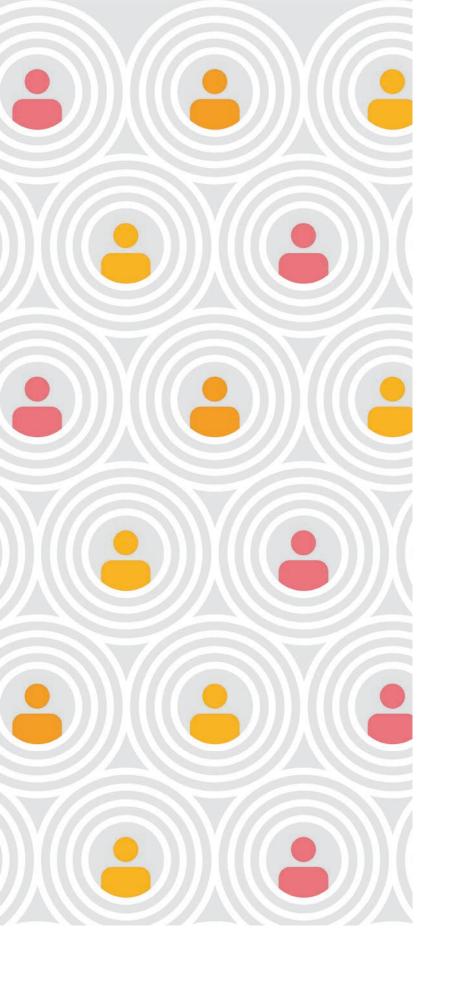


# The role of risk and trust in the adoption of robo-advisory in Italy

An extension of the Unified Theory of Acceptance and Use of Technology





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## **Abstract**

#### **Purpose**

This paper explores the behavioural determinants underlying the adoption of robo-advisory in the Italian market, i.e. digital platforms that use information technology to guide individuals through an automatic investment portfolio construction<sup>59</sup>.

The study analyses the different perceptions, expectations and behavioural traits that influence investors' attitudes towards robo-advisors and their consequent intention to use them. The main contribution of this study is the identification of the strengths and weaknesses of robo-advisory services as perceived by Italian investors and their expectations towards them.

Both robo-advisory providers and incumbent banks that face their competition can benefit from these findings, using them to create appropriate strategies and strengthen their services and offerings according to investors' needs.

#### Design and methodology

The respondents of this study (635) were all Italian employees of the professional services firm PricewaterhouseCoopers (PwC) who completed an online survey. Ordinary least squares (OLS) regressions were used to test the hypotheses formulated by the study, which were in turn based on an original conceptual model, adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT)<sup>70</sup>, to fit the context of robo-advisory adoption.

#### **Findings**

The results show a significant relationship between robo-advisors' perceived features and investors' favourable attitudes towards them, as well as between attitudes and behavioural intentions to use robo-advisors. Contrariwise, user characteristics (e.g., gender and age) did not appear to be significant in the attitude formation process. The contribution of this research is fundamental for the players that operate in the financial market, which are, directly or indirectly, unavoidably impacted by this new financial technology.



# **Executive summary**

#### **Background**

Robo-advisors are a FinTech innovation that can be described as automated investment platforms, offering portfolio management services using trading algorithms. Some of their advantages compared to traditional investment products or services are their advanced technology, their lower costs and their ability to carry out investment decisions without emotional biases through their automated portfolio functions<sup>59</sup>.

This research aimed to investigate robo-advisory adoption in Italy and what attitudes current and potential investors have towards it. The focus was on how different perceptions on robo-advisors' features (e.g. risk, required effort) and individual characteristics (e.g. financial knowledge) influence individuals' attitude and behavioural intention to use robo-advisors. The conceptual model at the base of this research was mainly derived from the Unified Theory of Acceptance and Use of Technology (UTAUT)<sup>70</sup>, modifying some of the original variables and adding new ones that were found to be relevant by previous studies on FinTech adoption.

The literature on this subject is often limited to studying how the new FinTech challenge the banking industry from the supply perspective<sup>34</sup>, while this research, focusing on the demand side, moved forward, studying the characteristics and behavioural traits that guide investors' choices towards portfolios passively managed by robo-advisors. Moreover, its findings can help traditional banks better understand challenges by new FinTech market entrants and create adequate strategies to meet demand in the financial sector, embracing FinTech innovation, even incorporating new technologies such as robo-advisors in their existing traditional offers, without perceiving them solely as competitors or threats.

Previous studies on robo-advisory in Italy found that individuals have very little knowledge on the subject and, most of all, they are not willing to try it because they do not trust its functioning and consider it riskier than the traditional forms of investments, such as banks and traditional financial advisors. This research, furthermore, focused on the processes prior to the actual adoption of an innovation, namely attitude and behavioural intention formation, two fundamental phases of the client onboarding process.

#### Method

A questionnaire was formulated and completed by 635 employees of PwC Italy, measuring their perceptions about robo-advisors' features, their personal characteristics, their attitudes and their behavioural intentions towards robo-advisory adoption. Following the conceptual model on which the study is based, a first analysis investigated the relationship between individuals' attitudes and robo-advisors' features and user characteristics. A further analysis, moreover, investigated the relationship between individuals' attitude towards robo-advisors and their behavioural intention to use them. Hypotheses were tested using OLS regression models and the order in which the variables were entered into the models was based on the conceptual model of the study and previous research.

#### **Key findings**

- Perceived relative advantage was found to be positively correlated with individuals' attitudes towards robo-advisors, meaning that those who believe that robo-advisors are more convenient and more efficient than human financial advisors, are more likely to develop favourable attitudes towards them and consequently use them.
- Effort expectancy was found to be negatively correlated with individuals' attitudes towards roboadvisors, meaning that people who perceive roboadvisors as difficult to understand and use are less likely to develop positive attitudes.
- Social influence regarding robo-advisory adoption was also found to be positively correlated with individuals' attitude towards them, meaning that people are more likely to develop positive attitudes towards robo-advisors if someone close to them or whom they trust recommends their use.
- The study also found that those who have already used a robo-advisor at least once report, on average, better attitudes than those without experience.

- Furthermore, the findings confirmed that trust and risk perception are essential factors in the roboadvisory adoption process: trust is positively correlated with favourable attitude formation, while perceived risk shows a negative correlation with the same dependent variable. Those who believe their information and data will be kept safe by roboadvisors are more likely to develop positive attitudes towards them.
- No significant relationship was found between gender or age and attitude. The coefficients of the interaction variables were also found to be not significant, meaning that gender and age do not moderate the effects of perceived robo-advisors' features on attitude towards robo-advisors.
- Financial knowledge (subjective and objective) had no significant relationship with attitude, meaning that better knowledge does not influence individuals' attitudes towards robo-advisors.
- One last important finding for robo-advisory providers regards the positive relationship found between individuals' attitudes towards robo-advisors and their behavioural intentions to use them. A positive attitude towards robo-advisors therefore becomes a prerequisite, the first objective in the customer engagement process, especially when robo-advisors are still at the beginning of their dissemination process.

#### **Implications**

This research aimed to investigate the adoption of roboadvisors in Italy and what attitudes current and potential investors have towards them. Knowing what roboadvisors' strengths and weaknesses are perceived by investors is fundamental both for robo-advisory providers and for incumbent banks, which must protect themselves from the new competition of these FinTech players. The former, in fact, can leverage on investors' perceptions and expectations to customise their services and carry out adequate marketing campaigns. The latter, on the other hand, can use the same findings to provide alternative products or services that can adequately satisfy their needs.

This research highlighted a scenario where most investors are not yet ready for an innovation such as robo-advisory or at least are not adequately prepared for it. Therefore, it is plausible to assume that the new market players offering robo-advisory services will not be able to subvert the position of the current market leaders in the nearest future. Consequently, rather than a disruption scenario, it is likely that a collaboration one will be established, where innovative companies will not compete directly with banks or other market incumbents, but will become part of their ecosystems, specialising in specific functions or integrating their current operating models.



# 1. Background

Technological progress, the pressure towards simplification and cost reduction and the growing demand for support for the unsatisfied or ill-served investors are leading to rapid change in the financial sector. Starting from 2008, robo-advisory platforms were launched on the market, services aiming to simplify asset management, making it accessible to almost anyone and allowing individuals to invest their savings without having to rely on a bank. These solutions were designed by FinTech start-ups, with their skills in both information technology and finance.

A clear definition of robo-advisors was given by Sironi<sup>59</sup>: "Robo-Advisors are automated investment solutions which engage individuals with digital tools featuring advanced customer experience, to guide them through a self-assessment process and shape their investment behaviour towards rudimentary goal-based decision-making, conveniently supported by portfolios rebalancing techniques using trading algorithms based on investments and diversification strategies".

This research aims to investigate robo-advisory adoption in Italy and what attitudes current and potential investors have towards it. The focus will be on how different perceptions on robo-advisors' features (e.g., perceived risk, trust) and individual characteristics (e.g., financial knowledge) influence individuals' attitude and behavioural intention to use robo-advisors. The main model on which the research is based is the Unified Theory of Acceptance and Use of Technology (UTAUT)<sup>70</sup>, which will be adapted specifically to robo-advisors, modifying some of the original variables and adding new ones that were found to be relevant by previous studies on the subject.

The literature on this subject is often limited to studying how the new FinTech challenge the banking industry from the supply perspective<sup>34</sup>. For instance, studies analysed the changes in banking business processes made to face the new competition coming from FinTech companies<sup>15</sup> or, in other contexts, they focused on the potential peer to peer cooperation between incumbent banks and FinTech players<sup>75</sup>. This research paper, focusing on the demand side, will offer a further contribution to the literature, as it will study the characteristics and behavioural traits that guide investors' choices towards portfolios passively managed by robo-advisors.

