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Robo-Advisors and Human Financial Advisory

Reliance on recommendations of Robo-Advisors

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To my grandfathers, Lino and Gino,
who inspired me with their lives and taught me
the value of things.

To my grandmothers, Rosetta and Mariagrazia,
who took care of me with immense love
and taught me happiness.

To my grandmother, Giuliana,
that since I was born watches me and
protects me from heaven.

Ai miei nonni, Lino e Gino,
che mi hanno ispirato con le loro vite e mi
hanno insegnato il valore delle cose.

Alle mie nonne, Rosetta e Mariagrazia,
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e mi hanno insegnato ad essere felice.

A mia nonna, Giuliana,
che da quando sono nato mi guarda
e protegge da lassù.

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INTRODUCTION AND RESEARCH IDEA

In a financial and social context characterized by growing inflation, high living costs, and deep uncertainty about the future, a correct and forward-thinking utilization and management of own money has progressively become a vital necessity for individuals and households. People need to carefully plan their financial choices to avoid the risk of being overcome by due expenses and unforeseen events. Here, we refer to all kinds of financial activities, from risk-management to investment and saving decisions.

Unfortunately, individuals and households are, on average, poorly trained for such task, with this often resulting in an incorrect, and sometimes even harmful, financial behaviour (Chen & Volpe, 1998; Calcagno & Monticone, 2015). People, indeed, tend to adopt naïve and non-coherent investment strategies, with their portfolios ending up being poorly diversified (Anderson, 2013; Dimmock et al., 2021; Goetzmann & Kumar, 2005) or characterized by excessive turnovers of stocks (Grinblatt & Keloharju, 2009; Barber & Odean, 2000; Daniel & Hirshleifer, 2015) and thus yielding low or even negative returns. This might be determined by a low level of financial literacy (Van Rooij et al., 2011; Li et al., 2020, Campbell, 2006), by the lack of trust in the financial markets (Guiso et al., 2008), or social factors (Hong et al., 2004). Moreover, people have been proven to be subject to some psychological biases that furtherly affect their financial choices. The well-known disposition effect (Weber & Camerer, 1998), for instance, determines a tendency to hold for too long on "loosing" stocks while selling early "winning" stocks; overconfidence-related biases lead individuals to autonomously determine, and often overestimate, the precision of their information (Statman, et al., 2006); illusion of control and excessive optimism may also affect the perception of risks and thus altering risk-management choices (Coelho & De Meza, 2012). While these represent only some key and widely discussed examples, it is clear that some individuals are not able to independently manage their money in a correct way and may need assistance from trained professionals.

In this environment, financial advisors represent a valuable resource, given their experience and ability to drive people towards healthy financial behaviours and help them with their investment and saving choices. Yet, the demand of advisory services is pretty low (Hung et al., 2008), especially in the Italian context (Consob, 2021). Many scholars have tried to analyse the reasons that determine this low demand of advisory services and have highlighted a series of factors that are believed to be crucial. First of all, advisory services work upon a trust-based relationship between the advisor and the client, thus low levels of interpersonal trust and, more in general, low levels of trust towards the financial system, dangerously determine a decrease in the demand (Cruciani et al., 2018; Westermann et al., 2020). The level of trust can be influenced, for example, by the fear of conflicts of interest and opportunistic behaviours from advisors. Also, for some categories, the lack of easy-to-access options becomes an obstacle to the utilization of advisory services (Çera et al., 2021; Riau, 2019), that cannot be easily accessed without physically reaching your local bank. Moreover, as pointed out by Van Dalen et al. (2016), meeting personally a financial advisor may constitute a source of anxiety for some individuals. Last but not least, people with limited fund availabilities, especially among the younger population, tend to refrain from hiring financial advisors because of their high fees that are not often compensated by adequate returns (White & Yanamandram, 2004; Alyousif & Kalenkoski, 2017; Gennaioli et al. 2015).

In recent years, to capture the demand of those that accuse these issues as the main determinant of their low demand of advisory services, a fintech solution has been introduced in the market: Robo-Advisors. Basically, Robo-Advisors are digital platforms comprising interactive and intelligent user assistance components (Maedche, et al., 2016) that use information technology to guide customers through an automated advisory process (Sironi, 2016; Ludden et al., 2015). While their utilization may raise newer issues, mainly related to "trust in automation" dynamics and cybersecurity concerns, they represent a powerful solution for the previously described limitations. Indeed, Robo-Advisors are (almost) immune from conflicts of interest; they cannot adopt opportunistic behaviours, and, in theory, they are not subject to most psychological biases that affect individuals. Moreover, the lack of human involvement in the advisory process results in a relevant decrease of fees and allows individuals to access such services from almost any physical location. Nonetheless, Robo-Advisory services are scarcely considered by investors and, although in recent times they are seeing a growing popularity, their utilization is pretty low. While we may assume that those who are more interested in the behavioural contributions that they can obtain from financial advisors, and those from older generations that show very low levels of comfort and trust towards machines, might be less willing to substitute the human professionals with an artificial intelligence, it is not clear why the demand is still low even for those that, conversely, consider advisors only as financial planners or as a mere source of information. For example, given the limited availability of funds of young people and their overall higher levels of trust in automation, we may imagine their demand of Robo-Advisory services to be consistent, but data show that this is not the case.

While some studies have tried to characterize and explain this phenomenon, pointing their finger mostly at the non-satisfactory returns and at the anyway reduced interest of people for managing their money, only few scholars have concentrated their focus on the Italian context. The main objective of this thesis is to analyse this issue and explain the reasons underlying the low demand of Robo-Advisory services. Specifically, we are interested in understanding whether people show a preference for human or robotic advisors and give a possible explanation of this result. Furthermore, reliance on recommendation provided by robotic advisors represents a key issue. Indeed, we want to understand whether recommendation provided by Robo-Advisors are perceived by subjects as reliable and of good quality, and what pushes people to choose to follow such recommendations.

The thesis is divided in two parts. The first four chapters present the preliminary theoretical discussion, substantially based on existing literature on these topics, that explores the main characteristics of each service and describes the context in which they operate. Indeed, before conducting any kind of experimental analysis, it is almost mandatory to carefully review the literature inherent to the phenomenon at issue. To this purpose, the first part of this thesis aims at describing the current state of the art of advisory services (human and robotic), analysing in depth their characteristics and usage. The discussion will be developed as substantially theoretical and will be based on the existing literature.

Specifically, we start in *Chapter 1* by describing the main features of "traditional" financial advisory services. Given the research objective of the thesis, we are interested in understanding not only the function covered in the financial system by these professionals, but also the context in which they operate – current regulation at the European and Italian level, demand of advisory services, factors that influence the demand, alternatives. *Chapter 2* substantially repeats the analysis contained in the first chapter, this time focusing on Robo-Advisors. Again, the idea is to highlight the characteristics of Robo-Advisors and the financial and regulatory environment that surrounds them. *Chapter 3* deals with the issues that individuals may experiment when deciding to hire a financial advisor. The purpose of the chapter is to review the existing literature on the topic and highlight some key factors that may hinder (or support) the demand of advisory services. Some models that analyse and predict the state of such factors will also be presented, with a particular focus on trust-related issues. Trust is, indeed, considered the most important determinant of the demand of advisory services in general (Hung & Yoong, 2010), and its counterpart in the "automated" field, trust in automation, can be hypothesized to become the main aspect to consider in the analysis of the demand of Robo-Advisory services. In conclusion, *Chapter 4*, developed as a formal review of the existing literature, investigates the possible horizons of cooperation between human advisors and robotic advisors, comparing the results and ideas of literature that supports the future possibility of a complete substitution and those that favours the idea of an integration between the two models, as an alternative to the only-human or only-robot solutions that we investigate in *Chapter 5*.

The second part of the thesis, *Chapter* 5, contains all the experimental analysis performed, describing for each one, after a brief review of the related literature, the methodology used, the main hypothesis and the importance of the results obtained. Given the purposes and the research idea of the thesis and considering the theoretical and empirical results obtained by other scholars highlighted in the literature review of the first part of the thesis, we decide to begin by looking at the approaches adopted by similar studies conducted among the Italian population. We start from the contribution of Consob (2020) that verified the determinants of the acceptance of recommendations of Robo-Advisors and analysed the preferences of young students. In this paper, the authors found that the main determinant of the acceptance of the recommendations was related to the so-called "Confirmation Bias": in their interpretation, when the Robo-Advisor confirmed the initial investment idea of the subject, the investor become thus more inclined to follow the recommendation. On the one hand, we argue the reliability of the way in which confirmation bias is assessed in the cited paper (see *Chapter 5*), and we propose a new way to test the relevance of this bias in the overall satisfaction with Robo-Advisors, aiming at improving the predictive validity of the measure. On the other hand, we also propose some new measures to complement and complete the study. Indeed, existing literature showed that one of the main determinants of the utilization of such services is the level of trust in automation. To investigate the phenomenon at issue, we develop and utilize an approach structured in three phases. First, we repeat the experiment performed in the cited paper with some little additions, to better understand eventual paths of improvement and reconfirm the various conclusions. Then, before drawing conclusions on the role of trust in automation, we utilize the data gathered in this "pilot" experiment, adding some extra data centred on the assessment on trust in automation, to conduct a validation of the approach and possibly to simplify the scale. In conclusion, we present results of our final "improved" version of the experiment.

