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ORIGINAL ARTICLE

Antecedents of robo-advisor use intention in private pension investments: an emerging market country example

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Abstract
Robo-advisor is one of the most up-to-date innovations in the financial world. So, the number of experienced users is also very limited, yet. The study investigates to reveal the components that determine the usage intention for robo-advisor by private pension investors who have not yet experienced the product in order to determine the real potential of robo-advisor. This study assimilated elements of the UTAUT "performance expectancy, effort expectancy, facilitating conditions, and social influence" and extended the model by adding in three vital elements "a need for interaction with service employees, financial risk tolerance, and trust." A survey was conducted involving 265 investors in Turkey who have private pension investments and have experienced digital banking. The outcomes of this study indicate that the factors affecting robo-advisor usage intention in private pension investments are performance expectancy, social impact, facilitating conditions, financial risk tolerance, and trust. Also, trust positively affects financial risk tolerance. However, effort expectancy and the need for interaction with service employees have no effect on the intention to use a robo-advisor. This research can support robo-advisor service providers and regulators in designing services and improving the adoption of robo-advisors. The study should also shed light on the future of distance services.

Keywords Robo-advisor · UTAUT · Needs for interaction with service employees · Financial risk tolerance · Trust · Turkey

Introduction

Among the most remarkable AI products of the current period are the robo-advisors used in financial investments. In fact, robo-advisor is a portfolio management system that offers investment advice based on customer analysis, unlike other online investment platforms (Jung et al 2018a). Robo-advisors, which are AI-based software aiming to provide financial advice, are among the most personalized products that assist investors in evaluating and tracking their private pension savings in the most suitable funds. A robo-advisor offers investment advice with personalized risk analysis, real-time service, and minimal human interaction to investors (Zhang et al. 2021). Robo-advisor has a dynamic design and is in a nascent period. In addition to having features such as market updates, opportunity/risk warnings, dashboards, and periodic portfolio reviews, it also allows for the intervention of the investor in this process, thus bringing personalization to the fore (Jung et al 2018a). Moreover, investors have the chance to change some parameters and portfolio weights in the investment advice by going beyond the algorithm suggested by robo-advisor (D'Acunto and Rossi 2020). Optimization of investment created with low cost and tax, allowing minimum investment, and less emotional decision making are the strongest aspects of robo-advisor (Jung et al 2019). On the other hand, its weaknesses can be listed as follows: Investment costs are not minimized, conflict of interests, poor assessment of risk tolerance and lack of personalization, no personal contact, and unfulfilled fiduciary duty (Jung et al 2019). However, while the robo-advisor is also criticized for not giving investors discretion in managing their savings, it is also thought that it may lead to great social impact in possible negative economic shocks by directing the majority of investors to invest in the same portfolio (D'Acunto and Rossi 2020). In addition, the fact that ethical and legal processes and personal data breach are still not defined for robo-advisors poses an obstacle to the protection of investors' rights (D'Acunto and Rossi 2020).

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The purpose of this research is to reveal the elements that determine the usage intention of investors who have not yet experienced the robo-advisors offered to private pension investors and to determine the real potential of the product. Questioning the interests of investors in robo-advisors should shed light on the future, since one of the important changes in consumer life created by the COVID-19 pandemic over the last two years is the distance service purchase. Researching the marketing and finance literature shows that studies are mostly theoretical (Wexler and Oberlander 2021; Tokic 2018), comparing trust and performance expectations for an advisor (human) and a robo-advisor (Zhang et al. 2021), examining the experience of meeting investors with a robo-advisor (Belanche et al. 2020; Jung et al. 2018a; Hildebrand and Bergner 2021; Hohenberger et al. 2019; Seiler and Fanenbruck 2021, Wu and Gao 2021), and trying to reveal the robo-advisor user profile (Fulk et al. 2018; Cheng 2021). D'Acunto et al. (2019) focused on the differences between investors who adopted and did not adopt robo-advisor in their studies and concluded that investors who had not adopted robo-advisor before obtained higher fund returns as a result of diversifying their investments after adopting robo-advisor. In their study, Rossi and Utkus (2020) focused on the differences between investors using robo-advisor and using a human advisor, and concluded that although investors using robo-advisor give importance to human interaction, they see it as a tool that will strengthen their own development and create time and opportunity to turn to different areas. On the other hand, Bruckes et al (2019)'s study related to robo-advisor has taken trust at the center of the research and examined the relationship between trust and intention to use in depth by including structural assurances. Flavián et al. (2022)'s study also examined robo-advisor use intention within the scope of the technology readiness model and reflected the results of customer experience in their work. However, possible variables that determine the product usage intention of potential users who have not yet experienced robo-advisors are limited in the literature. Yet, it is predicted that users' perceptions of AI can enhance individuals' acceptance of it in various services, thereby giving AI more strength and equivalence (Pelau et al. 2021). Therefore, the study is based on UTAUT model which has the power to explain 70% of users' behavioral intention to use technology and 50% of related technology usage behavior. Although Oehler et al (2022) examined the effect of individual personality traits on the decision to use robo-advisor when examining the rest of the literature seen that has not been given sufficient importance to needs for interaction with service employees, trust, and financial risk tolerance related to intention to use robo-advisor (Manrai and Gupta 2022). So, this research adopted UTAUT elements and expanded them by putting other essential elements. The most important reason for the extension of the UTAUT model with the NISE and trust variables in this research is the lack of research to reveal whether the service provided by robo-advisor meets the need for human contact, and trust and NISE's effects on the acceptance behavior of the users (Morana et al. 2020). Moreover, there is a need to better understand the implications of trust in interacting with robo-advisor, and with trust, financial risk tolerance on users' intention to seek investment advice from robo-advisor (Day et al. 2018; Morana et al. 2020). Therefore, the UTAUT model has been extended with the variables of confidence and financial risk tolerance, as well as NISE. Along this axis, the targeted contributions of the research are to reveal individual motivators that determine the intention to use a robo-advisor in private pension investments and in other investments and to determine the relationship between trust and financial risk tolerance.