This research will provide data that can help traditional banks better understand challenges by new FinTech market entrants and create adequate strategies to face them. Moreover, although Italian investors are often wary of these new algorithm-based technologies, this study will offer insights about the potential client base to incumbent financial intermediaries, who will be able to adopt the best approach to meet demand in the financial sector, embracing FinTech innovation, even incorporating new technologies such as robo-advisors in their existing traditional offers, without perceiving them solely as competitors or threats.



## 2. Introduction

# The development of automated advice and its functioning

Technology has been used for decades in the financial sector by consultants, traders and other professionals to access real-time news, updated research and financial data to make recommendations to their clients. Only since 2005, through a modification of an American law<sup>(a)</sup> issued by FINRA (the Financial Industry Regulatory Authority), also individual investors were granted the direct use of analytical and investment instruments.

The first robo-advisors were introduced after the global financial crisis of 2008, at a time when investors showed a preference for low-risk portfolios and passive investment management. Thus, at that moment, the financial companies offering robo-advisory platforms experienced high growth rates in a short time, attracting the interest of multiple subjects: investors who were not used to dealing with a traditional financial advisor and venture capital companies as financiers of start-ups in virtual consulting, followed by asset management companies and banks.

To analyse the reasons that may lead an investor to adopt or reject robo-advisors it is necessary to first understand their main features and their functioning. The strength of robo-advisors lies in their objective: bridging the advisory gap in the market, making a service precluded by traditional channels more accessible and at low cost, mainly targeting the private customer<sup>50</sup>. Their automated investing strategies avoid human psychological factors and emotions, eliminating irrational decision-making processes<sup>63</sup>.

Many features distinguish a robo-advisor from a traditional financial advisor. Firstly, robo-advisors allow individuals to invest even with low amounts, democratising the advisory service, expanding the client base and favouring the inclusion of the new generations (millennials) in an increasingly digital financial market<sup>50</sup>.

Secondly, the management fees applied to customers are extremely transparent and more convenient than the traditional advisors' ones and the costs are invoiced in a different way<sup>58</sup>. Robo-advisors, in fact, offer a flat rate, while the portfolios managed by traditional consultants generate commissions for each transaction, management costs and administration of the securities<sup>65</sup>.

Robo-advisors can offer such affordable rates because of the nature of the securities they offer. Their portfolios consist of ETFs (Exchange-Traded Funds), which are less expensive than mutual funds and other actively managed securities<sup>27</sup>.

Another difference between robo-advisors and traditional financial advisors, especially important for younger customers, is that of user experience. Robo-advisory platforms provide customers with quick access to their accounts on smartphone applications and user-friendly websites, their products and contracts are explained in simple terms, understandable to everyone, regardless of their financial background<sup>37</sup>. Overall, through simpler and more efficient formulations, users perceive a superior experience and assimilate information better<sup>57</sup>.

#### The low adoption rate of robo-advisory in Italy

To fully understand the reasons that lead Italian investors to develop positive or negative attitudes towards robo-advisors, it is necessary to consider their preferences, their knowledge and their capabilities related to this new technology. In Italy, as a matter of fact, robo-advisors have not had the same success as in other countries<sup>53</sup>. To understand the causes of this delay in the evolution of financial digitalisation, financial literacy and investment habits of the Italian population must be analysed as key elements for the development of the sector. Secondly, attitudes towards change and innovation must be considered necessary factors for the digitalisation of financial services.

#### The first obstacle: financial knowledge

The first identified obstacle to the diffusion of roboadvisors in Italy is financial knowledge, that is the degree of preparation in financial and investment matters that could make investors more or less willing to adopt a technology of which they can understand the objectives and the functioning. Given its importance in the robo-advisory adoption process, financial knowledge is therefore included as a variable in the conceptual model behind this investigation.

Research has indeed found that the motivation for the delay in the adoption of an innovative financial advisory service as robo-advisors, can be firstly explained by the low level of financial education of the Italian population.

In fact, the Italian financial literacy rate<sup>(a)</sup> (37%), higher only than Portugal's one (26%) among the Eurozone countries, appears to be even more critical when compared with the G20 countries, such as Canada (68%) or Germany (66%)<sup>53</sup>. Percentage of adults who are financially literate. Financial literacy is measured using questions assessing basic knowledge of four fundamental financial concepts, that are basic numeracy, interest compounding, inflation and risk diversification <sup>42</sup>.

Focusing on the Italian population, the CONSOB (Commissione Nazionale per le Società e la Borsa - Italian Companies and Exchange Commission), in collaboration with Gfk-Eurisko, publishes an annual report on the Italian households' investment choices, analysing the attitudes and the behavioural tendencies involved in their decision-making processes. This survey is addressed to the person in the household responsible for financial decisions (i.e. the component of the family with the highest income), aged between 18 and 74 years.

The last publication in 2018 shows once again the high rate of financial illiteracy that characterises Italians<sup>21</sup>. About half of the respondents can correctly define the concepts of inflation and the risk-return relationship, while the percentage is significantly reduced when it comes to describing stock riskiness (around 20%) and the interest rate and bond price relationship (lower than 10%). Another relevant variable is the mismatch between actual knowledge and perceived knowledge, that is the discrepancy between what the interviewees declare to know and what they actually know about a given concept, which ranges between 26% and 49%.

Furthermore, financial literacy appears to be not only the main determinant for the demand for financial advice but also a fundamental prerequisite for individuals to move towards innovative solutions without a human and empathic investment relationship<sup>22</sup>.

Overall, the considerations made on the Italian financial situation can partly explain the poor development of the automated financial advisory service. The most important determinant is financial knowledge, since a person with a good financial education is more willing to adopt financial innovative solutions and to understand their benefits.

Secondly, investment habits also play a very important role, considering that Italy is a country heavily dependent on banks. Although most Italians declare that they do not trust the traditional intermediary, they still heavily rely on them, without seeking more innovative and efficient non-banking solutions<sup>21</sup>.

#### Robo-advisory and attitude towards change in Italy

The addendum to the CONSOB Report on the financial choices of Italian families<sup>20</sup> investigated further the relationship between financial advisor (traditional or robo-advisor) and client. It found that, even if consultants declared that a good part of their customers knew the phenomenon of robo-advisory, only 5% of them declared they knew it and used it, while 91% of the interviewees declared they have never heard of it.

Moreover, confirming the importance of financial intermediaries and institutions, 50% of interviewees (mostly young and with low levels of financial wealth) declared themselves ready to interact remotely with a virtual consultant when promoted by an online service provider or a social network already used and therefore deemed reliable. Nonetheless, 20% of the sample stated that in any case they would entrust only a part of their portfolio to a robo-advisor, reinforcing the assumption concerning the lack of confidence of most investors towards technological and online solutions.

Despite the growing trend in online services, Eurostat data showed that in 2017 only 30% of Italians used internet banking, against 51% of the European average<sup>25</sup>. This result shows how Italy is rather rigid and defensive towards change, especially when it comes to financial services and banks, where trust is the central factor for the use of the services themselves. These data also explain why in Europe the preferred form of robo-advisory is the hybrid one, which combines the benefits of the online platform with the advantage of having a person to turn to in case of need<sup>53</sup>.

A further factor confirming these findings is the concentration of wealth between age groups. Wealth is in fact concentrated mostly between individuals of higher age, who are less likely to use digital channels to communicate with their bank and therefore less willing to turn to robo-advisors or online investment services<sup>8</sup>.

# Theoretical framework: Technology Adoption Models

Robo-advisors are still little known and thus not widespread in Italy and, similarly to other new technologies, there might be a period when people hesitate to trust and adopt them. Understanding what potential barriers to adoption there may be and why some people are more likely to adopt the new technology than others is therefore extremely important both for the players who want to enter the financial market providing robo-advisory services and for incumbent banks and intermediaries that must face this entry threat. For these reasons, the current section will revise the literature on technology adoption, relating it specifically to the robo-advisory innovation. Some of the variables analysed will then be combined to build the conceptual model on which this research is based.

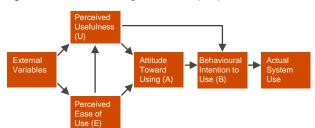
The literature on the acceptance and use of technological innovations dates to the 1990s and reaches the present, with many revisits and modifications of the original models, incorporating individual and environmental influencing factors<sup>1</sup>. More specifically, research started to focus increasingly on internet and mobile services acceptance from the 2000s<sup>11,31,49</sup>.

This section will analyse the main theories and models on the subject, more specifically: the Technology Acceptance Model (TAM), the Technology Acceptance Model 2 (TAM2), the Innovation Diffusion Theory (IDT) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

#### Technology Acceptance Model (TAM)

The first model that dealt with the specific analysis of the acceptance of a new technology is the Technology Acceptance Model (TAM; *Figure 1*)<sup>23</sup>. The period in which the TAM was theorised saw the spread of personal computers in companies and the consequent resistance to their adoption by many employees, even if their use would have generated significant improvements in performance<sup>24</sup>.