CHAPTER 1: TRADITIONAL FINANCIAL ADVISORY

The first chapter of this work introduces traditional financial advisory: the word "traditional" refers to the fact that the advisor here is a human being. The specification is fundamental because, as we will see in *Chapter 2*, recent years have seen the introduction in the financial panorama of the so called "Robo-Advisors", where the human advisor is replaced, at least from the investment and portfolio creation point of view, by an artificial intelligence.

The chapter is divided in 6 sections. The first section introduces financial advisors and the advisory process, trying to give a definition of what and who is an advisor and describing also the actors involved in the advisory process. *Section 1.2.* discusses the role and functions of the financial advisors, highlighting how they have shifted role from simple investment planners to proper life counsellors. The third section begins with an analysis of the main factors that determine the demand of financial advice and then provides data about the actual diffusion and demand of financial advice in Italy. In the fourth section an overview of the legal and regulatory context in which financial advisors operate is given, to provide a more complete and general view of the matter. *Section 1.5.* describes the most popular alternatives to traditional financial advice underlining the key features of each one, advantages, and disadvantages with respect to traditional advisory. The chapter concludes with a short summary of the key considerations made.

1.1. Financial advisors and the advisory process: some preliminary definitions

In recent years, households and individuals have shown a growing interest for having their financial resources adequately managed. In particular, they have increased their exposure to financial risk taking, possibly in response – at least partly – to the demographic transition and increased responsibility for retirement financing (Hackethal, et al., 2012). The progressive growth in the life expectancy of the world population and the radical changes in people's lifestyle, indeed, have raised the need for them to have higher financial resources later in life. Moreover, also younger aged individuals and households faced an increase in general expenses, not opportunely compensated by a proportional raise in their labour income. In such a context, properly managing financial resources is crucial to maintain an adequate level of well-being.

As pointed out by Campbell (2006) and Lusardi & Mitchell (2007) financial literacy and sophistication across households and individuals varies significantly and, as a consequence of this, people might not have the necessary competence to develop an effective strategy for managing their resources. In addition, households and individuals' financial "problems" have various special features that build up a complex environment: they must plan over long but finite horizons, they have important nontraded and or illiquid assets and they face relevant constraints on their ability to borrow. To accomplish the task of managing correctly financial resources in such a complicated environment, some households and individuals seek advice from external agents, while others prefer to make the decisions by themselves (Campbell, 2006). These external "forces" may be identified as financial advisors.

1.1.1. What is financial advisory?

What precisely is a financial advisor? There are various definitions of financial advisor. Fischer & Gerhardt (2007), for example, give the following definition: a financial advisor is "a person or organization that offers its professional financial expertise to individuals who seek assistance or want to completely delegate their investment decisions". Here, the major emphasis is put on the delegation from clients to advisors (see next paragraph) and on the expertise of the delegated. Based on this definition, the key to advisory usage seems to be, as said before, the fact that people do not have the necessary knowledge and time to self-manage their financial resources and so they externalise this activity. But there's more: financial advisors have also been defined by the economic literature as "multifaceted professionals, who provide economic advantage, financial information, financial education, bias management, and emotional support" (Cruciani, et al., 2021, p. 185). As we see, more recent and innovative approaches and definitions tend to concentrate more on other aspects of financial advisory, integrating psychological and behavioural aspects in the definition. Anyway, in great substance, while a unique definition cannot be found, we may identify a financial advisor as a specialized operator that provides people with recommendations and assistance (both psychological and technical) on financial resource management, in exchange for a compensation. Also, we need to point out that referring to the variety of services offered, the term "financial advisory" has quite a broad connotation and may refer to various activities like stock-brokering, tax planning, estate managing and so on. From now on, we will use the phrase "financial advisory" to refer only to the investment management and brokering services, leaving apart other activities.

The definitions provided above highlight how financial advisors play a key role in the financial life of households and individuals, but the actual function of financial advisory requires a further disclosure. In *Section 1.2.* the function(s) and role(s) of financial advisors will be analysed more in depth.

1.1.2. The actors involved

In order to explain the actors involved in the advisory process we may borrow the approach proposed by Schwabe and Nussbaumer (2009), where they highlight the main features of the actors involved and the characteristics of the relationships between them. *Figure 1.1.* is a reinterpretation of the one proposed in the paper by Schwabe and Nussbaumer and focuses on the actors relevant for our purposes at this stage of the dissertation.

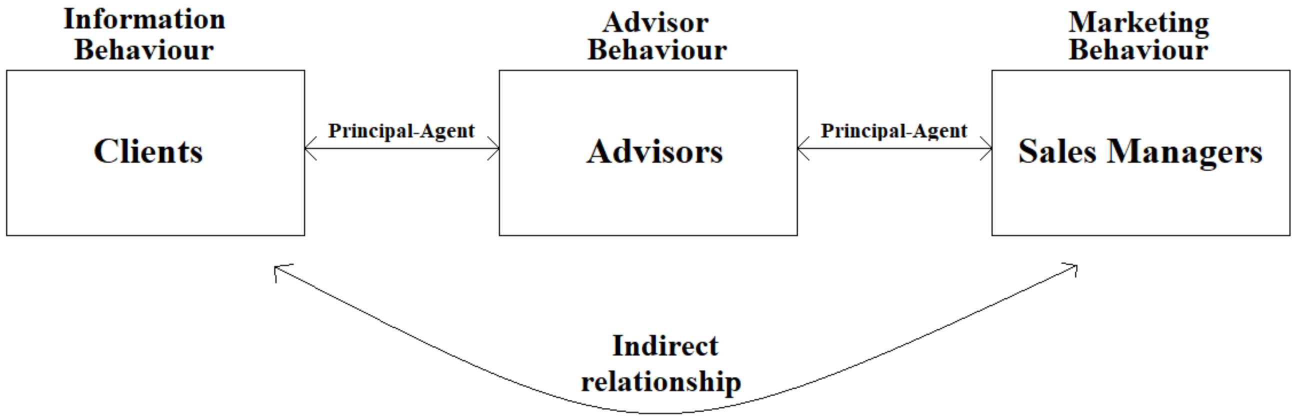

Figure 1.1.: The relationships between the actors involved in the advisory process. Source: personal reinterpretation of figure I of Schwabe and Nussbaumer (2009).

We may observe how the initiator of the whole process is the client: an individual (or a household) might seek financial advice for many reasons, e.g., because of their lack of knowledge, time, or interest in financial markets (Financial Services Authority, 2009). Models proposed by scholars, like the one from Wilson (1999), might explain the behaviour of the clients: they typically search, select, and use information – that has to be intended in its broadest meaning, referring to theorical knowledge and also to practical execution – that they prefer and sometimes they need help to uncover information that they are not aware of (information behaviour). Consequently, they hire a financial advisor that will help them managing their financial resources and deal with all the related issues (advisor behaviour). The type of relationship that exists between the client (advisee) and the advisor is the one explained by the well-known principal-agent theory. The client (principal) pays the advisor (agent) to work for him/her: the key issues typically highlighted by the agency theory are identifiable also in this context. The agent may have some hidden characteristics and intentions and may engage, if not properly monitored, in actions that may hinder the client's interest. While duties of correctness and transparency are imposed by law (this will be further explained in *Section 1.4.*), many strategies to bypass them may be employed by the advisor. Before de-structuring the relationship between the advisee and the advisor, the third actor of the process should be considered. While being often considered as only marginal and not directly involved in the principal-agent relationship described, the sales manager plays a key role in conditioning and guiding the advisor's activity. We may imagine this figure as the individual responsible for the activity of the advisor: he strives for competitive advantage (Porter, 1985) and is interested in preserving the relationship between the client and the advisory institution (marketing behaviour). Again, the relationship between the sales manager and the advisor may be represented as a principal-agent one. In this sense, we may consider the fact that the advisor might be interested to bind the customer to himself/herself as a person rather than to the institution (vice-versa for the sales manager). Also, the sales manager might aim at developing a standardized and structured advisory process that maximizes the income for the bank, while the advisor may focus on maximizing their personal income (Schwabe & Nussbaumer, 2009).

1.1.3. The advisory process

The advisory process has been defined in several different ways among scholars, but all the approaches proposed in literature seem to share four common phases (Nussbaumer, 2012a):

1. Contact: in this first phase the client shows what has been described previously as "information behaviour" and more in general he/she experiments and investment problem (e.g., buying stocks, bonds or investing in mutual funds). The advisor is then approached by the client to obtain advice. Some scholars highlighted how this phase may be initiated also by the advisor through advertisement initiatives (often promoted by their institutions) or direct contact, but this situation is less common, at least for new clients.
2. Advice: this is the key phase of the whole process. After getting to know the client through multiple face-to-face encounters, the characteristics of the investment strategy will be discussed. In this phase the advisor should identify the client's needs, risk profile and investment goals (Elfgen & Klaile, 1987). Time horizon of investment, desired returns and other details must be deeply analysed to assist the client in the most suitable way. Typically, the solution generated in this phase consists of a simple generic investment strategy and some specific additions depending on particular needs of the client as well as its mapping to a product portfolio. It is worth to mention that the advice phase, being the most relevant one, is also the one to which regulators gave the most attention, defining precise transparency and cooperation standards (see *Section 1.4.*).
3. Implementation: this is the phase in which the advisor implements the strategy discussed with the client.
4. Support: the strategy implemented must be adequately and continuously monitored by the advisor and adapted depending on eventual new requests of the client. The financial advisor must always be available to client needs and ready to adjust the strategy, if necessary.