There is an important deficiency in studies and statistics reflecting the views of investors about financial investments such as private pension investments, which require a high level of participation by the consumer in terms of decisions and include long-term investment. Similarly, some studies reflect the perspectives of developed countries on the robo-advisors used in the financial sector (Atwal and Bryson 2021), there is only limited information about users' interactions or expectations for potential interactions, especially in emerging markets. Based on these limitations, this study uses data from Turkey to reveal investor reflections in emerging market economies. The reason for choosing Turkey in this research is that the highest expected growth in the assets managed by robo-advisors will occur in Turkey (Statista 2021). The other important reason is that almost all private pension companies in Turkey offer their investors the opportunity to use robo-advisors. D'Acunto et al. (2019) focused on the differences between investors who adopted and did not adopt robo-advisor in their studies and concluded that investors who had not adopted robo-advisor before obtained higher fund returns as a result of diversifying their investments after adopting robo-advisor. In their study, Rossi and Utkus (2020) focused on the differences between investors using robo-advisor and using human advisor, and concluded that although investors using robo-advisor give importance to human interaction, they see it as a tool that will strengthen their own development and create time and opportunity to turn to different areas.

Theoretical background and hypotheses

Robo-advisors and private pension system

The robo-advisor is considered one of the most important AI products in finance, which has been accelerating its digitalization investments with the effects of innovation and

dynamism in technology (Belanche et al. 2020). It ensures that investors receive uninterrupted investment consultancy services, by taking into account the investor's character through the completion of risk surveys before developing a consultant–client relationship and giving suggestions on the most appropriate fund distribution. The first robo-advisor, that offers personalized service with minimal human interaction, was developed by Wealthfront and Betterment (Zhang et al. 2021). A robo-advisor is software that offers investors online financial advice with moderate or minimal human intervention. In general, there are five key dynamics in the operation of a robo-advisor service: selecting assets, defining the risk profile of investors, optimizing portfolios, monitoring and rebalancing, and performance reporting (Dong et al. 2021). In this context, the advantages a robo-advisor offers users include time savings, estimation accuracy and impartiality, and a low margin of error (Jung et al. 2018a). On the other hand, robo-advisors' popularity is increasing, as they allow small investors to gain entry into automated asset management with low minimum investment requirements and low fees, as well as minimizing conflicts of interest (Leow et al. 2021). The most striking feature of the robo-advisor is the assumption that, unlike an employee, it is relatively less likely to de-emphasize the investor's interests in favor of the interests of the financial institution. However, there are also concerns that there are conflicts of interest and investment decisions are made without being fully automatized, due to artificial intelligence and thus robo-advisor being developed and directed by humans (Jung et al 2019). Due to the advantages robo-advisor provides to the financial system in terms of cost, it places in focus mostly individual investors, regardless of the investor's investment size (Jung et al. 2018b).

The private pension system is a pension system created as a complement to existing public social security systems and financed by individuals' own investments; these individuals can thus live more comfortably and maintain their living standards in retirement. This system has been adopted by working populations to overcome poverty in old age, especially in European countries whose population is getting older every year and whose retirement income is not sufficient to provide comfort in current living conditions (Ebbinghaus 2021). Data for the end of 2021 shows that private pension system investments in Turkey have reached US$ 15.8 billion (Pension Monitoring Center 2022). The number of active participants in the system is 7 million people, about 10% of the country's population (Pension Monitoring Center 2022). In addition, despite the decrease in total assets under management (AUM) in 12 of 65 OECD countries in 2018, the private pension funds market in Turkey has the highest real growth rate for any country, with 20%. On the other hand, the fact that it had the fifth-lowest ratio among OECD countries of AUM to Gross Domestic Product (GDP) in 2020 (3.4%) points to Turkey's growth potential (OECD 2021). The robo-advisor initially emerged as a potential solution to increase the accessibility and affordability of investment assistance in savings for retirement. The management of investments by robo-advisors in private pension investments has developed significantly in OECD countries in recent years (OECD 2017). The assets managed by robo-advisors in Turkey are anticipated to reach US$5.861 m 2021 and US$17.241 m in 2025, with a projected growth of 30% each year (Statista 2021). Research conducted in this context indicates that the highest expected growth will take place in Turkey (Statista 2021). It is known that 7% of private pension investors prefer to use a fully automated system like a robo-advisor (TreasureData 2019). However, investors in the banking sector comparatively prefer human–human interaction (Luo et al. 2019). This is a sign that the use of robo-advisors is still in its infancy in both private pension and other financial investments. In this context, it is necessary to investigate whether the need among investors to receive services from human employees is an obstacle to the use of robo-advisors.

Behavioral intention and UTAUT

UTAUT which was put forward by Venkatesh, et al. (2003) as a synthesis of eight theories/models developed before it, aims to determine the behavioral intention (BI) to use a technology (Giovanis et al. 2019). Therefore, the dependent variable of the study is the use intention that reveals the degree of users' intention to use a robo-advisor. BI is the reflection of the user's mental state before the action takes place, which indicates the strength of their intention to act in accordance with the intended behavior (Fishbein and Ajzen 1975). Since BI is an approved possibility to perform a purchase or carry out a transaction (Han and Ryu 2006), determining the BI toward robo-advisors, which are still in the infancy stage, becomes important as a determinant of the use behavior of this product in the future. The literature also confirms that these four main determinants of UTAUT predict users' intentions to use and accept a new technology (Hossain et al. 2019).These are as follows:

Performance expectancy (PE)

PE is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al. 2003, p.447). It is accepted that PE comprises the expected benefits from the use of a technology, such as rapid response and high efficiency (Bhatiasevi 2015). In this study, the PE toward robo-advisors refers to the degree to which investors believe that using this product will help improve their investment performance and achieve higher returns. Users' performance

expectations that new technology will increase their productivity and efficiency affect their intention to use the technology (Kabra et al. 2017).

Studies in the finance literature confirm that one of the most important factors affecting the intention to use information technologies is the PE of the product's users (Tan and Lau 2016; Baabdullah et al. 2019a, b; Merhi et al. 2019; Jadil et al. 2021). On the contrary, Cho's (2019) research shows that PE related to robo-advisor does not positively affect usage intention. Accordingly, the following hypothesis is proposed:

H1 PE expectancy has a significant effect on investors' intention to use a robo-advisor in their financial decisions.