Figure 1. TAM - Source: Davis, Bagozzi, & Warshaw (1989)



Therefore, Davis's objective was to provide a predictive model, through the analysis of two variables: Perceived Utility and Perceived Ease of Use, which in turn influence the Behavioural Intention, leading to the adoption or rejection of a new technology. More specifically, the main variables in TAM are:

- Perceived Usefulness (U): the utility perceived by the user, that is the possibility that a specific technology generates higher performances in the working environment;
- Perceived Ease of Use (E): the user's perception about the effort required to learn how to use the new technology;
- 3. Attitude Toward Using (A): the attitude that, if positive, then leads to the
- Behavioural Intention (BI): intention to adopt the technology or innovation in question;
- 5. External Variables: both the perceived utility and the perceived ease of use are influenced by external variables as, for instance, training and support in the adoption of the new technology, as well as documentation provided in the implementation phase.

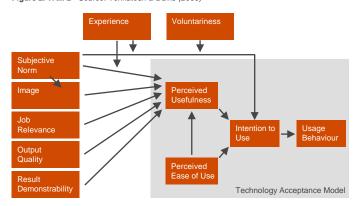
Subsequently, the TAM was further extended and modified, giving rise to the Technology Acceptance Model 2 (TAM 2; *Figure* 2)<sup>67</sup>.

The two authors recognised that the intention to adopt a new technology is influenced not only by its perceived usefulness and ease of use, but also by further social and cognitive variables, which are:

- Subjective Norms: the perception of the potential adopters about what their peers think about the adoption of the new technology;
- Image: the degree to which an innovation can improve the social status of those who intend to adopt it: if the new technology promotes a positive image then the perception of utility increases;
- Job Relevance: the perception of the utility generated by the new technology in the working context:
- Output Quality: the degree to which the adopters believe that the technology improves their work performance;
- Results Demonstrability: the quantitative version of output quality, the degree to which the measurability of results can improve the perception of utility of the new technology.

Moreover, Venkatesh and Davis<sup>67</sup> argued that adopters' previous experiences are also crucial to accept a new technology. In the case in which adopters have little or no previous experience with the technology, then the subjective norm will be preponderant, directly influencing both perceived utility and perceived usefulness.

Figure 2. TAM 2 - Source: Venkatesh & Davis (2000)



#### Innovation Diffusion Theory (IDT)

The innovation Diffusion Theory (IDT)<sup>54</sup> is a model commonly applied both in industrialised and developing countries, to illustrate and explain the process by which innovations are widespread and adopted by consumers. More specifically, the model distinguishes between those who adopt the innovation first and those who adopt it later, describing the mental processes followed when adopting it and identifying the innovation-decision processes involved.

Moreover, further expanding his theory, Rogers<sup>55</sup> identified five critical characteristics that an innovation must possess to be fully adopted:

- Relative advantage: the innovation must be perceived as better than the existing solutions, in economic terms or in subjective ones;
- Compatibility: the innovation must be perceived as consistent with values, experience and needs of its adopters;
- Complexity: innovations that are easier to understand and use are adopted faster than more complex ones;
- d) Triability: the innovation must have some features that allow it to be partially tried before being fully adopted;
- Observability: innovations whose results are easier to assess spread faster than those with a less transparent impact.

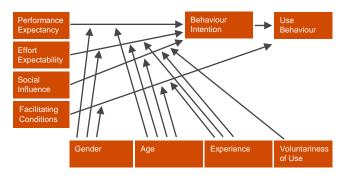
# Unified Theory of Acceptance and Use of Technology (UTAUT)

The last model that will be analysed is the Unified Theory of Acceptance and Use of Technology (UTAUT)<sup>70</sup>, based on an integration of different models, some of which are: the Theory of Reasoned Action (TRA) <sup>29</sup>, the TAM, the Theory of Planned Behaviour (TPB)<sup>3</sup>, the Model of Personal Computer Utilization<sup>64</sup>, the IDT and the Social Cognitive Theory (SCT)<sup>9</sup>.

The UTAUT, more specifically, extends the original TAM (1989) model by enriching it with two new constructs: Social Influence and Facilitating Conditions, thus conferring considerable relevance to previously neglected social factors (Figure 3).

The UTAUT model aims to explain the user's intention to adopt a technology and its potential subsequent use. On one hand, the theory identifies four fundamental constructs (Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions), which are direct determinants of Behavioural Intention and the consequent Use Behaviour. On the other hand, the variables Sex, Age, Experience, and Voluntariness of Use mediate the impact of the four fundamental variables on individuals' intention and behaviour.

Figure 3. UTAUT - Source: Venkatesh, Morris, Davis, & Davis (2003)



The conceptual model used for this investigation is based primarily on the UTAUT, with some modifications coming from TAM, TAM2 and IDT and will be explained in detail in the following section.

# 3. Conceptual model and research hypotheses

Many studies have used the UTAUT model to investigate the variables involved in the acceptance of financial technologies<sup>34</sup>, but they were unable to reach a consensus in different sectors about their role in the intention to use them. Khan, Hameed and Khan<sup>38</sup>, for instance, found that performance expectancy is a requirement for the behavioural intention to adopt mobile banking, but they found no significant correlation coming from social influence and effort expectancy.

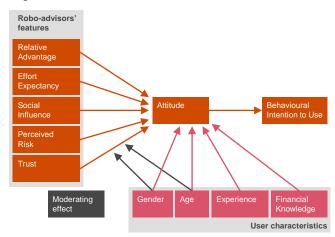
Further studies, focusing on the adoption of new technologies, used the UTAUT as the base model, but changed some of its variables and included others depending on their importance in the innovation under investigation. For instance, Kim and Lee<sup>39</sup> investigated the acceptance intention towards u-healthcare services, adding Perceived Risk to the UTAUT variables and found that performance expectancy, effort expectancy, social influence and perceived risk had a positive correlation with the behavioural intention to use the technology.

The model underlying this study is based on the UTAUT, with some modifications and further components. Its parameters are divided into roboadvisors' features and characteristics of potential users, which are both determinants of the attitude towards robo-advisors and behavioural intention to use them. In the first category, the variables are Relative Advantage, Effort Expectancy, Social Influence, Perceived Risk and Trust, while the user characteristics are Gender, Age, Experience and Financial Knowledge.

Furthermore, this conceptual model was also inspired by other studies on FinTech adoption<sup>35</sup>. Instead of directly investigating the determinants of the intention to use robo-advisors, this research focuses on an intermediate variable, that is attitude towards them. Before developing the intention to adopt robo-advisors, in fact, it is assumed that people must be well disposed towards them, considering them an interesting and advantageous investment and developing positive attitudes. Indeed, studies have shown that attitudes towards new technologies explain a large percentage of the variance in the intention to use them<sup>4</sup>.

Following the conceptual model on which the study is based, a first analysis will investigate how attitudes are correlated with robo-advisors' features and user characteristics. A further analysis will focus on the second part of the model, investigating the relationship between individuals' attitude towards robo-advisors and their behavioural intention to use them.

Figure 4. Revised UTAUT model - Source: Personal elaboration



#### Predictors - Robo-advisors' features

#### Relative advantage

The model used in this research substitutes the expected performance construct of the UTAUT with the relative advantage one, derived from the IDT<sup>54</sup>. Roboadvisors are a FinTech innovation still marginally adopted in Italy and above all little known. Therefore, it could be difficult to investigate the perceptions of individuals on their performance without a term of comparison more familiar to them. By measuring the relative advantage, indeed, the perceived performance and utility of robo-advisors is evaluated more accurately by the respondents comparing it to alternative forms of investment that are more popular among investors, such as the investments made with human financial advisors.

Moreover, between the different innovation diffusion characteristics of the IDT, relative advantage was found to be the most important determinant of innovation adoption, for instance in mobile technologies and internet banking adoption<sup>62,72</sup>. Robo-advisors in many cases have a relative advantage over traditional investments in terms of costs, performance and ubiquity. When people recognise these advantages, for instance, compared to traditional human advisors, they may be more likely to develop positive attitudes towards them. Thus, the current study hypothesises:

H1. The perceived relative advantage of robo-advisors is positively correlated with individuals' favourable attitude towards them.

#### Effort expectancy

Effort expectancy is defined as the degree of ease associated with the use of a system<sup>70</sup>. This variable is derived from three constructs of previous models: Perceived Ese-of-Use (TAM/TAM2), Complexity (MPCU) and Ease of Use (IDT)<sup>1</sup>.

Previous studies have found a positive correlation between effort expectancy, attitude and consequently the intention to adopt a new financial technology, meaning that user interfaces, design, and functional features such as help functions can increase the adoption of an innovation<sup>40</sup>. Based on these considerations, the second hypothesis of this study is:

H2. Effort expectancy towards robo-advisors is negatively correlated with individuals' favourable attitude towards them.

#### Social influence

In this context, social influence can be defined as the degree of influence that others' opinions can have on the adoption of a new technology<sup>70</sup>. It is a construct already covered by some variables of the models preceding the UTAUT, such as Subjective Norm and Image (TAM2) and Image (IDT).

The concept of social influence can be derived from the Theory of Social Comparison developed by Festinger<sup>28</sup>. According to the author, people are not sure of their preferences and their actions and are constantly seeking external approval, relying on others when making a decision as a way to appease the fear of making the wrong choice and to gain a favourable reaction from members of their social group<sup>71</sup>.

Furthermore, social influence has been widely considered in the technology adoption literature as a fundamental factor in determining attitudes and adoption intentions<sup>36</sup>. The underlying assumption is that individuals, before developing their own opinion about a new technology, confront themselves with their peers to reduce the anxiety caused by the uncertainty related to its adoption or refer to experts and opinion leaders' advice<sup>56</sup>.

More specifically, social influence was found to have a positive impact on attitude and acceptance intention towards new technologies, such as Ubiquitous Computing<sup>74</sup> and Near Field Communication<sup>18</sup>.