1.2. The function(s) of financial advisors

The definitions of financial advisor given before, may help us to understand which functions can be covered by these operators. Looking at the definition provided by Fischer and Gerhardt (2007, p. 18) we may highlight some key functions of the financial advisor:

> *"A financial advisor is a person or organization that offers its professional financial expertise to individuals who seek assistance or want to completely delegate their investment decision".*

The focus of this definition is on the "financial/investment function". This is the function that in less recent literature has been majorly underlined by scholars. Moreover, the advisors themselves tend to concentrate on this part of their job when they advertise advisory services.

More recent approaches, on the other hand, focus on different functions. The definition provided by Cruciani et al. (2021, p. 185) highlights how the financial advisor acts also as an educator, a bias manager and as a person that provides emotional support, performing what we are going to call non-financial functions:

> *"Financial advisors are multifaceted professionals, who provide economic advantage, financial information, financial education, bias management, and emotional support".*

We are in a situation in which traditional functions of advisory are being accompanied by newer behavioural-oriented functions, progressively transforming the role of the advisor, shifting from being seen just as a financial expert that helps people to correctly manage their money to a proper assistant and supporter that plays a role in the psychological and moral well-being of the individual.

The following two sub-sections will describe more in depth these two categories of functions covered by financial advisors, highlighting what an individual can obtain by hiring an advisor.

Figure 1.2.: Financial Advisors' functions: financial and non-financial. Source: personal elaboration.

1.2.1. The Financial/Investment Function(s)

As said, the most well-known and discussed, among the functions covered by financial advisors, is what we defined as the "financial/investment function". In this sense, the advisor's primary role is to help individuals or institutions to make proper investments, meeting individual investment goals of investors considering long or short-term investment horizons (Jung, et al., 2019). People, indeed, might not have the necessary knowledge, information, time, or abilities to correctly manage their finances (Reiter-Gavish, et al., 2021).

Information and knowledge providing

The development of technology and the increase in the availability of information about the financial world and markets, have surely empowered the instructional condition of individuals and households, but many still consider themselves to be too far from having the right degree of understanding of how financial markets work. And this is not only a matter of self-assessed level of financial knowledge: as underlined by Lusardi and Mitchell (2011) and Atkinson and Messy (2012), consumers' knowledge of basic financial principles and products is minimal and might not be sufficient to guarantee that households make sound financial decisions (Calcagno & Monticone, 2015). In this sense, at least in principle, people with a lower degree of investment knowledge should rely more on the help of a financial advisor that would possibly make up for their lack of competence. Nonetheless, a mixed literature on this topic exists: while some scholars confirmed that individuals that are less financially literate tend to seek more advice (see for example Hung and Yoong, 2010), others found the exact opposite, pointing out a positive relationship between financial literacy and financial advice seeking (see Lusardi and Mitchell, 2011, or Hacketal et al., 2012). Anyway, further considerations on this aspect will be made in *Section 1.3.*.

Time saving

Another factor that must be considered, is the fact that investing and managing your portfolio is a time-consuming activity: individuals and households who are not financial experts must incur in time cost (and consume mental resources) when managing their financial portfolios (Kim, et al., 2016). This might be, for some people, quite limiting or even frustrating. As highlighted by Arrow (1962) and Becker (1964), these costs become significantly important when people gain job-specific human capital on their jobs via learning by doing, leading to a potential future reduction of their labour income. For this reason, many investors may consider the opportunity cost of devoting part of their time to this activity as too high and though not worth it. On the other hand, it is true that people often comprehend the importance of investing and at a certain point of their lives they build a portfolio of investments. These two aspects considered together often results in some kind of portfolio inertia because investors – the ones that do not hire a financial advisor – and in particular workers, tend to behave like the typical inactive investor, that is, they tend to "set and forget" their investment portfolios. This is furtherly confirmed by Ameriks and Zeldes (2004), that proved how, over a 12-months period, more than 75% of the retirement accounts examined never altered their composition, and Bilias et al. (2010), that studied portfolio inertia also on equity owners. In this sense, a financial advisors could for sure be a remedy for portfolio inertia. The key here is in the actual convenience for the individual: while, on one hand, autonomous financial management results for the investor in substantial amounts of monetary and non-monetary transaction costs, on the other hand, hiring a financial advisor will cost you a certain fee (fixed or return-linked). Each individual/household will then decide on the basis of a trade-off between their time-costs and the fee that they would pay to the advisor. Anyway, it is worth to mention, that the advisor should not be seen just as a "time-saver" because of the multiple functions, besides the ones already presented, that he/she represents (see below).

Economic advantage

Last but not least, of course, financial advisors should have a role in obtaining satisfactory financial performances. This should be true at least in principle. To verify whether this holds in practice, we may analyse the work by Hacketal et al. (2012). Using data from two different sources (a large brokerage firm and a major bank) they compared the returns of self-managed investment accounts and advised accounts. They found out that in most cases advised accounts do not earn statistically significant higher returns with respect to non-advised accounts. On the other hand, Shapira and Venezia (2001) found, analysing Israeli investors, that, contrary to Hacketal findings, professionally managed accounts tend to have slightly better results, possibly because of a more precise and better management of psychological biases such as the disposition effect. We see that a mixed literature exists also on this topic.

In conclusion, even if it is true that delegation of portfolio decisions to advisors opens up economies of scale in portfolio management and information acquisition, because advisors can spread information acquisition costs among many investors, and also that such economies of scale, as well as possibly superior financial practices of advisors, create the potential for individual investors to improve portfolio performance by delegating financial decisions (Hackethal, et al., 2012), what is clear is that returns are not significantly higher (and sometimes not even statistically significant) for people who use financial advice than for people who don't. Then what does justify the usage of financial advisory? As said, recent research underlines that the advisor has some relevant non-financial functions, helping people dealing with various different problems in their life, acting as educators and as psychological counsellors. The following sub-section analyses the non-financial functions of advisors.

1.2.2 The non-financial functions

Besides the economic advantage and the information function, explained in the previous sub-section, the financial advisor acts also as an educator, as a “bias manager”, and as an emotional support.

Financial advisors as educators

Scholars have underlined several times the importance of financial literacy for the society: the OECD (2016) report on the “International Survey for Financial Literacy” highlighted how financial literacy is a key determinant of financial awareness and of the stability of the financial system. Other studies (Berg and Zia, 2017; Skimmyhorn 2016) documented also that financial education might have a noticeable effect on socially virtuous behaviours like delinquency rate, debt balances, and probability of facing adverse legal actions. This said, the development of adequate educational interventions is fundamental: as considered before, there is extensive evidence of widespread financial illiteracy (see for example Gathergood and Weber, 2014; Lusardi and Mitchell, 2011). In this sense, financial advisors may play an important role: we have already ascertained that advisors can help customers that do not have the necessary knowledge to invest by recommending them the soundest financial instruments and product or by managing their money directly (through the classical advisory delegation). But they should not be considered as a substitute for financial knowledge and capability, indeed, they might – and should – also have an educational function (Collins, 2012). The knowledge provided, in fact, will, at least for some customers, contribute to the development of some investment competences and progressively increase – even if very slowly – their financial literacy level and financial awareness. To prove this, Migliavacca (2020) conducted an experiment among bank-account holders (both retail and private banking clients) to test the influence of financial advisors on financial literacy and awareness of their customers. In particular, she ordered the sample depending on their observed degree of financial literacy and assessed the probability for each participant of being in the top quartile: the result showed that being assisted by a financial advisor increases the chance of being in the top quartile, supporting the thesis that financial advisors play a role as educators. And there’s more: the peculiarity of the educational relationship between advisor and client may help also to maintain the effects over time. According to Fernandes et al. (2014), in fact, even large interventions with many hours of instruction have negligible effects on behaviour after a certain time from the intervention. But here, the continuous interaction, indeed, helps to avoid the typical quick decay period that characterizes traditional one-spot finance courses delivered to the population through public initiative or other sources (Migliavacca, 2020).

Bias management

The second key non-financial function that advisors cover is the "bias management". Investors are, indeed, subject to a significant number of biases when they invest autonomously. While we should notice that advisors are investors themselves, research pointed out that investment experience and the fact that – at least when performing their services – they manage money for other individuals instead of their own, some of these biases might have a milder impact.

One of the most relevant biases affecting investors is the so called "disposition effect". The disposition effect can be seen as "the reluctance of investors to realize losses and the propensity to realize gains" (Feng & Seasholes, 2005). Behaviourally speaking, this effect is closely related to an emotional trait called "regret aversion", that describes the emotion of regret experienced after making a decision that turns out to be a bad or inferior choice (Baker & Ricciardi, 2014). The practical and financial implication of this bias is the fact that investors tend to keep "hold" positions on loosing stocks for too long and sell winning stocks too early. And while this affects – even if in different ways – all kind of investors, from financial corporations to governmental organizations and households (Grinblatt & Keloharju, 2001; Garvey & Murphy, 2004), literature has widely analysed whether more sophisticated and experienced investors (like financial advisors) may be able to control this effect and reduce damages. While scholars produced mixed evidence also on this topic, the prominent theory seems to be that experience and sophistication together – one of the two would not be sufficient – eliminate the reluctance to realize losses, but only reduce the propensity to realize gains, having, in complex, a positive and noticeable impact on the disposition effect (Feng & Seasholed, 2005; Dahr & Zhu, 2006; Shapira & Venezia, 2001). Chen et al. (2004) pointed out also that investors with larger accounts tend to be less prone to this bias, furtherly supporting the thesis that advisors, typically managing considerable amount of money, may help people managing and avoiding this bias, even though they are not completely immune to it.