Effort expectancy (EE)

EE is defined as "the degree of ease associated with the use of the system" (Venkatesh et al. 2003, 450). In studies of financial technologies (Bankole and Bankole 2017), EE is when using and learning the relevant technology is easy and requires no effort. In this study, EE toward robo-advisors reflects investors' belief that it will be easy to use and learn the product, as well as the openness of their interactions with it. There is a significant relationship between the user's expectation of the effort involved in using and learning of a new technology and the intention to use that technology (Abbasi et al. 2015; Bu et al. 2020).

The finance literature indicates that users' EE toward a new technology affects their intention to use it (Tan and Lau 2016; Cho 2019; Giovanis et al. 2019; Gupta et al. 2019; Jadil et al. 2021). One of the limited studies on robo-advisor shows that EE positively affects robo-advisor's usage intention (Cho 2019). Accordingly, the following hypothesis is proposed:

H2 EE has a significant effect on investors' intention to use a robo-advisor in their financial decisions.

Social influence (SI)

SI is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al. 2003, 451). However, the more users a technology has, the higher the expected acquisition of new users (Kraut et al. 1998). In this study, SI reflects the beliefs and attitudes of users or of individuals or groups whose advice to use a robo-advisor those users consider important. From a sociological perspective, users are likely to intend to use the relevant technology if they believe that others important to them should do so, or if they receive referral behavior (Slade et al. 2015; Bu et al. 2021).

An examination of the finance literature shows that key factors affecting the BI to use a new technology are positive attitudes and discourses in the users' close environment about the relevant technology (Tan and Lau 2016; Bankole and Bankole 2017; Albashrawi et al. 2019; Baabdullah et al. 2019a, b; Cho 2019; Jadil et al. 2021). Cho's (2019) and Song (2017)'s research shows that SI regarding to robo-advisor positively affects usage intention. Accordingly, the following hypothesis is proposed:

H3 SI has a significant effect on investors' intention to use a robo-advisor in their financial decisions.

Facilitating conditions (FC)

FC are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al. 2003, p.453). FC include "the availability of technological resources and technical infrastructure" (Arfi et al. 2021, p. 5). The concept of FC in the field of finance states that both the technical and organizational infrastructure of the finance business is appropriate and usable to support the individual's use of a technology (Albashrawi et al. 2019). The concept of FC in the study reflects the belief that users have the necessary information and resources to use a robo-advisor or that they can get support when they need it. Since users' concerns about security, privacy, and reliability are important in shaping expectations toward technology (Dwivedi et al. 2016), the existence of FC is considered an important factor in the adoption of and use intention toward robo-advisors. There is a linear relationship between the existence of FC for new technology and use intentions toward it (Venkatesh et al. 2012; Dwivedi et al. 2017; Shah et al. 2020).

Studies in the finance literature show that users' belief in the existence of FC is an important factor in determining their intention to use a technology (Thusi and Maduku 2020; Jadil et al. 2021). Accordingly, the following hypothesis is proposed:

H4 FC have a significant effect on investors' intention to use a robo-advisor in their financial decisions.

Need for interaction with service employee (NISE)

Human interaction is extremely important in the evaluation of much of the service industry (Bitner et al. 1990). Interpersonal communication and interaction remain important representatives of our social existence (Pelau et al. 2021). However, the use of AI applications in different service sectors necessitates human–robot interaction for the consumption or delivery of the service (Araujo 2018). NISE, which is accepted as an important determinant in the evaluation

of a technology-based service, can be described as "the importance of human interaction to the customer in service encounters" (Dabholkar 1996, p. 188). While past studies point out that customers in the service industry view interaction as inadequate or even unpleasant when they receive service from machines rather than employees (Meuter et al. 2003), current studies show that people are willing to receive service from AI (Hill et al. 2015) and even tend to interact with AI for longer periods of time (Ciechanowski et al. 2019). The fact that AI does not have a judgmental attitude (Mou and Xu 2017) provides an opportunity for a more positive evaluation of human–robot interaction. NISE is an individual characteristic; more social people are known to need more human interaction (Lee 2017). Although NISE is an important variable in understanding and determining user needs in technological applications, it is considered even more important for individuals who value and need human contact (Kokkinou and Cranage 2015). On the other hand, NISE in service consumption is a contradictory issue, as the current pandemic period has changed the shape and structure of interpersonal communication while forcing customers to receive socially distanced services. For this reason, it is thought that customers' NISE in service consumption should be reassessed.

Past studies indicate that human interaction is an effective factor in the acceptance of service from AI (Pelau et al. 2021). NISE is an important variable in understanding and determining user needs in technological applications, but it is even more important for individuals who value and need human contact (Kokkinou and Cranage 2015). In this context, depending on the preference to be more sensitive to human contact, it is known that NISE is important in determining the delivery of the service and different individuals prefer different interactions as employees or robots (Mou and Xu 2017). Lee and Choi's research (2017), about is on virtual financial advice tools, show that social presence improves users' intention to use. Jung et al. (2018b)'s research shows that many investors still prefer a human advisor. Studies show a negative relationship between NISE and the BI to use self-service technologies (Lee et al. 2010; Lee 2017). On the other hand, Curran and Meuter (2005), in a study in the field of finance, found no support for the predicted negative relationship between NISE and BI to use technology. Accordingly, the following hypothesis is proposed:

H5 NISE has a significant effect on investors' intention to use a robo-advisor in their financial decisions.

Financial risk tolerance (FRT)

FRT is defined as the maximum amount of uncertainty an individual is willing to accept when making any financial decision (Carr 2014). While the finance literature considers FRT a persistent predisposition for most individuals, it also suggests that it is a trait open to revision with changing personal characteristics (e.g., age) or in response to material life experiences or shocks (Hartnett et al. 2019). Although some studies accept FRT as a situational factor (Kahneman and Tversky 1979), most see an individual as having a high or low FRT personality trait (Hartnett et al. 2019). For this reason, FRT has been studied in previous studies mostly in association with demographic data (Rahman et al. 2020). Accordingly, although FRT mostly depends on a person's income and savings or financial return, it can sometimes vary according to demographic or psychological factors (Carr 2014).