Other studies showed also the indirect benefits of social influence on attitudes towards new technologies given by its ability to increase relative advantage and decrease risk perception in the adoption process<sup>73</sup>.

Therefore, it is possible that, even if the number of robo-advisory users is still very limited, their influence could improve the attitude of other people who trust their opinion and rely on them. Hence, this study hypothesises:

H3. Social influence regarding robo-advisory adoption is positively correlated with individuals' favourable attitude towards them.

#### Perceived risk

Perceived risk is defined as the degree to which the adopters of a new technology believe they may be exposed to certain types of risks, such as financial, social or psychological risk<sup>76</sup>. Previous studies showed the negative correlation between perceived risk and intention to adopt new financial technologies, such as Mobile Payments<sup>51</sup>, Internet Banking<sup>47</sup> and eservices<sup>52</sup>.

More specifically, between the different types of risks that may be perceived by individuals in the adoption of a new financial technology, studies found the risks concerning privacy and security to be the most relevant ones<sup>5</sup>. Moreover, previous research has also identified the negative impact that perceived risk has on trust formation<sup>16</sup>.

Undoubtedly, FinTech usually require users to reveal some sensitive information about themselves and their financial assets and could therefore be subject to dangerous information leakages or external hacker attacks. Giving the nature of robo-advisors and their limited popularity, it is possible that their risks are perceived as too high, holding investors back from using them. Based on these considerations, this study hypothesises:

H4. Perceived risk concerning robo-advisors is negatively correlated with individuals' attitude towards them.

#### Trust

Unquestionably, it is not enough to introduce a technological innovation for it to be used. If a new technology does not seem to be useful, appears highly risky or untrustworthy, it is very unlikely that it will be adopted, unless its adoption is promoted through specific measures that can change people's attitudes towards it<sup>66</sup>.

Trust, as well as perceived risk, is a subjective concept nested in social behaviour<sup>45</sup>. Studies found trust to be connected to environmental uncertainty, satisfaction and reputation<sup>30</sup>. Previous studies found a positive correlation between trust and intention to adopt new financial technologies, meaning that individuals who believe that the new technology will fulfil its stated objectives and functions will be more likely to develop positive attitudes towards it and adopt it<sup>33</sup>.

Moreover, trust was found to be the most important determinant in the commercialisation of the internet as well as in the adoption of online banking services<sup>14</sup>. Considering these facts, this study hypothesises:

H5. Trust in robo-advisors is positively correlated with individuals' favourable attitude towards them.

#### **Predictors - User characteristics**

#### Gender and age

Specific robo-advisors' features are not enough to predict individuals' intention to use them, since different dispositions and personal traits could lead to different evaluations. For instance, research found that different age groups have different opinions and attitudes in the adoption of a new technology: younger generations are usually more proactive, while older generations are more hesitant and cautious<sup>12</sup>.

Furthermore, there is evidence to suggest that women and men behave differently when faced with the same adoption decision. For instance, women were found to have higher levels of computer anxiety and lower computer aptitude compared to men. These two variables are strictly related to perceived effort, implying that perceived constraints and difficulties are more salient to women than men in the decision to adopt a new technology<sup>69</sup>.

Moreover, the UTAUT model theorises that both gender and age have a positive influence on the behavioural intention to adopt a new technology, given their moderating effect on performance expectancy, effort expectancy, and social influence<sup>70</sup>. This research will investigate the role of age and gender in the emergence of different attitudes towards robo-advisors and will also test their moderating effect on relative advantage, effort expectancy, social influence, perceived risk and trust.

#### Experience

Another variable whose effect has been investigated through the UTAUT model is experience. Experience can be defined as the degree to which a person can perform a behaviour automatically through learning<sup>10</sup>. Research suggested that the degree of experience with the new technology is a significant predictor of future usage and future behaviour, sometimes even overturning an individual's attitudes and first perceptions towards the given technology<sup>61</sup>.

Other studies focused on behavioural beliefs showed that direct experience-based beliefs predict intention and behaviour better than indirect experience-based beliefs: having direct experience with a technology, individuals can process more information about it and develop more confident and accurate evaluations that will influence their adoption decision<sup>26</sup>.

Given that robo-advisors are still little adopted in Italy, the number of individuals who have direct experience with them will likely be very low. Nonetheless, it is possible that those who have tried them were able to overturn the potential initial preconceptions about an unknown technology and objectively evaluate the benefits that they could derive from robo-advisory investing. Based on these considerations, it is hypothesised:

H6: Previous experience with robo-advisors is positively correlated with individuals' favourable attitude towards them.

#### Financial knowledge

Financial knowledge is the degree of knowledge individuals have about essential financial notions and their ability to apply this knowledge when making financial decisions<sup>60</sup>. Research found that financial knowledge has a significant influence on financial behaviours; for instance, individuals with higher financial knowledge were found to be more likely to participate in financial markets and invest in stocks<sup>44</sup>.

In the previously analysed models of technological innovation there is no analogous variable, although it could be considered a facet of the variable relative to the experience of individuals with the innovation to be adopted.

Given that robo-advisors are a financial innovation, individuals may be more or less willing to use them depending on their financial knowledge, a higher level of which would allow a deeper understanding of their functioning and features. Based on previous considerations regarding the positive correlation between financial knowledge and financial products' adoption, the following hypothesis is proposed:

H7: Financial knowledge is positively correlated with individuals' favourable attitude towards robo-advisors.





## 4. Data and methods

#### Sample and procedure

The respondents of this study are all Italian employees of the firm PricewaterhouseCoopers (PwC), who voluntarily chose to complete the Qualtrics questionnaire in English, taking part in the research. The latter was advertised on the internal PwC website and through an email sent to the PwC Italy mailing list (4,928 people).

Overall, 674 responses (13.7% response rate) were collected between the 12<sup>th</sup> of July and the 9<sup>th</sup> of August. The final sample (N=635) included individuals who had complete data on the variables of interest and can be considered representative of the PwC Italy workforce.

Table 4 in Appendix 1 provides an overview of the sample composition according to job position and table 5 according to the PwC market sector division they work for. Descriptive statistics for the other variables can be found in table 1.

#### **Measures**

#### Dependent variables

#### Attitude

Attitude, the main dependent variable of this study, was measured with three items adapted from the study on internet banking adoption by Grabner-Kräuter and Faullant<sup>32</sup>. The cronbach's alpha of the scale was 0.90, showing good internal reliability and the first item was: "In my opinion it is desirable to use robo-advisors".

Answers were recorded on five-point Likert scales, from "strongly disagree" (1) to "strongly agree" (5) and the final score for attitude ranged from 3 to 15, with higher values indicating a more favourable attitude. Responses had a mean of 9.8 and a standard deviation of 2.4.

#### Behavioural intention to use

Behavioural intention to use was measured with the question: "On a scale from 0 to 10, how likely are you to invest in robo-advisory services in the following 12 months?", with answer categories ranging from 0 ("very unlikely") to 10 ("very likely"). Responses had a mean of 3.9 and a standard deviation of 2.6.

#### Relative advantage

The four items used to measure this variable were adapted from the studies of Kim et al.<sup>41</sup> and Yang et al.<sup>73</sup>, modifying the wording to fit the robo-advisory adoption context. The cronbach's alpha of the scale was 0.71, and one item was: "Robo-advisors are more effective than human financial advisors in managing an investment portfolio". Answers used five-point Likert scales, from "strongly disagree" (1) to "strongly agree" (5), with a final score for relative advantage ranging from 4 to 20. The responses had a mean of 13.1 and a standard deviation of 2.8.

#### Effort Expectancy

The four items used to measure effort expectancy were adapted from the research of Abrahão et al.<sup>1</sup>. The cronbach's alpha of 0.85 for the scale showed good internal reliability and the first item was: "My interaction with robo-advisory systems would be clear and easy to understand". Answers used reverse-coded five-point Likert scales, from "strongly disagree" (5) to "strongly agree" (1), with a final score for effort expectancy ranging from 4 to 20. The recorded responses had a mean of 10.3 and a standard deviation of 3.

#### Social influence

The five items used to measure this variable were adapted from the studies of Yang et al.<sup>73</sup> and Lu et al.<sup>43</sup>, adjusting the wording to robo-advisory adoption. The cronbach's alpha of the scale was 0.86, revealing good internal reliability, and one item was: "Investing in robo-advisors is considered a status symbol among my friends". Answers used five-point Likert scales, ranging from "strongly disagree" (1) to "strongly agree" (5), with a final score for social influence from 5 to 25. The collected responses had a mean of 13.9 and a standard deviation of 3.5.

#### Perceived risk

The three items used to measure this construct were derived from the research of Hu et al.<sup>34</sup>, adjusting the wording to robo-advisory adoption. The cronbach's alpha of the scale was 0.82, showing good internal reliability, and the first item was: "I believe that money can be easily stolen when using robo-advisory services".

Answers used five-point Likert scales, ranging from "strongly disagree" (1) to "strongly agree" (5), with a final score for perceived risk ranging from 3 to 15. Responses had a mean of 8.6 and standard deviation of 2.5.

Among 635 respondents, only 55 declared to have ever used a robo-advisor, only 27 of them that they were currently using one, and between the latter, the willingness to recommend them to their friends had a mean of 6.8 and a standard deviation of 1.8.

