robo-advisors is strengthened for users with lower familiarity with robots. In addition, possible moderating effects of age and gender were checked as the influence of the antecedents of behavioral intentions may vary due to heterogeneity across users depending on personal characteristics (Sun and Zhang, 2006). To assess these moderating effects,

Model	χ^2 ($p > 0.05$)	NNFI (> 0.95)	CFI (> 0.95)	IFI (> 0.95)	RMSEA (< 0.08)	90% interval RMSEA
First order	755.444 (9 df), $p < 0.01$	0.777	0.866	0.867	0.231	(0.211; 0.251)
Second order	17.085 (8 df), $p = 0.029$	0.999	0.999	0.999	0.018	(0.000; 0.048)

Note: Recommended values for the fit indices are in brackets (see Hooper *et al.*, 2008 for a review)

Table II.
Fit indices for the
multidimensionality
analysis

a series of multisample analyses were performed. This method is widely employed to evaluate differences among groups formed either by respondents' perceptions (e.g. García *et al.*, 2008; Algesheimer *et al.*, 2005; Bagozzi and Dholakia, 2006; Belanche *et al.*, 2019) or by demographic characteristics such as gender or age (e.g. Hernández *et al.*, 2011; Choi *et al.*, 2005), facilitating comparison between parameters.

Focusing on the moderating role of familiarity – that is, to distinguish between users with high vs low levels of familiarity – the total sample was divided according to the arithmetic mean of the moderating variable, with some cases (± 0.5 standard deviation) eliminated around this mean (García *et al.*, 2008). Following this method, the first group consisted of 262 respondents who had a lower familiarity with robots; the second group comprised 277 participants who reported a higher level of familiarity. After generating an individual structural solution for each group, a significant difference emerged between the groups at the 0.1 level in the relationship between subjective norms and intention to use (see Table III).

As expected, the influence of subjective norms on intention to use the robo-advisor increases for users with a lower level of familiarity compared to users with a higher level of familiarity. That is, when consumers lack familiarity with robots, their first-hand experience is low and thus their decisions may be based on others' opinions or information disseminated through mass media (Bhattacherjee, 2001). However, the influences of perceived usability and attitude on intention to use are not altered by familiarity. Therefore, H_3 is only partially supported.

In addition, as aforementioned, this study controlled for potential differences in the influence of the antecedents of intention to use robo-advisors due to sociodemographic characteristics such as age or gender (Sun and Zhang, 2006). According to Sun and Zhang (2006), these personal characteristics may be relevant moderating factors that could contribute to a better understanding of the acceptance of a new technology. To assess the possible moderating role of gender, a second multisample analysis was performed, comparing between males ($n = 329$) and females ($n = 436$). In this case, no significant differences emerged between the groups (see Table IV). Therefore, the results suggest that gender does not alter the influence of antecedents of intention to use, which implies that both men and women tend to base their adoption decision on a similar basis.

Finally, to assess the moderating role of age, the same procedure was used to perform another multisample analysis. The sample was divided into two groups: participants aged less than 35 ($n = 395$) and those aged 35 years or more ($n = 370$). The age of 35 was used as a cutoff point as it represents the difference between the millennial generation (broadly

Table III.
Multisample analysis:
familiarity with robots

Constraints	Estimated coefficients				
	Low familiarity	High familiarity	df	χ^2 difference	Probability
Perceived usefulness → Intention to use	-0.053	0.058	1	0.475	0.491
Attitude → Intention to use	0.805*	0.758*	1	0.169	0.681
Subjective norms → Intention to use	0.287*	0.124**	1	3.091	0.079

Notes: *,**Significant at $p < 0.01$ and $p < 0.05$, respectively

Table IV.
Multisample analysis:
gender

Constraints	Estimated coefficients				
	Males	Females	df	χ^2 difference	Probability
Perceived usefulness → Intention to use	0.066	-0.053	1	0.002	0.964
Attitude → Intention to use	0.707*	0.851*	1	0.626	0.429
Subjective norms → Intention to use	0.231*	0.226*	1	0.382	0.536

Note: *Significant at $p < 0.01$

understood as born after 1981) and previous generations (Bolton *et al.*, 2013). However, the results in Table V indicate that there is no significant difference between the groups. Again, the empirical results indicate that age does not alter the influence of antecedents of intention to use, meaning that the determinants of adoption have a similar influence for both younger and older customers.