Behavioral trends help interpret the relationship between FRT and preferred future investments (Rahman 2020). Croy et al. (2010) also concluded that there is a negative relationship between FRT and BI to use a product. However, risk acceptance significantly affects the relationship between perceived risk and the intention to use technology in financial transactions (Marafon et al. 2018). Similarly, Nguyen et al. (2016) indicated that the client's FRT is positively related to client asset allocation decisions. Wu and Gao (2021) also emphasized a negative relationship between individuals' risk perception and their intention to use a robo-advisor. Perceived financial risk effects negatively robo-advisor's usage intention (Cho 2019). In this context, based on the connection between FRT and individuals' decision-making behavior with respect to investments, it is thought that there is also a connection between individuals' FRT and their BI to use a robo-advisor. Accordingly, the following hypothesis is proposed:

H6 FRT has a significant effect on investors' intention to use a robo-advisor in their financial decisions.

Trust (T)

Although many disciplines have investigated the effects of trust (T) on a range of variables, there are still challenges to define and conceptualize it (Ghanem et al. 2020). However, it is obvious that T is a vital element in determining individuals' intention to purchase (Venkatesh et al. 2011); indeed, it is the basis of trade (Gefen 2000). Trust is one party's belief that another party will act with integrity, capability, and benevolence (Zhou 2011). Here, integrity is the seller's ability to follow certain principles and disciplines acceptable to the buyer; capability comprises the features of the product, competence, and the seller's skills; benevolence refers to the general tendency of the seller to help and support the buyer (Suh and Han 2003). T is recognized as an important variable explaining BI toward new technologies (Yang et al. 2016).

T in new technology is the belief that this technology will properly fulfill its obligations to the user's needs. Because of the possible uncertainties and jeopardies inherent in robo-advisors or other AI products (such as chatbots)—a technological application that virtually does away with employee intervention—T is considered an important element that determines users' BI toward these services (Seo and Lee 2021; Nguyen et al. 2021). T in technology-based services positively affects BI related to the use of these services (Alalwan et al. 2017; Cho 2019; Wang et al. 2019; Karjaluoto et al. 2021; Khan et al. 2021; Nguyen et al. 2021). Gu et al. (2015) argued that since robo-advisor creates financial investment advice based on user responses, users will trust this technology and thus intend to use it. One of the limited studies on robo-advisor shows that T positively affects robo-advisor's usage intention (Cho 2019). Accordingly, the following hypothesis is proposed:

H7 T has a significant effect on investors' intention to use a robo-advisor in their financial decisions.

There is substantial evidence that greater T in financial markets is associated with lower perceived risk (Olsen 2008). Rahman et al. (2020) also showed that T tendency has an effect on FRT. In this context, T in a system/technology affects the risk perspective of investors in the complexity of the investment (Nguyen et al. 2019). Cho (2019) argues in his study that the financial risks that may arise during the use of robo-advisors (attacks and investment failures) affect trust. It is known that individuals with a high tendency to T also have a high FRT (Pan and Statman 2012; Rahman 2020). Previous studies indicate that the predicted financial risk associated with robo-advisor affects trust building (Nourallah et al. 2022). Accordingly, the following hypothesis is proposed:

H8 T in a robo-advisor has a significant effect on investors' FRT.

Figure 1 shows the research model developed in line with the research objectives and hypotheses.

Research methodology

Data collection, sample, and measures

In the study based on the quantitative research method, a questionnaire was used as the data collection method. As investing with a robo-advisor involves online investment transactions, participants must have a private pension investment account and digital banking experience. Before starting the questionnaire, the participants were briefed about robo-advisor and its operation, as they were not experienced in this service. The pilot study was first implemented for 32 participants. The questionnaire was administered in Turkish and academics who were experts in their fields confirmed its linguistic integrity. The data includes individuals living in Turkey who are Turkish and over 18, have a private pension investment account, and have digital banking experience. The sample size was calculated using the G.Power-3.1.9.7 program at a 95% confidence level before the data collection phase. The minimum sample number was determined as 262 by taking the effect size (p) 0.2, the alpha error value of 0.05, and the theoretical power of 0.95. The data was collected through Prolific and includes 265 responses. The

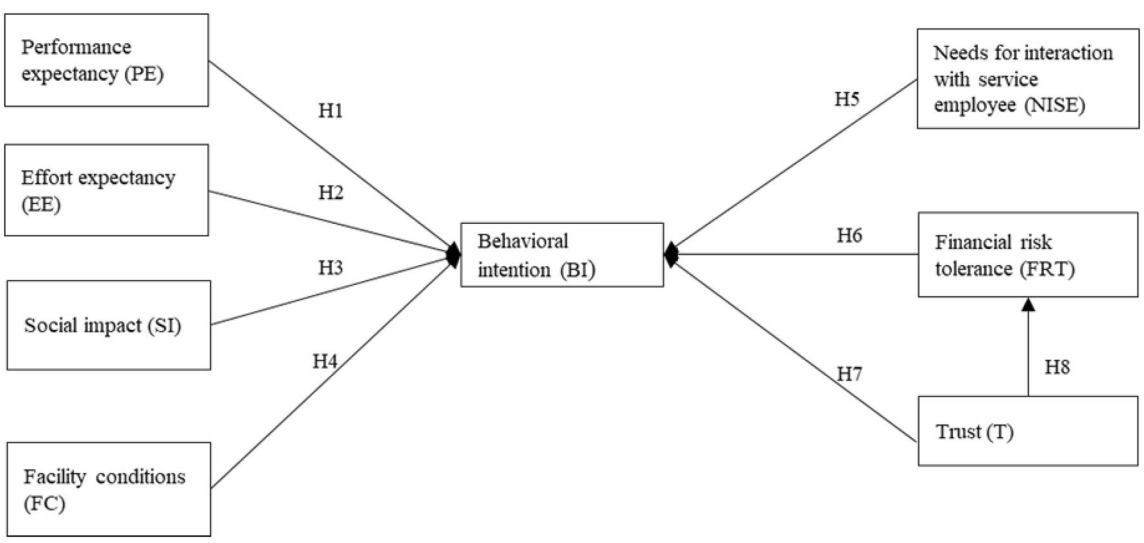

Fig. 1 Research model

most important reason for the low number of samples is that the participants have both experiences of private pension investment and the use of digital banking. There are 32 items in the survey. According to Kline (1994), a group of participants 2–10 times the total number of parameters in the sample, or a minimum of 200, is sufficient. Thus, 64–320 participants are sufficient for this study. Of the participants, 51% are female, 35% are undergraduate graduates, 46% are between the ages of 41 and 62, and 36% have a monthly income of $1400–2100.