#### Trust

The two items used to measure this construct were developed adjusting the wording of the scale constructed by Hu et al.<sup>34</sup> to robo-advisory adoption. The cronbach's alpha of the scale was 0.85, revealing good internal reliability. The two items were: "I believe robo-advisory services would keep my personal information safe", and: "Overall, I believe robo-advisory services can be trusted". Answers used five-point Likert scales, from "strongly disagree" (1) to "strongly agree" (5), with a final score for perceived risk ranging from 2 to 10. Responses had a mean of 6.7 and a standard deviation of 1.7.

#### **Predictors – User characteristics**

#### Gender and age

Gender and age were also measured as they are part of the conceptual model of the study. The sample consisted of 420 males and 215 females (i.e., 66% percent male), between the ages of 18 and 61, with a mean age of 34.6 and a standard deviation of 9.3. The gender and age composition roughly reflect the overall gender and age composition at PwC Italy, as indicated by the internal monthly turnover report published in July 2019.

#### Experience

To record whether an individual had experience with robo-advisors, the following question was asked: "Have you ever invested through a robo-advisor?". This question was also used as a filter to investigate further the attitudes of those who answered "yes", with the following question about their current use: "Are you currently investing through robo-advisor?". If they answered affirmatively, they were further asked about their willingness to recommend robo-advisors with this question: "On a scale from 0 to 10, how likely are you to recommend robo-advisory services to your friends?", with answer categories ranging from 0 ("very unlikely") to 10 ("very likely").

#### Financial knowledge

Financial knowledge was firstly assessed with the following self-reported question adapted from the study of Agnew and Szykman<sup>2</sup>: "How do you rate your financial knowledge relative to other people?". Responses ranged from 0 ("much less knowledge") to 10 ("a great deal more knowledge") and were used to derive the Subjective Financial Knowledge variable, which had a mean of 5.4 and a standard deviation of 2.2.

Following the same study, respondents were also given the chance to objectively measure their financial knowledge by taking a test of ten financial questions, which was made optional in the questionnaire. The score was made by the number of correct responses, ranging from 0 to 10. 311 respondents took part in the test, with a mean score for objective financial knowledge of 5.5 and a standard deviation of 2.7.

Two additional variables were recorded from those who chose to take the test. The first one, named Confidence, ranged from 0 to 10 and was derived from the following question: "In your opinion, how many questions did you answer correctly in the previous section?". This variable had a mean of 5.4 and a standard deviation of 2.3. The second variable, named Overconfidence, was derived subtracting the number of questions that respondents thought to have answered correctly from the actual number of correct responses, with a mean of -0.2 and a standard deviation of 2.1.

Moreover, a significant positive correlation of r=0.44 (p<0.001) was observed between subjective financial knowledge and objective financial knowledge, suggesting a moderate association between the two. The further regression analysis will, therefore, use subjective financial knowledge as a proxy for objective knowledge due to its larger sample size.

#### Other variables

Education and Investing Experience (from 0 to 30 years) were used as control variables following previous studies<sup>17,46</sup>. These studies also used income as a control variable, while this research avoided to ask it directly and used instead a proxy: job position (table 4 in Appendix 1).

This choice was dictated by the fact that asking one's income could have been perceived as an annoying and uncomfortable question by the respondents, who could have chosen to avoid it, ending the questionnaire without completing it. The variable ranges from "intern" to "partner" and implies an increase in income from one position to the higher one.

Variable	N	Mean	St. Dev	Min	Max	Cronbach's alpha
Attitude	635	9.8	2.4	3	15	0.90
Behavioural intention	635	3.9	2.6	0	10	
Relative advantage	635	13.1	2.8	4	20	0.71
Effort expectancy	635	10.3	3.0	4	20	0.85
Social influence	635	13.9	3.5	5	25	0.86
Perceived risk	635	8.6	2.5	3	15	0.82
Trust	635	6.7	1.7	2	10	0.85
Female	635	0.3	0.5	0	1	
Age	635	34.6	9.3	18	61	
Experience with robo-advisors	635	0.1	0.3	0	1	
Subjective financial knowledge	635	5.4	2.2	0	10	
Education	635	5.0	1.1	1	8	
Financial sector	635	0.4	0.5	0	1	
Job position	635	3.2	1.8	0	7	
Investing experience	635	4.2	6.9	0	30	
Understanding	635	4.0	2.6	0	10	
Objective financial knowledge	311	5.5	2.7	0	10	
Confidence	311	5.4	2.3	0	10	
Overconfidence	311	-0.2	2.1	-6	10	
Current use of robo-advisors	55	0.5	0.5	0	1	
Willingness to recommend robo-advisors to others	27	6.8	1.8	4	10	

Table 1. Descriptive statistics

#### **Analytical methods**

To test the hypotheses, Ordinary Least Squares (OLS) regressions were performed. The order in which the variables were entered into the models was based on the conceptual model of the study and previous research. Power analysis revealed the need of a sample size of 149 people to detect a medium effect with a power of 0.8<sup>(a)</sup>, a number that is far exceeded by the final sample size, rejecting any issues of a potential type II error.

The first regressions cover the first part of the model and use attitude as the dependent variable (table 2). Model 1 explored the relationship between attitude and robo-advisors' features, testing H1, H2, H3, H4 and H5. In model 2, user characteristics were added to the regression, testing H6, H7 and the influence that gender and age have on attitude. Moreover, model 3 included the control variables to further understand their relationship with attitudes. Model 4 and 5, following the original UTAUT model, added interactions to explore if gender and age moderate the relationship between attitude and the five robo-advisors' features. Finally, model 6 included objective financial knowledge and overconfidence; in model 2, in fact, subjective financial knowledge was used as a proxy of the objective one, while the objective measure was included only in the last model considering the sample reduction it causes to the regression.

The second regressions in table 3 covers the second part of the model, with behavioural intention to use as the dependent variable, including the same control variables previously explained, following preceding research on FinTech adoption.



## 5. Results

#### **Attitude**

Looking at model 1 of table 2, relative advantage was found to be positively and significantly correlated with individuals' attitudes towards robo-advisors (ß=0.222, p<.01), confirming H1. Moreover, a statistically significant negative relationship was found between effort expectancy and attitude towards robo-advisors ( $\beta$ =-0.160, p<.01), confirming H2. H3 and H4 were also confirmed with a significant positive relationship found between social influence and attitude (ß=0.157, p<.01) and a negative one between risk perception and attitude (ß=-0.103, p<.01). H5 was equally confirmed, as trust in robo-advisors was found to be positively correlated with individuals' attitude towards them (\(\mathbb{G}=0.245\), p<.01). Ultimately, model 1 found consistent results with the existing research that was previously discussed and explained 40.1% of the variance in attitude towards robo-advisors.

Model 2 added to the regression the user characteristics' variables. A significant positive relationship was found between attitude and experience  $(\beta=0.469, p<.1)$ , confirming H6 and meaning that individuals who have already invested in robo-advisors are more likely to develop more favourable attitudes than individuals who have no experience, in conformity with previous research on technology adoption<sup>69</sup>. No significant correlation was found between attitude and age, in contrast with previous studies, which saw younger generations as more proactive in technology adoption than older ones<sup>68</sup>. Similarly, no significant correlation was found between the variables female or subjective financial knowledge and attitude. Model 2 explained 40.8% of the variance in attitude towards robo-advisors and was therefore a better fitted model compared to the previous one.

Furthermore, model 3 included also the control variables, to further investigate the strength of the correlations found in the other two models. The relationships between attitude and robo-advisors' features remained consistent with the previous two models and significant, while the one with experience lost its significance<sup>(a)</sup>.

Among the control variables, job position was the only one to show a significant negative correlation coefficient (ß=-0.103, p<.1). Higher seniority implies higher income, meaning that individuals with higher available savings might be less willing to invest them in roboadvisors. This consideration is consistent with the nature of robo-advisors, which are designed especially for small retail investors, who, given their lower available income, can benefit more from their lower costs.

Moreover, this model was better fitted compared to the previous one, explaining 41.3% of the variance in attitude towards robo-advisors. VIF values were used to check for multicollinearity in models 1, 2 and 3. No collinearity was found, since these values were all less than 10 and their average was close to 1<sup>(b)</sup>, proving the reliability of the models.

The interactions between robo-advisors' features and gender and age were added respectively to model 4 and 5, separately to avoid issues with multicollinearity, which was nonetheless found in both models(c). The aim was to investigate whether gender and age moderate the effects of perceived robo-advisors' features on attitude towards robo-advisors, following previous studies<sup>69</sup>. In model 4, all variables related to roboadvisors' features still showed significant coefficients, as well as job position, while in model 5 relative advantage and trust were no longer significant. Moreover, the interactions in both models did not show any significant relationship with the dependent variable. These results nonetheless have low reliability, given the multicollinearity found among the predictor variables. Based on these findings, this study will proceed in the following sections excluding models 4 and 5 from the discussion.

In conclusion, model 6 added the variables measuring objective financial knowledge and overconfidence<sup>(d)</sup>, reducing the sample size from 635 to 311 observations. In this final model, interactions were excluded because of the multicollinearity and non-significance found in models 4 and 5. Contrariwise, no collinearity was observed in this model, which was therefore considered reliable. The variables measuring robo-advisors' features showed significant coefficients, consistently with models 1, 2 and 3.

<sup>(</sup>a) The change in significance may be caused by the introduction of the control variables, some of which may be correlated with experience.

<sup>(</sup>b) Myers<sup>48</sup> identified 10 as the value above which multicollinearity can become an issue, while Bowerman and O'Connell<sup>13</sup> suggested that multicollinearity begins to bias the regression model when the average VIF is greater than 1.