Together with the disposition effect, also the role of "overconfidence" has been widely analysed. We may summarize the meaning of this word as "unwarranted faith in one's intuitive reasoning, judgments, and cognitive abilities" (Pompian, 2006). Overconfidence affects the individuals' perception of both their own predictive ability and the precision of the information they have (better than average effect and miscalibration). Financially speaking, this bias has been proven to have two main consequences on investor's behaviour: excessive trading and underdiversification. The most agreed explanation of these consequences is that overconfident investors, overestimating their abilities and the precision of their private information signals, tend to apply more aggressive trading strategies and continuously trade upon new pieces of information, ignoring what is publicly available

(Trinugroho, 2011; Benos, 1998). And this has serious negative outcomes. In particular, Barber & Odean (2000) found that a portion of households and individuals have a high turnover in their portfolios and analysed whether this behaviour could possibly lead to better financial returns. The results proved that the high turnover, not only generated no better financial results, but rather severely hindered net returns because of transaction costs and commissions. Empirical studies also underlined the link between overconfidence and under-diversification (the tendency of investors to hold poorly diversified portfolios). It has been documented widely that poorly diversified portfolios are extremely risky, inefficient, and hazardous: so why do investors hold such portfolios? Specifically, Goetzmann & Kumar (2008) argued that overconfident investors might hold concentrated portfolios because they believe that they can earn superior returns by active trading. Moreover, overconfident investors might hold a biased belief that they can control the outcome of events and hence develop an illusory sense of control over their investment decisions (Phan, et al., 2018). So, under-diversification can, in this sense, be explained in light of the other two manifestations of overconfidence: excessive optimism and illusion of control. To be fair, research about the relationship between financial advisors and overconfidence takes various (opposite) directions. Anyway, most scholars agree on the fact that professionalism leads to a general increase in overconfidence, and that, despite the high experience and financial knowledge, this results typically in poor returns from financial advisors because overconfident financial planners could initiate more trades than can be justified on rational grounds. Additionally, as advisors place higher values on their own forecasts, they could become overconfident in their market timing and security selection ability, leading to insufficient portfolio diversification (Van de Venter & Michayluk, 2008).

Opposite to the overconfident investor, we find the so called “status-quo” investor, an investor that tends to stick on a static judgement and fails to update his/her beliefs in light of the economic changes that occur. These investors are quite similar to the ones that have been described previously in this dissertation, that we described as “set and forget” investors. The typical symptoms of the status-quo investors are the tendency to defer savings for retirement, postpone opening saving accounts (for retirement or general needs), and apply indistinctly “buy and hold” strategies in their portfolios (Baker & Ricciardi, 2014). The difference is that this is not motivated by excessive confidence in their own choices – that as we said would have led to excessive trading – but rather by inertia, laziness and/or inattention bias (Mitchell, et al., 2006). The function that the financial advisors may cover with respect to these investors has already been disclosed previously.

In summary, even though, when investing, financial advisors are not immune to behavioural biases – and rather, in some cases, they demonstrated to be more prone to them – they can exploit their knowledge to advise their clients on how to reduce these biases in their financial planning processes.

Emotional support and life coaching

Financial advisors also play a significant role as emotional supporters and life coaches, dealing with various aspects of their clients' lives. While financial advising has traditionally been thought of as a career dealing strictly with investment strategies and financial figures, recent years, in fact, have seen a complete transformation of the role of the financial advisor, switching from a mere financial planner that dealt only with the economic situation of households, to a proper life-counsellor, participating actively in people's personal environment (Jackson, et al., 2016). And scholars agree on the fact that in the future the role of the advisor will continue to acquire non-financial importance. The field has been widely explored by Dubofsky & Sussman (2009) that conducted a series of experiments and documented that, in their sample, more than 74 percent of the advisors surveyed (in total 1,374) have seen a relevant increase in the time spent dealing with personal issues of their clients. *Figure 1.3.* from Dufobsky and Sussman (2009) summarizes the non-financial issues that clients raised while dealing with their advisors.

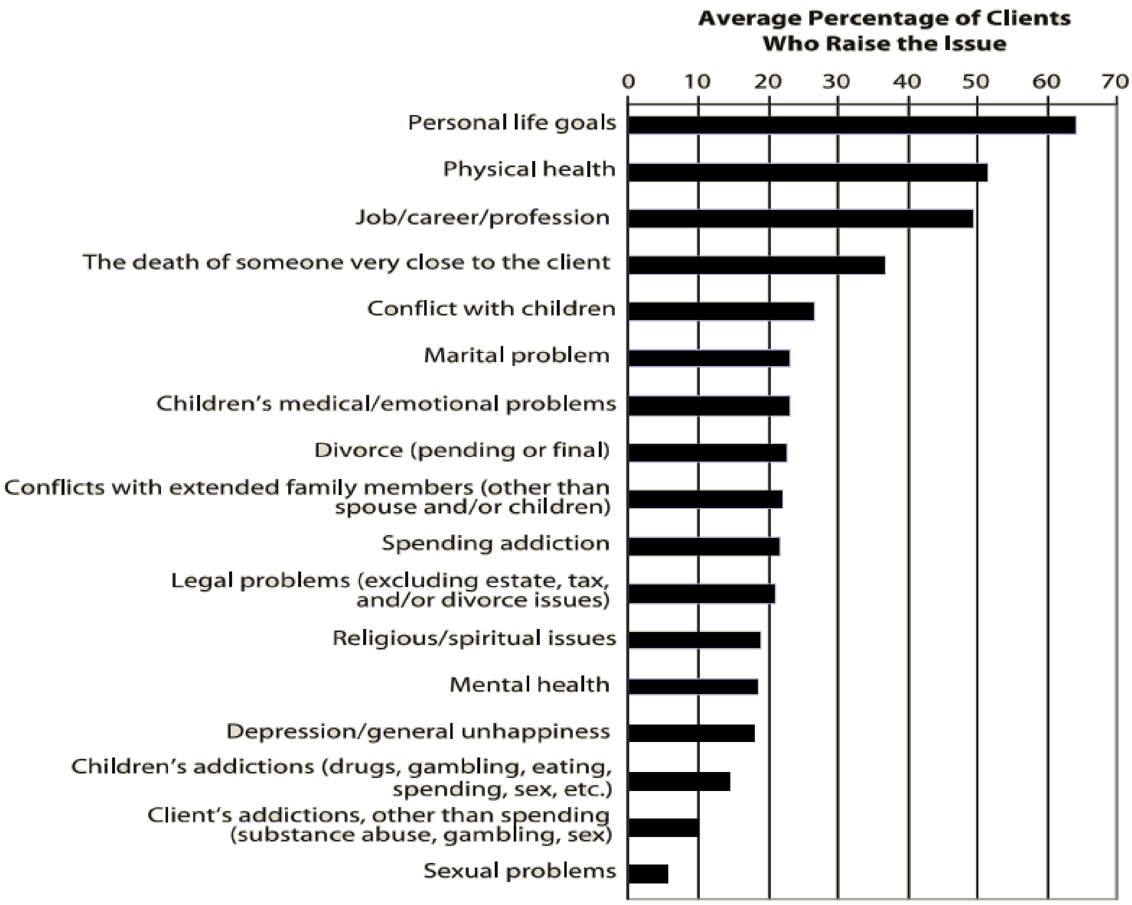

Figure 1.3.: Non-financial issues raised by clients while dealing with financial planners. Source: Dubofsky & Sussman (2009).

In particular, we see that advisors are asked to deal with personal life goals, physical health-related problems, emotional issues and even, at some points, with psychological or religious and spiritual issues. They key explanation given by the surveyed advisors is that if an individual trusts you enough to share data about their finances, then they will also open up about other issues. These last considerations also explain the role of the advisor as life coach and emotional supporter. Anyway, whether it is ethical for finance professionals to be handling matters involving life issues, is a question that still needs to be answered by the financial industry, but data confirms that the number of advisors enrolling in life-coaching classes is relevantly increasing (Jackson, et al., 2016).

1.3. Who uses financial advisory?

We discussed the various functions that financial advisors cover and highlighted some of the key advantages that they can provide to individuals and households. What still needs to be analysed is a key point of the discussion: who uses financial advisory? In particular, it would be relevant for us to underline the main characteristics of advisory users and isolate whether they share one (or more) particular trait. Moreover, we are interested in obtaining and analysing some data about the actual usage of advisory services. The geographical focus of this work is the Italian financial panorama.

1.3.1. Financial advisory users and their traits

There are many factors and personal traits that may influence an individual's decision to utilize financial advice. Each one of them is shortly discussed below and a description of its influence on the inclination of an individual to obtain financial advice will be given.