5.2 Post hoc analysis

Previous studies have suggested that cultural differences may affect the formation of consumer intentions (e.g. Belanche, Casaló and Guinaliu, 2015) – an aspect that is crucial in online services that are being spread globally, as is the case for robo-advisors. The sample comprised participants from three countries (i.e. Portugal, the UK and the USA), which involve Latin and Anglo-Saxon countries, as well as American and European ones, in order to evaluate whether the influence of antecedents of intention to use robo-advisors depends on the participant's culture.

To this end, and following previous studies that have evaluated path differences among samples from different countries (e.g. Sultan *et al.*, 2009), a final multisample analysis was performed considering three groups: participants from Portugal ($n = 220$), the UK ($n = 278$) and the USA ($n = 254$). The results of this analysis, depicted in Table VI, reveal interesting differences between countries. Specifically, even though the relationship between usefulness and intention to use is not significant in any case, this influence is lower in Portugal than in the UK ($\chi^2_d(1) = 4.200; p < 0.05$) and the USA ($\chi^2_d(1) = 19.528; p < 0.01$). In addition, this influence is higher in the USA compared to the UK ($\chi^2_d(1) = 9.759; p < 0.01$). Regarding the relationship between attitude and intention to use, this influence is always significant and is significantly higher for Portuguese users than for British ($\chi^2_d(1) = 2.901; p < 0.1$) and American users ($\chi^2_d(1) = 16.759; p < 0.01$), as well for Americans compared to British customers ($\chi^2_d(1) = 13.885; p < 0.01$). Finally, the influence of subjective norms on intention to use is significantly lower in Portugal than in the USA ($\chi^2_d(1) = 14.748; p < 0.01$) or the UK ($\chi^2_d(1) = 8.054; p < 0.01$); this influence is significant in all cases. No difference arises in the comparison between the USA and the UK for the influence of subjective norms. In spite of these differences due to participants' nationality, the parameters estimated for each country provide consistent results with the model considering the whole sample, with attitude revealed as the most relevant predictor of behavioral intentions, followed by subjective norms.

Constraints	Estimated coefficients				
	Less than 35 years	35 Years or more	df	χ^2 difference	Probability
Perceived usefulness → Intention to use	0.024	-0.047	1	0.165	0.684
Attitude → Intention to use	0.726*	0.869*	1	0.012	0.913
Subjective norms → Intention to use	0.297*	0.190*	1	1.523	0.217

Note: *Significant at $p < 0.01$

Table V.
Multisample
analysis: age

Constraints	Estimated coefficients		
	Portugal	UK	USA
Perceived usefulness → Intention to use	-0.178	-0.020	0.039
Attitude → Intention to use	0.849*	0.790*	0.823*
Subjective norms → Intention to use	0.118**	0.259*	0.259*

Notes: *,**Significant at $p < 0.01$ and $p < 0.05$, respectively

Table VI.
Multisample
analysis: country

6. Discussion

6.1 Conclusions

Among the advance of innovative FinTech, robo-advisors are of particular interest because of their differential features. Contrary to other initiatives, robo-advisors rely on AI systems; that is, automated platforms based on analytical intelligence that are replacing human advisory services. This service innovation needs to be understood under the expansion of robotic and AI systems, which are likely to gradually replace many human jobs in the coming years (particularly mechanical, analytical, intuitive and empathic tasks Huang and Rust, 2018). More precisely, from a consumer perspective, users need to adapt to new robotic service providers that play the social role traditionally attributed to a human employee. Recent literature has highlighted that this advance represents a disruptive innovation that companies need to carefully understand and integrate in order to achieve a successful transformation in the medium term (Singh *et al.*, 2017; Van Doorn *et al.*, 2017). In this line, based on TAM, the contribution of the research framework to previous literature on robo-advisors' adoption is twofold. First, this study identifies the key determinants of customers' decision to adopt robo-advisor systems focusing on a wide range of customers and considering both traditional antecedents (such as those proposed in TAM Davis, 1989; i.e. attitude, perceived usefulness, ease of use) as well as social influences (i.e. subjective norms). Second, this study evaluates possible differences in the adoption process depending on the customer's familiarity with robots (a crucial aspect taking into account that financial robo-advisors represent a disrupting service innovation) and sociodemographic characteristics (i.e. age, gender, culture), which may moderate the relationships proposed in the framework. The inclusion of these moderating factors helps to better explain this phenomenon from a wider scope.