<sup>(</sup>c) The average VIF (Variance Inflation Factor) was well above 1, meaning that multicollinearity is biasing the regression model<sup>13</sup>.

<sup>(</sup>d) The variable confidence was excluded from the model, given its high correlation with the variable overconfidence, more relevant to the model.

On the other hand, control variables, user characteristics and the newly introduced objective financial knowledge and overconfidence did not show any significant relationship with the dependent variable.

This model explained 41.9% of the variance in attitude towards robo-advisors, providing a better fit to the data than models 1, 2 and 3.

(0.030) (0.031) (0.031) (0.039) (0.120) (0.046)		Attitude towards robo-advisors					
Effort expectancy         (0.030)         (0.031)         (0.031)         (0.039)         (0.120)         (0.046)           Effort expectancy         -0.160"         -0.153"         -0.140"         -0.123"         -0.298"         -0.127"           (0.028)         (0.028)         (0.029)         (0.037)         (0.107)         (0.043)           Social influence         0.157"         0.152"         0.151"*         0.134"*         0.276"*         0.162"*           (0.023)         (0.023)         (0.023)         (0.029)         (0.091)         (0.034)           Perceived risk         -0.103"         -0.101"         -0.102"         -0.082"         -0.240"         -0.126"           (0.033)         (0.033)         (0.033)         (0.033)         (0.041)         (0.120)         (0.049)           Trust         0.245"*         0.250"*         0.255"*         0.256"*         0.189         0.337"           Trust         0.245"*         0.250"*         0.255"*         0.256"*         0.189         0.337"           Experience with robo-advisors         0.469*         0.417         0.398         0.422         0.363           Subjective financial knowledge         0.026         0.016         0.016         0.01		(1)	(2)	(3)	(4)	(5)	(6)
Effort expectancy         -0.160""         -0.153""         -0.140""         -0.123""         -0.298""         -0.127"           (0.028)         (0.028)         (0.029)         (0.037)         (0.107)         (0.043)           Social influence         0.157""         0.152""         0.151""         0.134""         0.276""         0.162""           (0.023)         (0.023)         (0.023)         (0.029)         (0.091)         (0.034)           Perceived risk         -0.103""         -0.101"         -0.102"         -0.082"         -0.240"         -0.126"           (0.033)         (0.033)         (0.033)         (0.033)         (0.041)         (0.120)         (0.049)           Trust         0.245""         0.250""         0.255""         0.256""         0.189         0.337"           Trust         0.245""         0.250""         0.255""         0.256""         0.189         0.337"           Experience with robo-advisors         0.469"         0.417         0.398         0.422         0.363           Subjective financial knowledge         0.026         0.016         0.016         0.013         -0.001           Subjective financial knowledge         0.026         0.016         0.016         0.013	Relative advantage	0.222***	0.218***	0.223***	0.240***	0.162	0.228***
(0.028) (0.028) (0.029) (0.037) (0.107) (0.043)		(0.030)	(0.031)	(0.031)	(0.039)	(0.120)	(0.046)
Social influence         0.157""         0.152""         0.151""         0.134""         0.276""         0.162""           (0.023)         (0.023)         (0.023)         (0.029)         (0.091)         (0.034)           Perceived risk         -0.103""         -0.101""         -0.102""         -0.082"         -0.240"         -0.126"           (0.033)         (0.033)         (0.033)         (0.041)         (0.120)         (0.049)           Trust         0.245""         0.250""         0.252""         0.256""         0.189         0.337"           (0.054)         (0.054)         (0.054)         (0.065)         (0.206)         (0.076)           Experience with robo-advisors         0.469"         0.417         0.398         0.422         0.363           Subjective financial knowledge         0.026         0.016         0.016         0.013         -0.001           Subjective financial knowledge         0.026         0.016         0.016         0.013         -0.001           Go.036)         (0.042)         (0.043)         (0.042)         (0.042)         (0.042)         (0.042)           Female         0.050         0.007         1.044         0.001         -0.170           Go.04	Effort expectancy	-0.160***	-0.153***	-0.140***	-0.123***	-0.298***	-0.127***
(0.023) (0.023) (0.023) (0.029) (0.091) (0.094) (0.034)		(0.028)	(0.028)	(0.029)	(0.037)	(0.107)	(0.043)
Perceived risk	Social influence	0.157***	0.152***	0.151***	0.134***	0.276***	0.162***
Trust (0.033) (0.033) (0.033) (0.041) (0.120) (0.049) Trust (0.245" (0.250" (0.252" (0.256" (0.266" (0.206) (0.076) (0.076) (0.054) (0.054) (0.065) (0.206) (0.076) (0.076) Experience with robo-advisors (0.264) (0.267) (0.268) (0.268) (0.268) (0.363) Subjective financial knowledge (0.026 (0.016 (0.013 (0.042) (0.042) (0.043) (0.042) (0.072) Female (0.036) (0.042) (0.043) (0.042) (0.072) Female (0.161) (0.162) (1.584) (0.163) (0.268) Age (0.016 (0.008) (0.011) (0.011) (0.077) (0.017) Education (0.008) (0.011) (0.011) (0.077) (0.017) Education (0.068) (0.068) (0.068) (0.068) (0.116) Job position (0.053) (0.053) (0.053) (0.053) (0.083) Investing experience in years (0.014) (0.014) (0.014) (0.014) (0.022) Understanding of robo-advisors (0.041) (0.014) (0.014) (0.0022)		(0.023)	(0.023)	(0.023)	(0.029)	(0.091)	(0.034)
Trust 0.245*** 0.250*** 0.252*** 0.256*** 0.189 0.337***  (0.054) (0.054) (0.054) (0.054) (0.065) (0.206) (0.076)  Experience with robo-advisors 0.469* 0.417 0.398 0.422 0.363  (0.264) (0.267) (0.268) (0.268) (0.385)  Subjective financial knowledge 0.026 0.016 0.016 0.013 -0.001  (0.036) (0.042) (0.043) (0.042) (0.072)  Female 0.050 0.007 1.044 0.001 -0.170  (0.161) (0.162) (1.584) (0.163) (0.268)  Age -0.013 0.0002 0.0002 -0.066 0.0002  (0.008) (0.011) (0.011) (0.077) (0.017)  Education 0.029 0.024 0.034 -0.100  (0.068) (0.068) (0.068) (0.068) (0.16)  (0.068) (0.068) (0.068) (0.068)  Investing experience in years -0.005 -0.005 -0.008 -0.026  (0.014) (0.014) (0.014) (0.014) (0.022)  Understanding of robo-advisors	Perceived risk	-0.103***	-0.101***	-0.102***	-0.082**	-0.240**	-0.126**
Experience with robo-advisors 0.469' 0.417 0.398 0.422 0.363 (0.264) (0.267) (0.268) (0.268) (0.268) (0.385) Subjective financial knowledge 0.026 0.016 0.016 0.013 -0.001 (0.036) (0.042) (0.043) (0.042) (0.072) Female 0.050 0.007 1.044 0.001 -0.170 (0.161) (0.162) (1.584) (0.163) (0.268) (0.268) Age -0.013 0.0002 0.0002 -0.066 0.0002 (0.008) (0.011) (0.011) (0.077) (0.017) Education 0.029 0.024 0.034 -0.100 (0.068) (0.068) (0.068) (0.068) (0.116) Job position -0.103' -0.106'' -0.101' -0.133 (0.053) (0.053) (0.053) (0.083) Investing experience in years -0.005 -0.005 -0.005 -0.008 -0.026 (0.014) (0.014) (0.014) (0.022) Understanding of robo-advisors 0.044 0.049 0.042 0.041		(0.033)	(0.033)	(0.033)	(0.041)	(0.120)	(0.049)
Experience with robo-advisors 0.469' 0.417 0.398 0.422 0.363 (0.264) (0.267) (0.268) (0.268) (0.385) Subjective financial knowledge 0.026 0.016 0.016 0.013 -0.001 (0.036) (0.042) (0.043) (0.042) (0.072) Female 0.050 0.007 1.044 0.001 -0.170 (0.161) (0.162) (1.584) (0.163) (0.268) Age -0.013 0.0002 0.0002 -0.066 0.0002 (0.008) (0.011) (0.011) (0.077) (0.017) Education 0.029 0.024 0.034 -0.100 (0.068) (0.068) (0.068) (0.068) (0.163) (0.268) Job position -0.103' -0.106'' -0.101' -0.133 (0.053) (0.053) (0.053) (0.053) (0.083) Investing experience in years -0.005 -0.005 -0.008 -0.026 (0.014) (0.014) (0.014) (0.012) Understanding of robo-advisors 0.041	Trust	0.245***	0.250***	0.252***	0.256***	0.189	0.337***
(0.264) (0.267) (0.268) (0.268) (0.385)		(0.054)	(0.054)	(0.054)	(0.065)	(0.206)	(0.076)
Subjective financial knowledge         0.026         0.016         0.016         0.013         -0.001           Female         0.050         0.007         1.044         0.001         -0.170           Age         -0.013         0.0002         0.0002         -0.066         0.0002           (0.008)         (0.011)         (0.011)         (0.077)         (0.017)           Education         0.029         0.024         0.034         -0.100           (0.068)         (0.068)         (0.068)         (0.068)         (0.16)           Job position         -0.103*         -0.106**         -0.101*         -0.133           (0.053)         (0.053)         (0.053)         (0.053)         (0.053)         (0.088)           Investing experience in years         -0.005         -0.005         -0.008         -0.026           (0.014)         (0.014)         (0.014)         (0.014)         (0.014)         (0.042)         0.041	Experience with robo-advisors		0.469 <sup>*</sup>	0.417	0.398	0.422	0.363
Female (0.036) (0.042) (0.043) (0.042) (0.072)  Female 0.050 0.007 1.044 0.001 -0.170  (0.161) (0.162) (1.584) (0.163) (0.268)  Age -0.013 0.0002 0.0002 -0.066 0.0002  (0.008) (0.011) (0.011) (0.077) (0.017)  Education 0.029 0.024 0.034 -0.100  (0.068) (0.068) (0.068) (0.068) (0.116)  Job position -0.103* -0.106** -0.101* -0.133  (0.053) (0.053) (0.053) (0.053)  Investing experience in years -0.005 -0.005 -0.008 -0.026  (0.014) (0.014) (0.014) (0.014)  Understanding of robo-advisors 0.041			(0.264)	(0.267)	(0.268)	(0.268)	(0.385)
Female         0.050         0.007         1.044         0.001         -0.170           (0.161)         (0.162)         (1.584)         (0.163)         (0.268)           Age         -0.013         0.0002         0.0002         -0.066         0.0002           (0.008)         (0.011)         (0.011)         (0.077)         (0.017)           Education         0.029         0.024         0.034         -0.100           (0.068)         (0.068)         (0.068)         (0.014)           Job position         -0.103*         -0.106**         -0.101*         -0.133           (0.053)         (0.053)         (0.053)         (0.053)         (0.083)           Investing experience in years         -0.005         -0.005         -0.008         -0.026           (0.014)         (0.014)         (0.014)         (0.014)         (0.014)         (0.042)           Understanding of robo-advisors         0.044         0.049         0.042         0.041	Subjective financial knowledge		0.026	0.016	0.016	0.013	-0.001
(0.161) (0.162) (1.584) (0.163) (0.268)  Age -0.013 0.0002 0.0002 -0.066 0.0002 (0.008) (0.011) (0.011) (0.017) (0.017)  Education 0.029 0.024 0.034 -0.100 (0.068) (0.068) (0.068) (0.068) (0.116)  Job position -0.103* -0.106** -0.101* -0.133 (0.053) (0.053) (0.053) (0.083)  Investing experience in years -0.005 -0.005 -0.008 -0.026 (0.014) (0.014) (0.014) (0.014)  Understanding of robo-advisors 0.044 0.049 0.042 0.041			(0.036)	(0.042)	(0.043)	(0.042)	(0.072)
Age -0.013 0.0002 0.0002 -0.066 0.0002 (0.008) (0.011) (0.011) (0.077) (0.017)  Education 0.029 0.024 0.034 -0.100 (0.068) (0.068) (0.068) (0.116)  Job position -0.103* -0.106** -0.101* -0.133 (0.053) (0.053) (0.053) (0.083)  Investing experience in years -0.005 -0.005 -0.008 -0.026 (0.014) (0.014) (0.014) (0.022)  Understanding of robo-advisors 0.044 0.049 0.042 0.041	Female		0.050	0.007	1.044	0.001	-0.170
(0.008) (0.011) (0.011) (0.077) (0.017)  Education 0.029 0.024 0.034 -0.100  (0.068) (0.068) (0.068) (0.068) (0.116)  Job position -0.103* -0.106** -0.101* -0.133  (0.053) (0.053) (0.053) (0.053) (0.083)  Investing experience in years -0.005 -0.005 -0.008 -0.026  (0.014) (0.014) (0.014) (0.014) (0.022)  Understanding of robo-advisors 0.044 0.049 0.042 0.041			(0.161)	(0.162)	(1.584)	(0.163)	(0.268)
Education 0.029 0.024 0.034 -0.100 (0.068) (0.068) (0.068) (0.016)  Job position -0.103* -0.106** -0.101* -0.133 (0.053) (0.053) (0.053) (0.083)  Investing experience in years -0.005 -0.005 -0.008 -0.026 (0.014) (0.014) (0.014) (0.022)  Understanding of robo-advisors 0.044 0.049 0.042 0.041	Age		-0.013	0.0002	0.0002	-0.066	0.0002
(0.068) (0.068) (0.068) (0.116)  Job position -0.103* -0.106** -0.101* -0.133  (0.053) (0.053) (0.053) (0.053) (0.083)  Investing experience in years -0.005 -0.005 -0.008 -0.026  (0.014) (0.014) (0.014) (0.014)  Understanding of robo-advisors 0.044 0.049 0.042 0.041			(800.0)	(0.011)	(0.011)	(0.077)	(0.017)
Job position -0.103* -0.106** -0.101* -0.133 (0.053) (0.053) (0.053) (0.083)  Investing experience in years -0.005 -0.005 -0.008 -0.026 (0.014) (0.014) (0.014) (0.022)  Understanding of robo-advisors 0.044 0.049 0.042 0.041	Education			0.029	0.024	0.034	-0.100
(0.053) (0.053) (0.053) (0.083)  Investing experience in years  -0.005 -0.005 -0.008 -0.026  (0.014) (0.014) (0.014) (0.012)  Understanding of robo-advisors  0.044 0.049 0.042 0.041				(0.068)	(0.068)	(0.068)	(0.116)
Investing experience in years -0.005 -0.005 -0.008 -0.026 (0.014) (0.014) (0.014) (0.022) Understanding of robo-advisors 0.044 0.049 0.042 0.041	Job position			-0.103*	-0.106**	-0.101*	-0.133
(0.014) (0.014) (0.014) (0.022) Understanding of robo-advisors 0.044 0.049 0.042 0.041				(0.053)	(0.053)	(0.053)	(0.083)
Understanding of robo-advisors 0.044 0.049 0.042 0.041	Investing experience in years			-0.005	-0.005	-0.008	-0.026
				(0.014)	(0.014)	(0.014)	(0.022)
(0.034) (0.034) (0.034) (0.050)	Understanding of robo-advisors			0.044	0.049	0.042	0.041
				(0.034)	(0.034)	(0.034)	(0.050)