Financial Literacy

We already disclosed the importance of financial literacy. It has been widely analysed whether advice following can be a substitute for financial literacy: the rationale behind this hypothesis is that a more knowledgeable investor should be better than other non-literate individuals at collecting and interpreting information (Chalmers & Reuter, 2012). To this regard, a growing number of studies proved how, in reality, financial advisory should be interpreted more as a complement to financial literacy (Bhattacharya, et al., 2012). The high information providing capacity of the advisor may contribute to a complete integration of the view of the economic situation and lead consequently to better investments. We might say that the advisor shifts from being a substitute for literacy and an educator for those who can be considered as highly illiterate, to a complement and more of an information provider and a behavioural counsellor for the ones that have a high degree of financial knowledge (Stolper, 2018). The in-between category is the one that tends to resort less to advisors and tends to follow less scrupulously the advice received.

Investment experience and sophistication

We have already discussed the role played by investment experience and investor's sophistication in the previous section, explaining that, typically, these characteristics increase the investor's overconfidence, resulting in a smaller demand of financial advice.

Gender

There is plenty of literature addressing directly or indirectly the possible differences in the demand of financial advice between men and women. One of the key paths of research is related to behavioural traits of individuals, and, specifically, to overconfidence and risk aversion (we have already discussed before the negative relationship existing between overconfidence and the demand of financial advice). Women, in particular, have been demonstrated to be less overconfident (see for example Dahlbom et al., 2011) and more risk averse (Croson & Gneezy, 2009) and for these reasons more incline to obtain financial advice. And this effect resists also when controlling for trading experience, professionalism, and familiarity with risky holdings (Olsen & Cox, 2001). Anyway, evidence on this topic is quite mixed and, depending on the experimental context, scholars have found different results. For example, Bhattacharya et al. (2012) found, on the contrary, that men tend to seek more advice; Hung & Yoong (2010), on the other hand, found no significant differences related to gender.

Age

Regarding age, another key factor used to explain the demand of financial advisory, Reiter-Gavish et al. (2021) proved that it has a variable effect on the demand of financial advice, linked also to gender. In particular, using data for about 290,000 investment accounts, they documented that the discrepancy between the demand for women and men shrinks as the age increases. Women, indeed, demand more financial advice than men, and this happens in particular at earlier stages of life. When men age, they tend to start progressively increasing their demand of advice. Still, mixed evidence exists on the relationship between age and financial advice demand. For example, Bhattacharya et al. (2012) reported no significant effect of age, but Hackethal et al. (2012), instead, confirmed the positive relationship that we hypothesized before.

Income and Wealth

Income and wealth are among the most important and relevant determinants of financial advisory demand. Whether richer people are more inclined to seek financial assistance is a fundamental information that could be exploited to shape specific services and to have a broader and more precise view of the determinants of this demand. Income and wealth are variables that have a strong correlation with many other theoretical factors. In particular, we know that older people tend to be wealthier, and also that married people typically have a higher combined income than each spouse considered separately, and this remains true even when we account for the fact that now two people are sharing the same wealth and have higher expenses. Also, wealthier people tend to be less uncertain about the future, thanks to safer and more solid financial availabilities. While some mixed results exist even on this topic, the majority of scholars seems to agree on the fact that richer people are significantly more likely to demand professional financial advice (Collins, 2012; Von Gaudecker, 2015)

Uncertainty about the future

Another factor that has been taken into considerations by scholars is uncertainty about the future and in particular on the economic side. Reiter-Gavish et. al (2021) tested whether an investor intensified his/her demand of financial advice as a response to high perceived economic uncertainty, as a possible way to hedge risk. The rationale here is that an individual or household, worried about the possibility of unforeseen negative events – such as losing their jobs, properties and more in general their income sources – will hire a professional advisor to help him/her to correctly manage their finances and be ready for any happening. Moreover, as pointed out by Qadan and Zoua’bi (2019), individuals should be interested in obtaining more information to reduce uncertainty and exploit the information providing function of advisors. While, on one hand, a study by Reiter-Gavish et al. (2022)

documented that during the financial crisis of 2008, people were less inclined to leave the market when assisted by a financial advisor suggesting the existence a positive relationship between economic uncertainty and advice demanding, on the other hand, part of the research proved also that many investors, during troublesome periods, might prefer to avoid looking at the state of their portfolios, to avoid regret and negative feelings because of poor results (Golman et al., 2017; Sicherman et al., 2015), and this suggests, conversely, a negative relationship. In conclusion, we should note that the effect of economic uncertainty is still debated.

Family status

Family status is also a key variable to understand one's demand for financial advice. In particular, singles have been demonstrated to be less risk averse than married (or engaged) people (Bertocchi, et al., 2011). The idea behind this distinction is that when you are in a relationship with someone – and this effect becomes even more relevant in the presence of one or more children – you also feel the importance of the responsibility for a correct management of your finances towards the other person and engaging in risky behaviours may lead to extra disappointment because of the damage created to the family as a whole. Another explanation can be the fact that after getting married the couple starts to share a part of their personal income, increasing the general level of wealth. Some scholars suggest that this appreciation in wealth may lead married couples to increase their demand of financial advice because, as we reminded before, wealthier investors tend to be more likely to seek financial advice. Moreover, Haslem (2008) suggests also that the advisor may have the key role of mediator between the spouses for difficult financial decisions. Finally, Grable and Joo (1999) also analysed the possible shifts in the demand for financial advice for widowed investors, finding that, because of the emotional and financial stressor given by the death of the spouse, they tend to seek financial (and non-financial) support to improve their money management abilities and face the new "widowed" life.

Figure 1.4. summarizes the effect of the various factors highlighted here on the demand of financial advice from individuals and households.

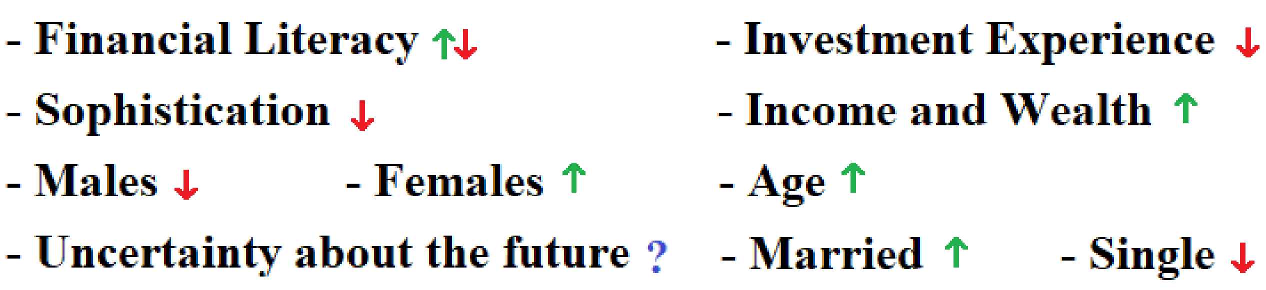

Figure 1.4.: effect of traits on the demand of financial advice. Red arrow indicates a negative relationship; green arrow indicates a positive relationship; both arrows indicate a mixed effect; question mark indicates mixed evidence. Source: personal elaboration.

1.3.2. Diffusion of financial advisory in Italy

Preliminary information

Before going through the actual demand of financial advisory in Italy, some preliminary data need to be presented. In the previous sub-section, we analysed the various determinants of the demand of financial advice: we will now briefly describe the distribution of each factor – excluding "uncertainty about the future" because of its undefined effect, and "investment experience" and "sophistication", that are quite harder to measure objectively – among the Italian population. For this purpose, we will only consider individuals above 18 years old.

We start with some demographic data obtained from ISTAT (2018).

Regarding gender, we observe how the population over 18 is approximately equally split between males (24,052,764) and females (25,832,336).

Data regarding age, show that the majority of the population is concentrated in the median age groups. In particular we see that in total we have around 1/3 of the population that ages between 40 and 50 years old, denoting an averagely old population. The average age is 45.2 years (also including people in the age range 0-17). Last but not least, regarding marital status, recent years have seen a quick decrease and postposition of nuptiality. Indeed, married people in the age range 25-34 dropped between 1991 and 2018 from 51.5% to 19.1% for males and from 69.5% to 34.3% for women. In the age range 45-54 almost 1 in 4 men never got married and 1 in 5 for women. In the age range over 65 years, we observe that approximately 4 in 10 women are widowed.

Following with data about the income and wealth of Italians, data show that, in total, Italians, have 10,010 billion in wealth, with the great part of it (approximately 51%) being represented by real estate. Regarding financial assets, 48% of the wealth belongs to this category, but it is fundamental to consider that the greatest part of this assets is represented by ordinary deposits, other saving instruments and insurance reserves. In 2021 the average income in Italy was approximately €21,570 per person per year and the total reported income was around €865 billion (Banca d'Italia, 2022). We can also analyse the distribution of wealth among the population: Oxfam (2020) documented that the richest 20% of the population owns approximately 72% of the global wealth while the poorest 20% owned only 1.2% of the wealth.