The constructs were measured using a five-point Likert scale, ranging from 1 "strongly disagree" to 5 "strongly agree". The questionnaire includes seventeen items from the five structures of the UTAUT scale (PE, EE, SI, FC, and BI) (Venkatesh et al. 2003), seven items from the trust scale (Komiak and Benbasat 2006), four items from the NISE scale (Dabholkar and Bagozzi 2002), and four items from the FRT scale (borrowed from the survey of consumer finance). The questionnaire also asks questions about the demographic characteristics of the participants.

Common method bias (CMB) results from a common rater, a common measurement context, a common item context, or the characteristics of the items themselves (Podsakoff et al. 2003). CMB refers to the amount of spurious covariance shared by variables due to the common method used in data collection (Buckley et al. 1990). To prevent the findings from being subject to bias and therefore the results of the study from being misleading, biased, or invalid, some procedures were followed when designing the questionnaires. Also, data statistical solutions were used to minimize and control the potential impact of the CMB (Podsakoff et al. 2003). At the start of the questionnaire, study participants were reassured about their anonymity and the confidentiality of their responses, to reduce evaluation anxiety (Johnson and Fendrich 2005). Then, to reduce the perception of any direct connection among the respondents, the study attempted to create a psychological distinction by presenting the study variables in a different order and adding marker variables, control variables, and questions about the respondent's demographic profile (Podsakoff et al. 2003). As a statistical solution, Harman's 1-factor (single factor) test via explanatory factor analysis (EFA) and confirmatory factor analysis (CFA) was applied to the data as a post hoc corrective test to control for the probability of CMB (Podsakoff et al. 2003).

Results

Measurement model

Data distribution, missing data, and outliers were checked before the CFA. Skewness and kurtosis values are statistics that provide information about the normality of the data distribution, being normal when the data distribution is between − 2 and + 2 (George and Paul 2010). For extreme values, each z variable was converted to a standard normal distribution score. There were no Z-scores for variables outside this range, so no outliers were found. The descriptive analysis showed that the data was close to normal distribution and acceptable for EFA. Applying principal component analysis to the data showed that the sample size was sufficient for factor analysis, as compared to the KMO test (KMO value: 0.902) (Tabachnick and Fidell 2013). The Bartlett test of sphericity was also significant ($X2 = 7535.637$; $p < 0.001$) (Tabachnick and Fidell 2013). In addition, since the sampling adequacy criterion (MSA) value was over 0.50, the analysis could continue without asking any questions. The assumption of multivariate normality also indicates an assumption of linearity (Fornell and Larcker 1981). The first table shows data analysis' outcomes.

The data was analyzed using EFA. Except for one expression from the FC, NISE, and FRT scales, each expression was loaded on its own factors, with factor loads above 0.60 (Henseler et al. 2009). Three items were thus excluded from the analysis. The results are shown in Table 1. First, the measurement model was evaluated with CFA. To control the fit of the research model with the data, the fit indices were examined; the findings appear in Table 2. NFI (0.966, 0.966,

Table 1 EFA results

Variables	İtems	Factor loads	Mean	SD
BI	3	0.973–0.980	2.880	1.159
EE	4	0.758–0.921	3.412	0,974
FC	3	0.721–0.836	3.574	1.108
NISE	3	0.690–0.987	4.350	1.179
PE	4	0.812–0.890	3.381	1.018
FRT	3	0.755–0.882	2.931	1.197
SI	4	0.726–0.862	2.861	0.951
T	7	0.863–0.934	4.215	1.068

Table 2 CFA results and compatibility indexes

Variables	Cronbach's α	CR	AVE
BI	0.944	0.983	0.951
EE	0.887	0.923	0.750
FC	0.761	0.813	0.593
NISE	0.902	0.885	0.724
PE	0.884	0.920	0.741
FRT	0.749	0.854	0.662
SI	0.818	0.877	0.642
T	0.954	0.970	0.822

Indexes: SRMR = 0.072 NFI = 0.966 d_ULS = 2.599 d_G = 1.257 Chi Square = 1840.019

0.952) and SRMR (0.072, 0.069, 0.075) values for the data indicate that the model has acceptable fit (Kline 2005). To accomplish this, the upper bound of the confidence interval must be greater than the original value of the d_ULS and d_G perfect fit criteria. Therefore, the upper limit of the confidence interval was chosen as 95% or 99%. The model is suitable when the difference between its correlation matrix and the empirical correlation matrix is statistically insignificant ($p > 0.05$). The d_ULS and d_G values obtained for the data have $p > 0.05$, so the data appears to support the model. Also, PLSpredict was run to measure the predictability of the model, showing that all the Q^2 values in PLSpredict were positive in the model. However, the linear regression model (LM) provides prediction errors and summary statistics that ignore the specified PLS path model. Comparing these with the PLS-SEM results indicates whether using a theoretically established path model improves (or at least does not worsen) the predictive performance of the available indicator data (Shmueli et al. 2019). This comparison confirms that the PLS-SEM results have a lower prediction error (for RMSE, MAE, and MAPE) than the LM. For the model, The Q^2 values of all items in the BI scale are above 0.34, and the items in the FRT scale are between 0.02 and 0.03. When the Q2 value is between 0.02 and 0.14, this indicates a small predictor between variables; a value between 0.15 and 0.34 indicates a medium predictor; and one greater than 0.35, a large predictor (Shmueli et al. 2019). These values thus show that there is a large predictor among the BI variables and a small predictor among the FRT variables.

In the dataset, 76.8% of BI and 9% of FRT are explained by variables. Besides evaluating R^2 values as a criterion of predictive accuracy, Stone-Geisser's Q^2 value accepts as a criterion of predictive relevance, and the Q^2 value of the latent variables in the PLS path model is obtained by using a blindfolding procedure (Hair et al. 2017). Blindfolding results show the Q^2 values of both BI and FRT are higher than 0.00 (Q^2 for BI = 0.79 FRT = 0.032).