Regarding the first contribution – the identification of key determinants of customers' intention to use robo-advisors – the results suggest that attitude is the strongest predictor of behavioral intention to use financial robo-advisors, followed by subjective norms. Therefore, as proposed by Fishbein and Ajzen (1975), customers are not only motivated by their favorable or unfavorable evaluation of the use of these services, but also consider the expectations of others when making such usage decisions. This may be explained by the fact that, in a new situation for which there is no obvious course of action – as is probably the case when using financial robo-advisors – customers may need some basic social confirmation and may seek information from sources around them to better interpret and navigate it (Wei and Zhang, 2008). In turn, the influence of perceived usefulness on intention is non-significant. This is consistent with previous literature, as the sample comprised individuals that did not have direct previous experience with financial robo-advisors. Previous studies have suggested that the influence of perceived usefulness on intention to use is more consistent in post-acceptance stages (i.e. after several months using the system Bhattacherjee, 2001; Casaló *et al.*, 2010). In addition, attitude is positively influenced by perceived usefulness and perceived ease of use, wherein the influence of the former is greater. Again, this is consistent with previous literature suggesting that attitude plays a central role in the adoption of a new technology-based service (Hernández *et al.*, 2009), as in the case of robo-advisors. On the one hand, literature has found that perceived usefulness impacts attitude consistently in both pre-adoption and post-adoption stages; on the other hand, the influence of perceived ease of use seems to become non-significant in later stages of adoption (Davis *et al.*, 1989; Karahanna *et al.*, 1999; Bhattacherjee, 2001). Taking into account that preliminary findings on the robo-advisor field have suggested usability as a relevant factor for customers (Jung, Dorner, Weinhardt and Pusmaz, 2018), the results of the current study also advance this knowledge and support that not only perceived usefulness but also perceived ease of use play a crucial role in shaping customers' attitudes toward robo-advisors in early stages of the adoption process.

Second, the study contributes to the literature by evaluating possible differences in the robo-advisor adoption process. In this respect, familiarity is revealed as a key moderating variable to understand the intention to use this specific type of service. Specifically, the influence of subjective norms was found to be greater when participants have a lower familiarity with the use of robots than when they have a high familiarity. This is also consistent with previous findings, as consumers who are more familiar with interacting with robots have been shown to have more direct and realistic first-hand experience (e.g. Fazio and Zanna, 1981). Thus, users with higher familiarity will tend to value usefulness and personal attitudes to a greater extent, instead of relying on subjective norms based on others' opinions. In turn, when familiarity is low, first-hand information is more limited, leading to consumers' behavioral intentions toward robo-advisors being based on others' opinions to a greater extent, as previously proposed in the literature (Venkatesh and Davis, 2000). In turn, age and gender do not moderate the influence of antecedents of intention to use financial robo-advisors, suggesting that there is no technological divide related to these demographic characteristics. This finding is not surprising considering that recent studies have found that these variables may not affect the adoption process of a new technology when it is targeted to a wide population (e.g. Belanche, Casaló and Pérez-Rueda, 2015). In the present case, anyone who will potentially make investments during their life is a potential user of financial robo-advisors, as these systems are specifically designed to simplify and democratize finance management (Sironi, 2016).