Last but not least, we need to consider the level of financial literacy. Many institutes conducted various surveys and questioned Italians to test their degree of financial literacy: Consob (2021) conducted an analysis interviewing more than 3500 households, testing them with some basic and some more advanced questions to sage their level of financial literacy: they documented that almost half of the interviewed subjects had insufficient knowledge about basic financial topics and concepts, with lower scores concentrated on “diversification” (almost 70% of the sample couldn’t answer correctly) and “interest mechanism” (almost 55% of wrong/non-given answers). Even though results are not homogeneous and vary depending on the geographical part of Italy we are analysing (southern regions obtained lower scores), we need to notice that this highlights quite a severe and worrying situation of financial illiteracy. Moreover, the inquiry showed also that there is a wide discrepancy between the self-assessed level of financial literacy and the actual level externally assessed, possibly highlighting a noticeable degree of overconfidence (or at least a sort of upwards/downwards mismatch) among Italians that could even possibly be followed by a reluctance to exploit educational opportunities.

Advisory usage in Italy

The Consob (2021) analysis among Italian households cited above, surveyed also the financial and investment habits of the population. We will use this report as the main source of data for this paragraph. Starting with some general data about the participation in financial markets, despite the low level of financial literacy, we see an encouraging result: participation has been growing in the last years, shifting from 30% (of the population) in 2019, to 34% in 2021. Still, the most popular products are deposit certificates, Government bonds, and low-risk mutual funds. The diffusion of the products anyway is strongly linked to the degree of financial literacy, with more literate investors holding more sophisticated and riskier instruments (like stocks or mutual funds). Many households, anyway, still accuse the lack of saving as the main reason for avoiding financial investments. Regarding specifically the demand of financial advice, we observed an increase in the last years, probably motivated by a partial growth in financial literacy and also by the troublesome economic situation experimented by households and individuals during and after the Covid-19 pandemic. In particular, in 2021 approximately 28% of household declares to receive support from an advisor (in 2019 it was a mere 17%), while the numbers for self-directed investors have significantly dropped from 42% in 2019 to 31% in 2021. We need also to point out that the most popular investment style remains the informal advice, that is, seeking advice from friends, relatives, and colleagues, with this data possibly highlighting the prominent role of trust in the person that gives advice (rather than competence, experience, or level of financial literacy). Last but not least, *Figure 1.5.* shows that assisted investors tend also to hold more, more sophisticated, and more diversified (also geographically) products.

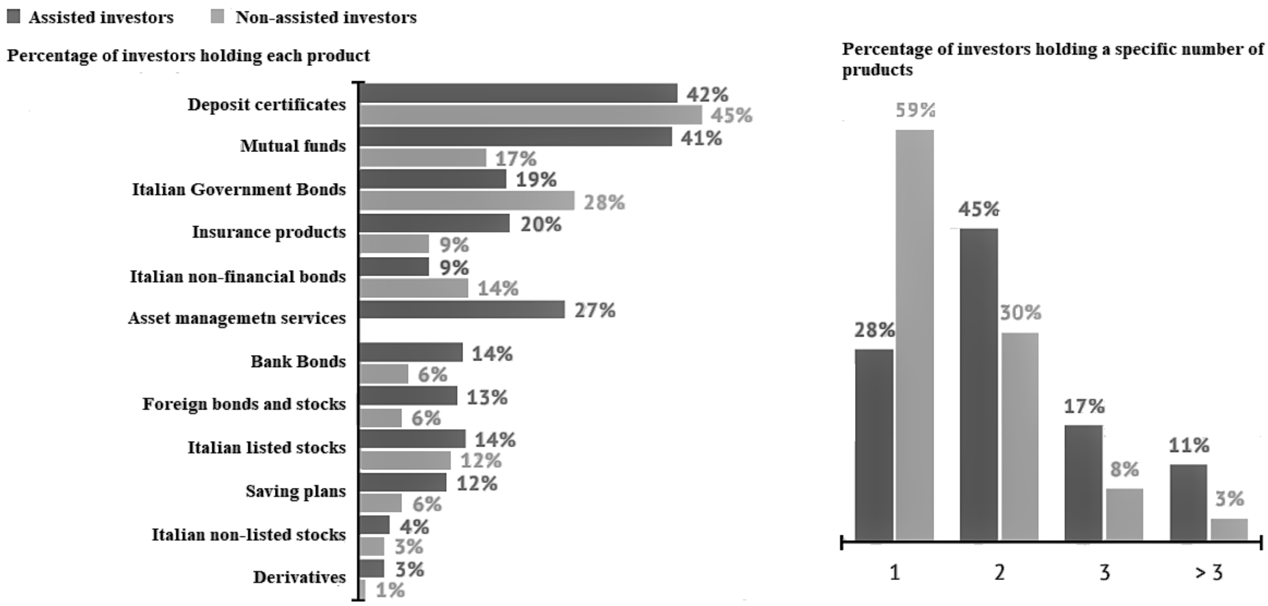

Figure 1.5.: Bar-chart showing the percentage of investors holding each kind of product (left). Bar-chart showing the percentage of investors holding a specific number of products (right). Source: Consob (2021).

Another interesting fact documented in this report gives us a precious intuition about the nature of the relationship between advisor and client: the majority of households (39%), in 2021, interacted with their advisor after being reached by the latter, and not on their own initiative (only 28%). If we compare these figures with the ones of 2020, we see that the pattern was reversed with the majority households reaching advisors on their own initiative (35%). A possible explanation of this might be the fact that people tend to reach their advisors more when they feel more uncertain about the economic situation (in 2020 the pandemic reached its peak in terms of mediatic impact and uncertainty, and preoccupation generated) highlighting again the importance of the advisor as an emotional supporter and as a psychological comfort provider.

1.4. Regulatory aspects of financial advisory services

The present section will focus on the regulatory aspects of financial advisory in order to complete the frame outlined so far.

Regulators concentrated their efforts in trying to protect adequately investors while at the same time safeguarding the activity and freedom of the advisors, without imposing too restrictive constraints, and promoting competition in the banking sector. As highlighted by Zitzewitz (2014) market inefficiencies are, also in this context, the main rationale for the regulation of financial advisory. In particular, legislators and scholars pointed their finger to information asymmetry between advisors and investors, that might give raise to agency conflicts, and might potentially pose some behavioural limits on investor processing, monitoring and oversight. In the European panorama, the most relevant act, in this regard, is the MiFID II (Markets in Financial Instruments Directive). In the following sub-sections, the content of this directive and the various steps that lead to this regulation will be synthesized.

1.4.1. Pre-MiFID and MiFID I discipline

Pre-MiFID regulation: the Investment Services Directive (ISD)

In the past century, a quite fragmented and national-based regulatory environment characterized investment services. Indeed, there were no general agreed rules or principles and the degree investor protection varied significantly across the European Countries. In this regard, in 1993, the European Council launched the Council Directive 93/22/EEC of 10 May 1993, also known as “Investment Services Directive” (ISD). This directive aimed at reaching harmonized requirements of authorization and activity for investment firms and introducing common rules for the organization of regulated markets. In particular, the directive established some key conditions and actions that Member States should ensure and perform through the implementation of the directive. The content of the directive is synthesised below, concentrating on the aspect relevant for our purposes of highlighting how consumer protection has been addressed. Specifically, the directive contains seven sections (Titles). Title I defines the scope of application (art. 2) and gives some key and precise definitions of the main objects and subjects of the directive (art 1).

Title II regulates the conditions for taking up investment businesses and sets some solid requirements to ensure stability and soundness of investment firms, to protect investors against fraudulent actions and unsecure businesses or inequalities. Specifically, it states: that each Member State should make access to the business of investment firms subject to authorization, specifying the investment services to which the firm is authorized, and that this authorization should not be granted to firms with an insufficient initial capital (in accordance with the previous directives, e.g., Directive 93/6/EEC) or in case of an insufficiently good reputation and experience of the administrators of the business; that each Member State should require investment firms to have a registered head office in the Member States that released the authorization; that each Member State should require also the authorization to be accompanied by a programme of operations and that the applicants should be informed withing no more than six months of the outcome of the request for authorization, and, in case of refute, the responsible commission should precisely state the reasons underlying the negative response; art. 3 concludes listing a series of reasons for which the authorization may be withdrawn. Moreover, the authorization should not be granted until: i) the authority has been informed about the identity of the shareholders and members that have qualifying holdings and about the amounts of those holdings, and ii) is satisfied with the suitability of these persons (art. 4). Favourable treatments should not be applied to branches of investment firms that have registered offices outside the Community and are commencing their activity in a Member State (art. 5); authorities of other Member States involved should be consulted beforehand on the authorization of investment firms which are subsidiary or controlled of an institution authorized in another Member State (art. 6).

Title III addresses relations with third countries outside of the European Community.

Title IV deals with the requirements and operating conditions of investment firms. In particular, it states: that Member States should ensure that firms comply at all times with the requirements and conditions imposed at art. 3 (*see above*) and in Directive 93/6/EEC, and that the competent authorities of each home Member State hold the responsibility for the prudential supervision of their firms, independently from the fact that these firms provide services in other Member States or not (art. 8); that Member States should require any person who wants to acquire, dispose or significantly increase/decrease a qualifying holding, to first inform the authorities, that will verify the identity and decide whether to stop such a plan and also that, in case that the influence exercised by one person with a qualifying holding becomes harmful or dangerous for the soundness of the institution, the competent authority intervenes taking appropriate measures to stop this situation (art. 9); that Member States should draw up prudential rules to ensure that each investment firm has sound administrative and accounting procedures, makes adequate arrangements for instruments or funds belonging to investors with a view to safeguarding their rights, and arranges for records to be kept of transactions executed that should be sufficient to allow authorities to monitor compliance with the prudential and conduct rules and that each firms is structured in such a way to minimize risks for their clients of being prejudiced by conflicts of interest or other activities (art. 10); that each Member State should draw up conduct rules which investment firms should observe at all times, ensuring honesty and fairness in their actions, that they pose skill, care and diligence in the best interest of the client, and that each firm seeks from their clients regarding financial situation, objectives and experience and makes adequate disclosure of relevant information when dealing with clients, completely avoiding any kind of conflict of interest (art. 11); each investment firm should inform investors about the compensations and protections that will apply in respect of each transaction envisaged (art. 12).