Convergent and discriminant validity were examined via CFA, and the results are shown in Table 2. They reveal that all the criteria for the measurement model fit within acceptable ranges. The measurement scales' reliability, also known as factor loading, exceeds 0.70, which satisfies item-level convergent and discriminant validity, respectively (Henseler et al. 2009; Hair et al. 2009). It also shows that the internal consistency of items toward the construct was satisfied, such that every scale's Cronbach's α and internal composite reliability (CR) were greater than 0.70 (Hair et al. 2009). In addition, Table 2 shows the average variance extracted (AVE), obtained through measures of the same concept, was higher than the recommended value of 0.50 and thus satisfied the criterion of convergent validity at construct level (Fornell and Larcker 1981).

Tolerance and VIF values are statistics that provide information about whether there are multiple connections. If the tolerance value is less than 0.10 and the VIF value is greater than 10, this indicates multiple connections (Tabachnick and Fidell 2013). According to Table 3, there is no multicollinearity problem. Discriminant validity shows how much a dimension can be distinguished from other dimensions. To ensure discriminant validity, the square root of the mean residual variance of a dimension must be greater than the square of the correlation between this dimension and others (Cooper and Zmud 1990). Finally, Table 3 shows that the square root of AVE in all the data models exceeds the inter-construct correlations and satisfies the criterion of discriminant validity at the level of the construct (Fornell and Larcker 1981). To determine discriminant validity, this study also used Henseler et al.'s (2015) heterotrait–monotrait ratio (HTMT) criteria. Tables 3 and 4 show to be supported discriminant validity.

Assessment of structural model

The regression coefficients of the EE and NI variables on the BI variable are negative, and the other variables' regression coefficients on each other are positive. Table 5 and Fig. 2 show which of these regression coefficients are meaningful and which are not.

Table 3 Discriminant Validity (Fornell and Larcker 1981) and Multicollinearity

Total	VIF	Tolerance	BI	EE	FC	NISE	PE	FRT	SI	T
BI			*0.975*							
EE	2.488	0.399	0.471	*0.866*						
FC	2.306	0.413	0.504	0.665	*0.770*					
NISE	1.143	0.862	−0.059	−0.056	0.045	*0.851*				
PE	2.127	0.466	0.560	0.678	0.559	−0.011	*0.861*			
FRT	1.150	0.868	0.278	0.245	0.320	0.156	0.239	*0.814*		
SI	1.580	0.649	0.513	0.517	0.512	0.125	0.512	0.217	*0.801*	
T	1.780	0.536	0.291	0.507	0.588	0.208	0.513	0.212	0.374	*0.907*

Italic values reflect square root of AVE, for discriminant validity = square root of AVE > inter-construct correlations

Table 4 Discriminant validity (Henseler et al. 2015)

	BI	EE	FC	NISE	PE	FRT	SI
BI							
EE	0.505						
FC	0.613	0.822					
NISE	0.034	0.053	0.173				
PE	0.598	0.766	0.746	0.041			
FRT	0.311	0.275	0.435	0.248	0.275		
SI	0.554	0.604	0.658	0.179	0.600	0.274	
T	0.295	0.550	0.785	0.264	0.550	0.227	0.406

Table 5 Outcomes of the path analysis

Hypothesis	Path	*t*-value
H1. PE → BI	0.343	4.349***
H2. EE → BI	−0.026	0.307 ns
H3. SI → BI	0.262	4.475***
H4. FC → BI	0.227	3.009***
H5. NISE → BI	−0.095	1.438 ns
H6. FRT → BI	0.110	2.191**
H7. T → BI	0.107	1.709*
H8. T → FRT	0.212	2.684**

ns not significant *$p<0.05$; **$p<0.01$; ***$p<0.001$ (two-tailed)

According to Table 5 and Fig. 2, PE, SI, FC, FRT, and T have a significant impact on BI ($\beta=0.343$, p = 0.000; β = 0.262, p = 0.000; β = 0.227, p = 0.002; β = −0.095, p = 0.03, β = 0.110, p = 0.013; β = 0.107, p = 0.047). Hence, H1, H3, H4, H6, and H7 are supported. Similarly, T has a significant impact on FRT (β = 0.212, p = 0.003). Therefore, H8 is supported. However, the impact of EE on BI is not statistically significant (β = −0.026, p = 0.382), nor is the impact of NISE on BI (β = −0.05, p = 0.500). So, H2 and H5 are not supported.

Discussion

This study shows that the factors affecting the intention to use a robo-advisor in private pension investments are performance expectation, social impact, and facilitating conditions. Thanks to the use of a robo-advisor, which is a personalized product, investors expect an increase in efficiency and productivity, and high earnings positively affect the intention to use a robo-advisor. This result is supported by Cho (2019), Baabdullah et al. (2019a), Baabdullah et al. (2019b), Merhi et al. (2019), Manrai et al. (2021), Khan et al. (2021), Widyanto et al. (2021), Hanif and Lallie (2021), and Jadil et al. (2021). In addition, as positive thoughts, experiences, and recommendations increase in an investors' social environment toward the use of a robo-advisor, the intention of investors to