Finally, since the sample comprised participants from three different countries (Portugal, the UK and the USA), this study also contributes to previous research on robo-advisor adoption by considering the moderating role of culture on this adoption process. The results suggest that there are relevant differences in the influence of antecedents of intention to use depending on participants' culture. In this respect, the influence of attitude seems to be greater for Portuguese users. This may be explained by differences in Hofstede's (2018) cultural dimensions; compared to the USA and the UK, in Portugal there is very high uncertainty avoidance, as well as lower rates of individualism and masculinity. Following Hofstede's (2018) description of cultural values, in cultures with higher uncertainty avoidance, attitude may be a crucial predictor of intention because of individuals need to be secured when making a decision involving uncertainty. In turn, the influence of usefulness is greater in the USA and the UK than in Portugal. This may be explained by the fact that the USA and the UK are countries with higher masculinity values, where people's motivations are more driven by aspects such as achievement and success (Hofstede, 2018). Thus, previous literature has found that in countries with higher masculine values, perceived usefulness (as a functional aspect linked to perceptions of successful performance) determines consumer behavior to a higher extent compared to in countries with more feminine values (Belanche, Casaló and Guinaliu, 2015). Finally, in spite of the fact that the USA and the UK score higher in individualism (Hofstede, 2018), the influence of subjective norms is greater in these countries than in Portugal. This represents an interesting finding because it reveals that subjective norms are crucial even in countries where individualistic or performance-based values are dominant, in contrast to social values. Perhaps American and British customers perceive others' opinions about robo-advisors as a kind of opportunity or invitation to participate in a competition to achieve greater value for their finances (i.e. convenience, profitability).

6.2 Implications for managers and customers

The successful introduction of robo-advisors in the context of AI and FinTech expansion represents a challenging issue, but also a source of competitive advantage for many firms in the finance sector (Park *et al.*, 2016). On the one hand, consumers may be reluctant to switch to an automated robo-advisor, because of its novel and particularly different features (e.g. lack of human–employee supervision). On the other hand, the advantages of robo-advisors have ensured that these systems are coming to manage a growing amount of

assets, revealing an opportunity to increase the market by spreading the service to a wider public (Jung, Dorner, Weinhardt and Pusmaz, 2018).

Our study provides managers with advice about the introduction of robo-advisors to a wide spectrum of consumers. A relevant finding of the research is that basic demographic variables do not alter the relationships within the proposed framework, which suggests that robo-advisors could be targeted to users independently of their age and gender. However, the strength of the influence of determinants of intention to use varies among participants from different countries, which suggests that more precise strategies that could be targeted to each market can be developed.

As the main finding, the study reveals that consumer attitudes toward these systems are the key driver of the intention to use them; therefore, the design of an easy to use and useful platform is fundamental to shape users' favorable predisposition toward the use of robo-advisors. In order to increase the number of robo-advisor users, financial companies must be able to assuage customers' doubts and enhance their perceptions of these systems. For this purpose, informing customers about the benefits and profitability of using robo-advisors, allowing them to interact with the robo-advisor platform (even if they do not invest any money or the investment is very low) or including supporting conversational systems (e.g. chatbots or digital assistants that simplify human-machine interactions and improve the interface's interactivity SAP, 2018) could be of help. This is especially recommended for countries with high levels of uncertainty avoidance (like Portugal in the present case) because, in these countries, customers need to be secure when adopting an innovation that involves uncertainty. That is, customers need to have a very positive opinion about financial robo-advisors in order to decide to use them.

In turn, subjective norms also have a remarkable impact on robo-advisor adoption. Both interpersonal comments and mass media information contribute to increasing consumers' intentions to start using robo-advisors. In this regard, banks and other companies in the industry should seek to enhance public opinion by providing information about the benefits of robo-advisors by means of expert users and professional reports. Interestingly, the effect of subjective norm is even greater in Anglo-Saxon countries (i.e. the UK and the USA), suggesting that even putting extra effort into advertising, publicity or lobbying would be highly beneficial in these countries to boost the social approval of robo-advisors for a higher adoption of such systems.

Finally, the results reveal that effects of the determinants of intention to use vary depending on users' familiarity with robotic and AI systems (Young *et al.*, 2009). As theoretically expected (e.g. Venkatesh and Davis, 2000), others' opinions (i.e. subjective norms) have a greater impact on users with lower familiarity than on users with higher familiarity, who already have their own perceptions about robo-advisors. This finding suggests a twofold strategy to attract users: marketing campaigns could focus on consumers who already have experience with robots following cross-selling practices (e.g. agreements with robotic engineering faculties or associations, alliance with companies in the AI and robot industry such as iRobot, etc.). Indeed, establishing an ongoing alliance with robot developers would help finance firms to promote breakthrough innovations (Zheng and Yang, 2015). Alternatively, and considering the relevance of subjective norms for users with lower familiarity with robots, firms could address more familiar users to spread the message to less familiar ones by means of social media campaigns or advertisements in which expert users explain their favorable experiences with robo-advisors.