Title V sets off and disciplines the eventual limits of the right of establishment and the freedom to provide services.

Title VI defines the authorities responsible for authorization and supervision of firms providing investment services.

Title VII contains final provisions and implementation guidelines.

As we see, this Directive had as a general objective to lay down some key rules and set a minimal harmonization of European financial regulation and services. The directive was later implemented in Italy in 1996 with the so called "Decreto Eurosim" and T.U.F. (Testo Unico della Finanza). Anyway, we still had no harmonized rules or requirements specifically designed for financial advisory at a European level. In conclusion, it is worth to mention, to be fair, that in Italy Consob and Banca d'Italia issued some specific prescriptions for financial advisors, regulating their activity and introducing limitations and mandatory requirements.

MiFID I and financial advisory regulation

MiFID directive was first introduced in 2004 and aimed at regulating more specifically and adequately investment services and firms. It consists of three main levels: Directive 2004/39/CE that contains general principles of the new discipline, Directive 2006/73/CE and Regulation 1287/2006 that contains technical regulation about investment firms and transparency, and CESR guidelines.

MiFID furtherly specified some aspects of the previous discipline about requirements of investment firms by adding the following prescriptions to the one listed in the ISD:

- elaborate procedures assuring compliance with duties stated in the MiFID directive, proportionally to the nature, dimension, and complexity of the activity of the firm and services provided;
- create a specific division and internal audit systems to monitor the compliance with requirements and effectiveness of processes;
- periodically evaluate and manage risks, in particular when some operating functions are externalised;
- introduce a risk management division;
- keep property and control rights of clients separated from the firm's rights of property and control.

With respect to conduct and investor protection rules, the legislator stated that:

- clients should be classified depending on their degree of financial knowledge, investment experience, capability of bearing losses and financial risk attitude. MiFID distinguished between retail clients (highest protection level with duties of transparency, information, and risk profile evaluation), professional clients (with lower protection motivated by a greater financial knowledge and experience) and qualified counterparties (with minimal protection).

- clients should be informed of any risk source, possible conflict of interest and firm's policy against these conflicts;
- clients should also be informed about their classification as retail, professional or qualified counterparty and be given the possibility to require a higher (or, in certain cases, a lower) level of protection;
- firms must comply with the *best execution* principle, adopting all the reasonable measures to obtain the best possible result for the client when executing instructions, and communicating to clients the strategies adopted;
- firms must avoid receiving any kind of compensation or incentive from third parties when providing an investment service, unless they prove that these incentives are used to increase the quality of the service.

For our purpose, we note that MiFID Directive introduces for the first time a definition of investment advice, describing that as "the provision of personal recommendations to a client, either upon its request or at the initiative of the investment firm, in respect of one or more transactions relating to financial instrument". While, as we outlined previously, financial advisors provide much more services than the mere investment advice, the regulators addressed advisory for the first time in this way, in line with the main definitions given by scholars in that period (non-financial functions became relevant only more recently). Moreover, in the directive, financial advisory has been considered for the first time as an independent (and not accessory) financial service with specific regulation and the requirement for an authorization. Also, for the first time at a European level, a distinction between different kinds of advisory was made: specific advisory and general advisory. The former is characterized by personalized recommendations regarding a certain specific financial instrument (even though a sub-type of specific advisory exists when recommendations are provided not for a specific product but for a category of instruments), and the latter – still considered as an accessory service – consists of generic recommendations, diffused trough public or private distributions channels to a pool of investors (substantially it lacks the requirement of personalization). Specific advisory requires authorization and needs to comply with the requirements of transparency and adequacy evaluation stated in the directive, while general advisory can be performed by any person without any authorization and without providing any kind of protection to recipients.

The Italian legislator implemented the directive with the D.Lgs n. 164/2007 by modifying the T.U.F. and Consob regulations. While this initial implementation addressed only partially the prescription of the MiFID, in 2009 the legislator modified one more time the T.U.F. introducing art. 18-*ter* and finally complying almost completely with European directives.

1.4.2. The introduction of MiFID II and its innovations

The financial crisis of 2008 highlighted some most critical issues of MiFID I and how the protection given to investors and to the whole stability of the financial system was insufficient. The legislator decided to reform the previous directive, introducing in 2014 the Directive 2014/65/UE, called MiFID II and the linked Regulation 2014/600/UE (MiFIR). One of the main goals of these reforms was to rebuild trust in the financial system by strengthening requirements of transparency and information between intermediaries and clients. Among the most noticeable innovations introduced by MiFID II and MiFIR we have the faculty of intervention attributed to the European Securities and Markets Authority (ESMA), to prohibit the trade of certain particular financial instruments, when considered highly dangerous for inexperienced investors. In this way, an external and specialized entity could intervene in troublesome situations and adopt strong and effective measures to protect investors. Regarding specifically financial advisors, one of the most important innovations was the formal distinction between independent and non-independent financial advisors: an independent advisor is an advisor that is completely autonomous and has no links with any kind of financial institution. For this reason, to maintain independence, they must not accept any kind of commission or incentive from external entities, and in particular from financial instruments issuers or distributors, to avoid conflicts of interest. Independent financial advisors can be remunerated only in the form of fees, paid directly by the clients receiving advice (*Section 3.1. will focus on the economic and behavioural convenience of each type of structure of fees and on the implications for the advisor/client)*. In addition, the following general provisions are worth to mention:

- providing financial advice remains an activity that can be performed only by authorized entities or persons;
- each person providing financial advice must be subject to continuous supervision and periodical evaluation of his/her knowledge and performances;
- each single advisor must have an individual authorization and should be enrolled in a specific register.

While the core provisions in terms of information and transparency of the MiFID I were maintained, some key innovations were introduced also on this side:

- after conducting a strict and precise profiling of the client, assessing their trading experience and financial knowledge, financial situation, capacity to bear losses, and investment goals and risk tolerance, the firm or advisor should inform the client in written form about their classification;

- firms and advisors should collect information in such a way that allows them to precisely determine the most appropriate financial strategy and instrument for each client i) so that the client has the necessary experience (or support) to understand the risks (and bear them) and the functioning of the instrument, ii) so that the instruments chosen are appropriate for the specific needs and investment goals of the client and iii) so that the nature of the instruments is in line with the risk tolerance of the client;
- firms and advisors should explain each choice to clients and provide them with a suitability report on a durable support, describing the features of the advice provided and motivates each choice;
- firms should inform clients about all the possible costs (economical and non) implied in the contract.

The MiFID II directive was implemented in Italy in 2016 with the "Delibera n. 19548 del 17 Marzo 2016" modifying and updating one more time the T.U.F. and Consob internal regulations.

1.5. Alternatives to financial advisory

After analysing the different aspects of financial advisory, we want to present some of the various alternatives that exist in the financial environment. Some investors, or potential investors, indeed, may prefer not to resort to financial advisors, or they might be discouraged by the high fees that some "traditional" advisors charge for their services. The most obvious alternative is autonomous investing: while we have already underlined the potential inefficiencies of investing just using your own knowledge (time consumed, behavioural biases, poor information, etc.), some hybrid paths exist, through which the individual can obtain non-personalized financial recommendations or invest in funds with various degrees of risk. The following paragraphs will briefly highlight the main feature of some of these alternatives.

Mutual Funds

Mutual funds can be described as a particular type of financial vehicle that collects financial resources from a large pool of investors and then invests them in a diversified mix of securities (stocks, bonds, and other assets). Each mutual fund has one (or more) manager, called "fund manager", that is responsible to allocate the assets and obtain returns for the investors. These vehicles are particularly popular among small individual investors because of the low perceived risk and the low fees requested. Many different kinds of funds exist, varying both in riskiness, composition, and geographical region of the investments. From the point of view of financial performance, many scholars have analysed the returns of mutual funds both in recession and expansion periods obtaining mixed results. Fama and French (2010) and Malkiel (1995) have shown that mutual funds significatively “underperformed” the benchmark indexes in various occasions. On the other hand, Moskovitz (2000) and Glode (2011), for example, found that in particular circumstances, it can still be advantageous to invest in mutual funds, and in particular in those who tend to perform abnormally well when the economy is in recession phases. In conclusion, we understand that even if in some cases there might be a rationale for investing in such funds, they offer no constant satisfactory results. In this regard, the direct economic benefits of mutual funds are quite similar – and, at some points even greater – to the one provided by financial advice. Moreover, fund managers are subject to the exact same biases as other categories of financial advisors (Puetz & Ruenzi, 2011). The main downside of mutual funds, if compared to financial advisory, is the complete lack of non-financial gains. The relationship between the fund manager and the investors is radically different from the one between advisor and advisee: the level of interaction, in mutual funds, is close to zero, with the fund manager being mainly an expert financial operator, working in the best interest of the fund and of the clients as a pool, but without any personal one-to-one design of the investments. Still, for some of those investors that have no desire in obtaining behavioural and emotional support, mutual funds might be convenient for their substantially low fees and pool-hedging effect.