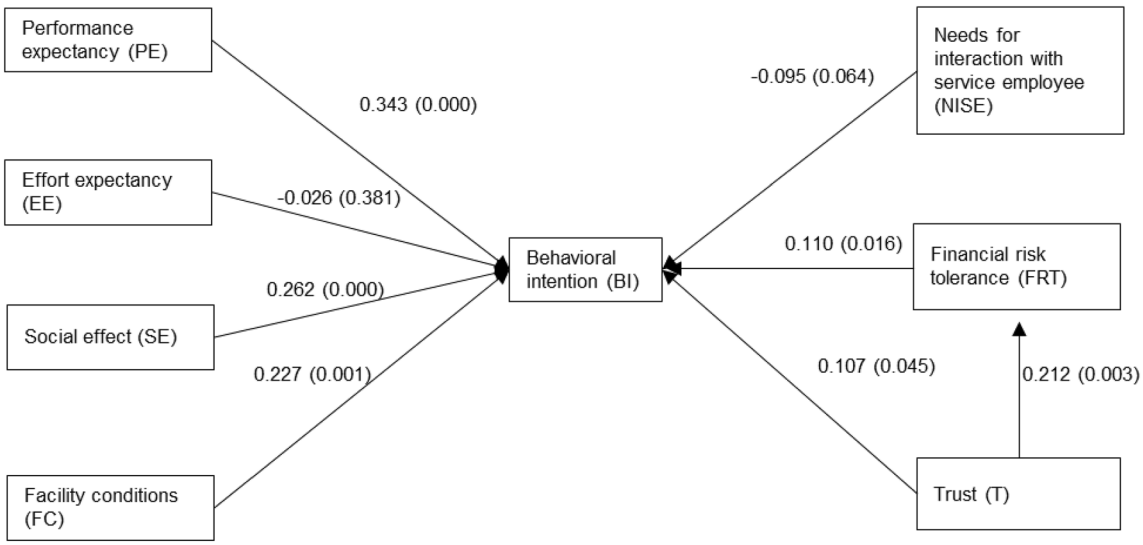

Fig. 2 The standardized path coefficients and significance levels

use a robo-advisor also increases. This result is in line with Cho (2019), Baabdullah et al. (2019a), Merhi et al. (2019), Widyanto et al. (2021), Khan et al. (2021), Manrai et al. (2021), and Jadil et al. (2021). Also, the fact that investors have the necessary information and resources to use a robo-advisor positively affects their intention to do so. This parallels Baabdullah et al. (2019a), Manrai et al. (2021), Widyanto et al. (2021), and Jadil et al. (2021). However, contrary to the proposed hypothesis, the investors' effort expectation toward a robo-advisor does not affect their behavioral intention. This result contradicts Cho (2019), Baabdullah et al. (2019a), Baabdullah et al. (2019b), Merhi et al. (2019), Manrai et al. (2021), Hanif and Lallie (2021), and Khan et al. (2021). It is possible that the fact that the study was applied to a group inexperienced with robo-advisors meant that the investors' effort expectations for new technology could not be evaluated clearly, which affected the result in this direction. Moreover, the robo-advisor product is still new to investors; the uncertainty and concerns of users about learning and applying new financial technology products may have also contributed to these result. The research shows that investors' need for interaction with service workers does not affect their behavioral intention to use robo-advisors. This result contradicts Lee et al. (2010), Kokkinou and Cranage (2015), Morosan (2015), Kamboj and Gupta (2020). With the increase in the technological literacy of individuals and the place that artificial intelligence often occupies in their daily flow, the need among individuals for human interaction when acquiring services is also reduced. During the current pandemic period, the necessity and obligation of consumers to receive distance service may potentially turn into a habit or routine, and this affects the result in this way. Investors' financial risk tolerance positively affects robo-advisor usage intention. As individuals gain a higher tolerance for loss or gain in their investments, their intention to use a robo-advisor also increases. This result is supported by Fan and Chatterjee (2020) and Fan (2021). The study also indicates that users' trust in robo-advisors affects investors' financial risk tolerance: as investors' trust in robo-advisors increases, so does their tolerance for risk. This result is in line with Cho (2019), Rahman (2020), Rahman et al. (2020), and Nourallah (2023). Finally, the factor that affects the use intention of robo-advisors is trust. As trust in robo-advisors, still a new product for investors, develops, the uncertainty and anxiety these investors feel about the product will decrease, and so the intention to use it will increase. This result is supported by Merhi et al. (2019), Widyanto et al. (2021) and Khan et al. (2021). However, Oehler et al. (2022)'s studies indicate that trust does not affect the decision to invest with a robo-advisor.

Research's theoretical and managerial contributions

This study, which represents the attempt of investors to examine the factors affecting the intention to use a robo-advisor, makes a significant contribution to the existing literature seeking to determine the factors that affect the intention to use a new technology and receive service from a robo-advisor. It is one of a limited number of empirical studies that use a holistic and integrative approach to explain the intention to use and future adoption of AI product investment services such as robo-advisors in emerging market countries, specifically Turkey. The study provides important empirical evidence to explain investors' intention to receive services from a robo-advisor, with a high explanatory power of 76.8%. In the past, most studies describing this phenomenon were descriptive. The model used in this research is a version of UTAUT, expanded to include the need for interaction with service employees, financial risk tolerance, and trust. Other empirical studies seeking to explain use intent for a new technology have extended the UTAUT model with subjective norms that explain approximately 44.4% (Gan et al. 2021) and 69% (Widyanto et al. 2021). This study has provided a theory that can better predict the behavioral intention of the investor and should thus make an important contribution to existing knowledge. In addition, this study also tested the effect of investors' perceptions of trust in a robo-advisor on their financial risk tolerance. Such a test of association is not available in the previous literature. Therefore, this study makes an important contribution to the literature.

The research has important implications for understanding the motivations of managers and the financial sector regarding investors' intentions to use an AI product rather than an employee to seek investment advice and shape decisions accordingly. These findings can benefit managers when introducing a new AI-driven service channel to the consumer experience. Likewise, the findings will create significant benefits for the financial sector by reducing their costs, increasing their profitability, minimizing human error, and reducing conflicts of interest. For this, both managers and the financial sector, especially pension companies, need to better understand investor expectations. If managers and businesses in the industry can sufficiently understand the investor perspective, they can make robo-advisors more appealing and attractive to individuals. Based on the results of the study, it is important for customers who have experienced this product to share their experiences, especially in pension companies and other financial areas where the product will soon be used more frequently, in forming an intention to use it. As positive experiences will serve as a reference, this will encourage investors to use this product and even make it easier to adopt in the future. This will strengthen investors' confidence in the product, and the

confidence thus created will moderate investors' financial risk tolerance. Since the income expectation that individuals will gain from investment recommended by a robo-advisor also helps determine the intention to use the product, designing the product to ensure it is protected against negative gains can also positively affect trust and financial risk tolerance. Sharing the earnings of experienced investors using robo-advisors with potential users through simulation and experience sharing can also fill gaps in the investor for the product and remove the obstacles to the development of usage intention. In addition, this simulation and sharing of experience will also contribute to the development of solid arguments for the performance of the robo-advisor. This research also emphasizes that investors are moving away from human–human interaction while making investment decisions. In this context, it is important to emphasize that a robo-advisor prioritizes the interests of potential investors more than does interaction with a human employee, and that it gives completely personalized recommendations for investments, albeit at a low amount, and should be used as a tool both to strengthen intention of use and to create potential investors. In this context, it is important that robo-advisor is designed to give confidence to the user and to reflect the perception of social presence. In fact, it should be considered that AI advice will replace human–employee advice in the near future, and technology investment should thus be sped up. In addition, the study allows the financial sector and its managers, especially in emerging market countries, to make important inferences about the potential of AI products such as robo-advisors to transform their investment and wealth management activities in the near future.