	(1)	(2)	(3)	(4)	(5)	(6)
Relative advantage*female				-0.044		
				(0.064)		
Effort expectancy*female				-0.048		
				(0.059)		
Social influence*female				0.049		
				(0.049)		
Perceived risk*female				-0.054		
				(0.070)		
Trust*female				-0.026		
				(0.118)		
Relative advantage*age					0.002	
					(0.003)	
Effort expectancy*age					0.005	
					(0.003)	
Social influence*age					-0.004	
					(0.003)	
Perceived risk*age					0.004	
					(0.003)	
Trust*age					0.002	
					(0.006)	
Objective financial knowledge						0.025
						(0.065)
Overconfidence						0.063
						(0.073)
Constant	5.578***	5.827***	5.300***	4.944***	7.632***	5.622***
	(0.723)	(0.798)	(0.903)	(1.059)	(2.790)	(1.431)
Observations	635	635	635	635	635	311
R <sup>2</sup>	0.401	0.408	0.413	0.416	0.420	0.419
Adjusted R <sup>2</sup>	0.396	0.400	0.401	0.399	0.403	0.390
Residual Std. Error	1.828 (df = 629)	1.823 (df = 625)	1.821 (df = 621)	1.825 (df = 616)	1.818 (df = 616)	1.916 (df = 295)
F Statistic	84.164*** (df = 5; 629)	$47.873^{***}$ (df = 9; 625)	33.674*** (df = 13; 621)	24.338*** (df = 18; 616)	24.767*** (df = 18; 616)	14.208*** (df = 15; 295)
Note:					*p<0.1; *	*p<0.05; ***p<0.01

#### Behavioural intention to use

To investigate the relationship between attitude and behavioural intention to use, covered by the second part of the conceptual model of this study, the OLS regression in table 3 was performed. After having verified that no collinearity was present among the variables, the validity of the model was confirmed by the significant positive relationship found between attitude towards robo-advisors and behavioural intention to use them (\$\mathcal{B}=0.410, p<.01).

Among the control variables, it is interesting to notice that some that where not significant in models 1, 2, 3 and 6 of table 2, were now found to have significant correlation coefficients with behavioural intention to use.

More specifically, education, understanding of roboadvisors and investing experience were all found to have significant positive relationships with the dependent variable (respectively  $\beta$ =0.139, p<.1;  $\beta$ =0.350, p<.01;  $\beta$ =0.051, p<.01), meaning that individuals with higher education, higher investing experience and higher understanding of robo-advisors reported, on average, a higher intention to use them compared to individuals with lower education, lower investing experience and lower understanding. Moreover, the significant negative coefficient of job position ( $\beta$ =-0.113, p<.1) is consistent with the models using attitude as the dependent variable. The model explained 34.9% of the variance in behavioural intention to use robo-advisors.

	Behavioural intention to use robo-advisors
Attitude towards robo-advisors	0.410***
	(0.036)
Female	-0.084
	(0.179)
Age	-0.009
	(0.012)
Education	0.139 <sup>*</sup>
	(0.076)
Job position	-0.113*
	(0.060)
Investing experience	0.051***
	(0.015)
Understanding of robo-advisors	0.350***
	(0.034)
Constant	-1.683 <sup>***</sup>
	(0.640)
Observations	635
R <sup>2</sup>	0.349
Adjusted R <sup>2</sup>	0.342
Residual Std. Error	2.079 (df = 627)
F Statistic	48.109*** (df = 7; 627)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3. OLS regressions for behavioural intention to use robo-advisors

## 6. Discussion

This research aimed to investigate the adoption of roboadvisors in Italy and what attitudes current and potential investors have towards them. For this purpose, a conceptual model based on the UTAUT was developed, firstly to investigate the correlation of robo-advisors' features and user characteristics with attitude towards robo-advisors, testing the seven hypotheses of the study, and secondly to explore the relationship between attitude and behavioural intention to use robo-advisors.