Turning to customers, it is strongly recommended that they look for information (e.g. reports, news, etc.) that explain the characteristics (e.g. profitability, advantages, disadvantages, etc.) of financial robo-advisors. These customers are encouraged to look for other customers' opinions and comments (e.g. on social media or on specialized publications on finance). Since it is difficult to develop expectations before consuming services, the use of second-hand information from others may be of help in forming realistic expectations about a given service (Casalo *et al.*, 2015).

Therefore, testimony from peers may be useful in forming more precise expectations about financial robo-advisors, reducing the perceived risk of using them.

As well, customers should interact with robo-advisor platforms directly in order to evaluate their ease of use and usefulness via first-hand experience, which is considered as more accurate than second-hand experience (Fazio and Zanna, 1981). In this way, their beliefs about the robo-advisor and, subsequently, their positive or negative evaluation of robo-advisors (attitude) will be more stable, helping them in their decision making. This is especially recommended for customers with low levels of familiarity with robots, due to their lack of first-hand experience with any kind of AI.

6.3 Further research and limitations

Despite these interesting contributions, this work has some limitations that suggest lines for further research. First, this study focuses on behavioral intentions as the main dependent variable. Previous research (Venkatesh and Davis, 2000) has confirmed that intention to use and actual use are habitually highly correlated in the case of volitional behaviors, as per the current study. Although the study of intention to use helps to understand initial stages of the adoption process – afterwards, intentions are continuously refined and modified, which impacts long-term continuance or discontinuance (e.g. Bhattacherjee, 2001) – a longitudinal study that collects data about the actual use (Bagozzi, 2007) of financial robo-advisors would be beneficial to further validate the findings of this research. Second, even though the study analyzed the moderating role of some individual characteristics, other personality traits (e.g. technology readiness, need for social interaction, etc.) may also moderate the relationships of the proposed framework. Third, other variables, such as consumers' personal experience with human-assisted management of their finances, may also be relevant in this context. Similarly, a customer's relationship and familiarity with the company offering the financial robo-advisor – or other variables related to the company (e.g. reputation) – may affect the adoption process; therefore, future research could focus on these aspects. Finally, most participants in this research come from Portugal, the UK and the USA; since the results show significant differences according to country, future studies could incorporate other cultures (e.g. Asian, Latin American, Jewish, etc.) to obtain a global understanding of the adoption of financial robo-advisors.

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Perceived ease of use

- EASE_OF_USE1 Learning to use robo-advisors would be easy for me
EASE_OF_USE2 I would find it easy to manage investments using robo-advisors
EASE_OF_USE3 It would be easy for me to become skillful at using robo-advisors
EASE_OF_USE4 I would find robo-advisors easy to use

Perceived usefulness

- USEFUL1 Using robo-advisors would improve my performance in managing investments
USEFUL2 Using robo-advisors would improve my productivity in managing investments
USEFUL3 Using robo-advisors would enhance my effectiveness in managing investments
USEFUL4 I would find robo-advisors useful in managing investments

Interpersonal influence

- INT_INF1 My peers/colleagues/friends think that I should use robo-advisors for managing investments
INT_INF2 People I know think that using robo-advisors is a good idea
INT_INF3 People I know could influence me to try out robo-advisors for managing investments

External influence

- EXT_INF1 I have read/seen news reports that using robo-advisors is a good way of managing investments
EXT_INF2 The popular press depicts a positive sentiment related to using robo-advisors
EXT_INF3 Mass media reports influence me to try out robo-advisors for managing investments

Attitude

- ATT1 Using robo-advisors for managing investments seems like a good idea
ATT2 I like the idea of using robo-advisors for managing personal investments
ATT3 Using robo-advisors for implementing my investments seems like a wise idea

Intention to use

- INT_USE1 I intend to use robo-advisors for managing investments
INT_USE2 Using robo-advisors for managing investments is something I would do
INT_USE3 My intention is to use robo-advisors rather than any human financial advisor

Familiarity with the use of robots

- FAMI1 I have worked with or studied robotic artificial intelligence
FAMI2 Throughout my life I have had experience interacting with robots
FAMI3 I am familiar with robots or robot contents (texts, audiovisuals, etc.)

Table AI.
Measurement scales

About the authors

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