Research's implications for society

The ability to manage individual pension investments, which will greatly assist in overcoming poverty in old age, with a robo-advisor, will also make a significant contribution to the inclusion of individuals who have relatively little knowledge about the pension investment system and who lack time and technical knowledge. Thanks to the risk surveys conducted before developing an advisor-client relationship, the robo-advisor provides recommendations for appropriate fund distribution to investors while taking into account the character of the investor, investment return expectation, and risk appetite and uninterrupted investment consultancy services. A robo-advisor not only increases the productivity and efficiency of investors by shortening the time to follow the market or reach the fund advisor, it also enables investors to manage their own future more easily, less tiringly, and less anxiously. Also, similar to past research (Oehler et al. 2022), the preference of individuals to spend their effort and time on different personal development areas may cause robo-advisor to become widespread. In addition, obtaining this personalized service for a low amount of savings and investments may have a strong effect on directing individuals to savings. It is critical for individuals to be able to accrue long-term savings and turn them into an investment tool, both to improve their own welfare and help them contribute to their country's economy. The robo-advisor may also have a multiplier effect on this contribution thanks to the convenience, opportunities, and confidence it creates in the investor. Therefore, the robo-advisor may be an indirect element contributing to the social issue of "enhancing wellbeing."

Limitations and future research

To reveal an intention to use a robo-advisor in private pension investments, research participants should have private pension investments and be digital banking users. So, the research was managed with the restricted respondents. Hence, the results reflect only part of the population of Turkey. In addition, although Turkey is representative of emerging market economies, the results should not be generalized to all emerging market economy countries due to the self-dynamics of each.

Expanding the UTAUT with different variables in future studies should create an opportunity to look at the subject from a wider perspective. Today, robo-advisors are used by businesses in different sectors and in different channels. In this context, studies from different countries, as well as research in different sectors, will bring new perspectives to academics and practitioners. Also, the study includes the evaluation of the individuals' savings, such as a private pension, as a long-term investment. It should not be forgotten that individuals may have different perspectives for shorter-term investments. Although robo-advisors are used among a very limited group, they have more users, especially in countries with developed market economies. Studies designed to reflect experienced investors' satisfaction and loyalty in these countries, and the results of their word-of-mouth communication about robo-advisors, will be an important guide for academics and professionals. For this reason, investigating the experiences of investors who are currently using these products and evaluating the deficiencies in the system, or different investor expectations, will accelerate the development phase of the product, as well as increasing the intention to use and satisfaction among current users. The fact that control variables were not included in the study can be considered as a limitation of the study. In this context, it is thought that the inclusion of variables such as gender and financial literacy in future studies will shed light on the usage behavior of robo-advisor.

The study focuses on the advantages that robo-advisor offers to investors and tries to put the factors that determine the usage intention of robo-advisor. However, it may be the case that individual investors who are competent and

experienced in investment do not prefer the use of robo-advisor. So, in future studies, examining the results of investments made by experienced investors, using or not using robo-advisor, maybe more guiding in revealing the acceptance behavior of robo-advisor.

Conclusions

This study seeks to reveal the factors that determine the usage intention for robo-advisors offered to private pension investors of those investors who have not yet experienced this product and to determine the product's real potential. The results of this study indicate that the factors affecting robo-advisor usage intention in private pension investments are performance expectancy, social impact, facilitating conditions, financial risk tolerance, and trust. Also, trust positively affects financial risk tolerance. This study will assist robo-advisor service providers and policymakers in planning their services and increasing the adoption of robo-advisors. The study should also shed light on the future of distance services.

Appendix: Scale items

Performance expectancy
I would find robo-advisor useful for my investment transactions
Using robo-advisor would enable me to accomplish my investment transactions more quickly
Using robo-advisor would increase my productivity
If I use robo-advisor, I would get higher earnings
Effort expectancy
My interaction with robo-advisor would be clear and understandable
It would be easy for me to become skillful at using robo-advisor
I would find robo-advisor easy to use
Learning to operate robo-advisor is easy for me
Social influence
People who influence my behavior think that I should use robo-advisor
People who are important to me think that I should use robo-advisor
Finance organization has been helpful in the use of robo-advisor
In general, the finance organization has supported the use of robo-advisor
Facilitating conditions
I have the resources necessary to use robo-advisor
I have the knowledge necessary to use robo-advisor
Robo-advisor is not compatible with other systems I use
A specific person (or group) is available for assistance with the difficulties of using robo-advisor
Behavioral intention
I intend to use robo-advisor in the next 12 months
I predict I would use robo-advisor in the next 12 months
I plan to use robo-advisor in the next 12 months
Need for interaction with service employee
Human contact in providing services makes the process enjoyable for me
Personal attention by the service employee is very important to me
I like interacting with the person who provides the service
It bothers me to use robo-advisor when I could talk to a person instead
Financial risk tolerance
The robo-advisor should have a good knowledge of financial planning
The robo-advisor should be a real expert in financial planning
The robo-advisor should be unbiased
The robo-advisor should be honest
Investors should feel secure about relying on the robo-advisor
Investors should feel comfortable about relying on the robo-advisor
Investors should feel content about relying on the robo-advisor
Trust
I take substantial financial risk expecting to earn substantial returns
I take above average financial risk expecting to earn above average returns
I take average financial risk expecting to earn average returns
I am not willing to take any financial risk

Declarations

Conflict of interest The author states that there is no conflict of interest.

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