Knowing what robo-advisors' strengths and weaknesses are perceived by investors is fundamental both for robo-advisory providers and for incumbent banks, which must protect themselves from the new competition of these FinTech players. The former, in fact, can leverage on investors' perceptions and expectations to customise their services and carry out adequate marketing campaigns. The latter, on the other hand, can use the same findings to provide alternative products or services that can adequately satisfy their needs.

Firstly, perceived relative advantage was found to be positively correlated with individuals' attitudes towards robo-advisors, meaning that those who believe that robo-advisors are more convenient and more efficient than human financial advisors, are more likely to develop favourable attitudes towards them and consequently use them. Considering this, robo-advisory providers should use their campaigns to compare themselves with traditional market operators, highlighting their relative advantage in the most efficient way according to investors' expectations. For instance, some of robo-advisors' advantages they could leverage on are their advanced technology, their lower costs and their ability to carry out investment decisions without emotional biases through their automated portfolio functions. On the other hand, incumbent banks can use the same comparison to highlight robo-advisors' weaknesses, such as their limiting reliance on passive management, their untailored model portfolios and their not yet demonstrated ability to retain assets during severe market downturns<sup>59</sup>.

Moreover, this study found effort expectancy to be negatively correlated with individuals' attitudes towards robo-advisors, meaning that people who perceive robo-advisors as difficult to understand and use are less likely to develop positive attitudes. This result is in line with previous studies, which found that individuals are more likely to accept and adopt a new technology when they perceive it is easy to use and it requires little labour and time<sup>17</sup>.

Robo-advisory providers are already focusing on user experience, offering investors quick access to their accounts and user-friendly interfaces<sup>37</sup>, but they could stress more in their campaigns their advantages compared to traditional players, who are still less advanced in terms of client experience innovation. On the other hand, incumbent players could also integrate their services with technological inputs, offering their clients more efficient interfaces, to satisfy their increasing desire for speed and immediacy.

Social influence regarding robo-advisory adoption was also found to be positively correlated with individuals' attitude towards them, meaning that people are more likely to develop favourable attitudes towards robo-advisors if someone close to them or whom they trust recommends their use. The diffusion process of a new technology is not homogeneous among the potential users, since some are more likely to adopt the innovation sooner than others depending on their personal characteristics and attitudes<sup>55</sup>.

Contrariwise, no significant relationship was found between gender or age and attitude. The coefficients of the interaction variables were also found to be not significant, meaning that gender and age do not moderate the effects of perceived robo-advisors' features on attitude towards robo-advisors, in contrast with previous studies<sup>69</sup>. This difference to previous research can be explained by the nature of robo-advisors, which are not only a technological innovation, but also a financial one. The complexity and novelty of the situation, therefore, makes it difficult to specifically characterise, in this case by gender or age, the users who might be interested in investing in this new technology.

Moreover, this study found that financial knowledge (subjective and objective) had no significant relationship with attitude, meaning that better knowledge does not influence individuals' attitudes towards robo-advisors. Previous studies found that people with higher financial knowledge are more likely to make superior financial decisions and adopt safer financial behaviours in many life domains<sup>60</sup>. Nonetheless, financial knowledge allows investors to adequately assess an investment, but not the technology supporting it, as in the case of robo-advisors<sup>7</sup>. The decision to invest or not in a robo-advisor, therefore, could be based both on financial and technological criteria that must be investigated with measures that go beyond the mere individuals' financial knowledge.

One last important finding for robo-advisory providers regards the positive relationship found between individuals' favourable attitudes towards robo-advisors and their behavioural intentions to use them. Given the innovative nature of robo-advisors and their scarce diffusion, this result offers a significant insight for market operators. It is essential that investors grow positive attitudes towards robo-advisors, even if they have little knowledge on the subject, so that they can develop an actual intention to invest in them afterwards. A favourable attitude towards robo-advisors therefore becomes a prerequisite, the first objective in the customer engagement process, especially when robo-advisors are still at the beginning of their dissemination process.

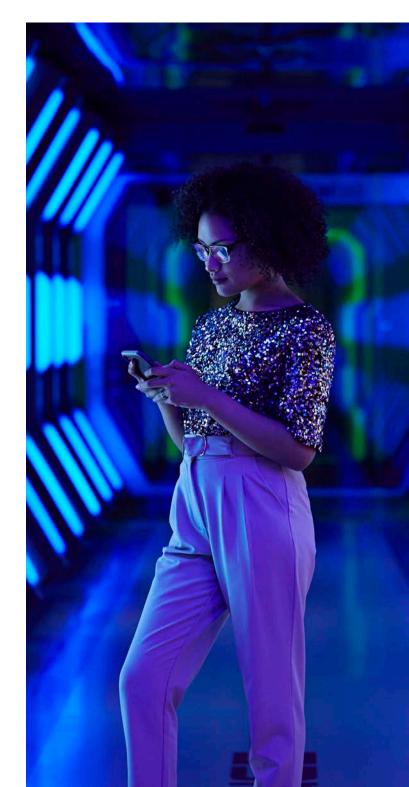
Limitations and future research

Finally, this research has some limitations that must be considered in the interpretation of its results. The first one is given by the fact that attitude is a broad and abstract concept, subject to contextual variations and defined by many factors that affect each other<sup>6</sup>. Other studies, for instance, have found that personality traits influence the technology adoption process<sup>73</sup>. Future research including personalities and other personal characteristics could offer further meaningful insights in the context of robo-advisors' acceptance and adoption.

Moreover, a second limitation of this research is its correlational nature, which does not allow causal inferences. Experimental manipulation would have been needed to determine if the relationship between attitude or behavioural intention and the variables tested are causal in nature, but was nonetheless impossible to implement, given the size and the uniqueness of the sample. Future research could focus on a smaller sample, establishing an experimental and controlled environment to study the variables that may cause attitude formation and behavioural intentions.

Thirdly, this study focused on a very specific population segment: PwC Italian employees, who may have higher financial knowledge and investing experience compared to the average of the Italian population. Future research should, therefore, focus on other segments of the market to gain a deeper knowledge on individuals' attitudes and intentions towards robo-advisors. Furthermore, the same study conducted with a larger geographical scope or in a different country may give different perceptions, attitudes and behaviours.

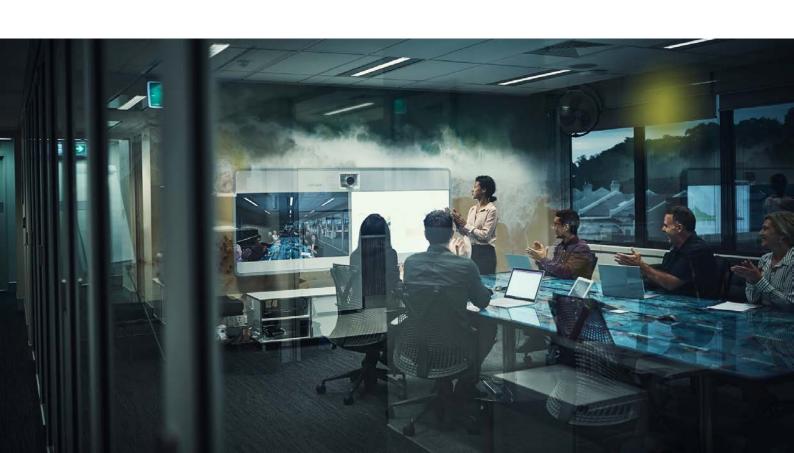
Undoubtedly, financial technologies will continue to develop and change in the future as well as investors' understanding and experience with them<sup>7</sup>. Future research on robo-advisors should, therefore, employ longitudinal data on their adoption to investigate the evolutions and changes in the market and to measure investors' needs, expectations and attitudes as market conditions and tools at their disposal change.



# 7. Conclusion

In recent years, FinTech innovations have radically transformed the banking and financial sector, generating a progressive disintermediation and deregulation and forcing banks and financial institutions to implement necessary changes to survive a highly competitive market. This research focused on the specific FinTech of robo-advisory, primarily investigating the potential investors' attitudes and behaviours towards these little-known instruments.

This research highlighted a scenario in which most investors are not yet ready for an innovation such as robo-advisory or at least they are not adequately prepared for it. Therefore, it is plausible to assume that the new market players offering robo-advisory services will not be able to subvert the position of the current market leaders in the nearest future. Consequently, rather than a disruption scenario, it is likely that a collaboration one will be established, where innovative companies will not compete directly with banks or other market incumbents, but will become part of their ecosystems, specialising in specific functions or integrating their current operating models.



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# 9. Appendix 1: Sample insights

Job position	Number of respondents
Intern	71
Associate	177
Senior associate	124
Manager	99
Senior manager	60
Director	46
Salaried partner	16
Partner	42

Table 4. Respondents divided by job position

Job market sector	Number of respondents
Financial Services	260
Automotive	8
Telecommunications	12
Energy, utilities & resources	20
Entertainment & Media	12
Government & public services	42
Healthcare	9
Pharmaceuticals & Life Sciences	1
Retail and consumer	16
Technology	89
Industrial manufacturing	28
Other	138

Table 5. Respondents divided by market sector



Angelica Milani is the author of this report, which was presented in 2019 as the final dissertation for the MsC Behavioural Economics at City University of London, in cooperation with PwC Italy.



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