Index-linked investments and passive strategies

Index-linked investments are typically used for passive investment strategies. These investments include many different kinds of financial instruments:

- Index funds: these funds are a particular category of mutual funds. The main idea of these products is to invest in a basket of securities used to match (or, if not possible, to track) the performance of a market index (e.g., S&P500, Fortune500, etc.), differently from other mutual funds that invest in many securities but with no precise replicating intent. Operating expenses of these funds are quite low, and the portfolio turnover is minimal. Index funds are regarded as ideal for retirement accounts, but they are quite popular among investors and strongly pushed and recommended by experts as safe and remunerative investments.
- Exchange traded funds (ETFs): quite similar to an index fund, they have even lower fees and can use securities to replicate various different indexes, currencies, sectors. The main difference is that these instruments are easily accessible, indeed, they are normally traded on stock exchanges like stocks and other products. This allows individuals to buy and sell them virtually at no cost and this is one of the main reasons that made these instruments very popular among the majority of retail investors.

- Index derivatives: these are a particular kind of derivatives that have as an underlying asset an index. Among the most diffused ones we find index options and futures. These instruments are quite less popular among households and retail investors because of their complexity.
- Other index-linked financial products.

The main advantage of these products is that some of them are easily accessible, and their financial returns are quite satisfactory. Indeed, in recent years, their popularity has grown substantially, displacing higher-cost active investment styles (Vladyslav, 2020). Again, here the individual has no manager to confront with and the behavioural and psychological gains are absent. Moreover, several scholars agree on the fact that these passive index-linked investments are dangerous for the general financial stability of markets, progressively distorting stock prices and risk-return trade-offs: in various studies (see for example Bolla et al., 2016), it has been documented that productive firms that use, for example, index commodities, typically make worse production decisions, have higher operating costs and lower profits (Brogaard, et al., 2019). Also, financial firms are affected, because the use of indexed investments distorts portfolio allocation choices and creates some difficulties in the evaluation of the choices and behaviour of fund managers (Wurgler, 2010).

External recommendations: brokers, newsletters, and websites

Following external recommendations is another widely diffused option. Substantially, many analysts offer public or private recommendations on financial instruments and stocks of companies that they forecast to have positive performances. In this way investors may have insights about the future (forecasted) trends of the market and consequently choose their securities. Alternatively, also some newsletters or websites that provide such recommendations are available: we may encounter both access-free newsletters and restricted newsletters, with a monthly or annual fee and a limited number of accesses. These resources are easily exploitable but require the individual to have a way to enter financial markets and have no form of insurance (nor assurance) attached to the recommendations. Such recommendations are, in fact, completely subjective and based on analysis conducted using various techniques and methods. While we have to say that this might be considered also when talking of traditional financial advisory, with these recommendations there is no responsibility of the analyst, exposing investors who follow them to the risk of conflict of interest (resulting in vitiated recommendations), poorly conducted analysis, or other issues. Moreover, literature has widely documented how analysts tend to be “over-optimistic” (Rajan & Servaes, 1997), and this results in them being statistically more inclined to make “buy” or “hold” recommendations rather than “sell”, even for stocks of companies that are not performing well, and in particular for those which have a banking relationship with the brokerage house they work with (Michaely & Womak, 1999).

Researchers have also tried to verify the economical convenience of exploiting these recommendations to make investment decisions. Black (1971) and Copeland & Mayers (1982) analysed, for example, the recommendations of some investment websites, finding a quite accurate precision, but with modest results: “top-rated” stocks statistically overperformed the market – and “worst-rated” ones underperformed it – but the abnormal returns were meagre. Su et al. (2018), focused on traditional brokers’ recommendations and, through a rolling window analysis, conducted using a unique dataset of UK brokers from 1995 to 2013, proved that, again, no significant positive abnormal returns were obtained for those stocks that were put in the “upgrade” list, while “downgrade” stocks, on the other hand, showed in some cases negative abnormal returns (but even these returns lost significance after accounting for transaction costs). In conclusion, Metrick (1999) analysed the returns of the stocks recommended by 153 newsletters but found no evidence of superior performances or relevant stock-picking ability.

These reasons underline why this way of investing is one of the most dangerous and risky. Furthermore, again, non-financial gains are not included for those who trade upon these recommendations.

1.6. Summary and final remarks

The present chapter has summarized and described all the key functions and roles of the financial advisor, highlighting also the main experimental results obtained by scholars in analysing each function and trait. What seems evident is that financial advisors are nowadays only marginally (and sometimes poorly) covering the traditional functions for which they have been hired for decades, and that the demand for financial advisory is consequently changing its connotations. The reasons underlying the existence of financial advisors are, indeed, being revolutionized. In this sense, we documented how advisors are increasingly being asked for non-financial advice, and are seen by clients as life coaches, switching from “financial planners” to “financial counsellors”. Indeed, we might say that the investment function seems to be just the initial reason that pushes people to hire an advisor, but then, along with the development of the relationship and trust between planners and clients, the financial issues are progressively set aside and replaced – or, better, integrated – with other personal issues. We also reviewed the main regulatory prescriptions and issues regarding financial advisory, highlighting the key importance of transparency, client profiling and avoidance of conflicts of interest. Last but not least, we analysed some of the possible alternatives to financial advisory highlighting pros and cons of each one.

Regarding these alternatives to traditional advisory, and keeping in mind what we said about the role of the advisor, scholars have widely researched and proposed some solutions that allow individuals and households to obtain a more “refined” and punctual service that at the same time could enable advisors to concentrate more on the behavioural side and to develop more their interpersonal skills, without anyway excessively revolutionizing the figure of the advisor: in this regard, the following chapter will present and analyse one of the most recent innovations in the fintech field, called robo-advisory.

CHAPTER 2: THE ADVENT OF ROBO-ADVISORS

The second chapter of this thesis will describe the characteristics of the Fintech revolution and will introduce Robo-Advisors. The idea is to replicate the structure of the first chapter and employ that to describe the main features of automated advisory services.

In particular, the first section gives a general overview about the determinants that originated the fintech revolution and describes the financial and social context in which the innovations are taking place. *Section 2.2.* discusses the automation and digitalization of services in the banking and financial industry. The third section introduces the concept of Robo-Advisor and analyses the differences between the Advisory Process described in the first chapter and the Robo-Advisory Process. Also, the way in which Robo-Advisors form their recommendations and assign portfolios to clients will be discussed in depth. The fourth section highlights the characteristics of the users of Robo-Advisory services and reports some data about the usage of these services in Italy. In *Section 2.5.* the performances of Robo-Advisors will be analysed and compared with the performances of traditional advisors. The chapter will conclude with an overview of the regulatory environment in which Robo-Advisors operate.

2.1. The fintech revolution

If we think about the financial industry of a couple of decades ago, we may imagine it as a huge and hard-to-access sector, where the key to transactions was the physical presence of specialized operators and intermediaries. Even services like commercial banking, before the '90s, required individuals to reach their local branches to perform even most basic operations. Later, in 1995, "home banking" was introduced and allowed people to manage their money "remotely". The lightning-fast development of technology and its growing utilization in all sectors, led to a radical change in the needs of people, and also in the banking industry: in a world where you could obtain groceries, books, DVDs, and any kind of article in a short time, while safely staying at home, individuals started demanding new – easier and smoother – ways of accessing the financial industry and services. Spending hours queueing in banks, calling your broker to buy and sell financial instruments or reaching physical locations to obtain a basic insurance policy was becoming progressively unacceptable. Moreover, various financial institutions realized that the old way of doing business was no longer efficient and did not perfectly meet the requirements of their clients (Martincevic, et al., 2020). Technological innovations were taking place in all sectors and digital-disruptive currents were leading to the birth of new successful businesses: the long-standing dominance of leading firms of the sector was at stake (Gomber, et al., 2018). Indeed, traditional financial and banking industry could not afford to miss this opportunity or to have a sluggish response to these changes if they wanted to avoid a complete overcome by newer and more agile tech companies. Typically, scholars defined these innovations and new businesses using the expression “FinTech”.

2.1.1. A definition of “Fintech”

FinTech is a word obtained as the composition of the words “financial” and “technology” and refers, in general, to the new part of the financial industry that applies technology to improve financial activities (Schueffel, 2016). To be fair, while this is one of the most agreed definitions, the term “fintech” has been used widely and inconsistently to define several concepts. To this purpose we should note that the fintech industry – and the word “fintech” itself – contains a multitude of concepts: it comprises some of the material components such as the computer algorithms applied in finance to develop a more efficient and agile service, to facilitate trades, corporate businesses or interaction with customers (Micu & Micu, 2016), the physical persons involved in the processes, and all the new-born institutions that offer these opportunities and combine them with the banking expertise and management science (Bettinger, 1972) to obtain a powerful result and deliver value to the customer in an alternative way (Maier, 2016). It also has some other key non-material components: the interconnectedness of the various firms and the technological and information networks, together with the knowledge provided by researchers and entrepreneurs, represent the real neuralgic point of the fintech industry (Kauffman, et al., 2017). Continuous innovation and fast improvement of services, indeed, constitute the functioning-engine of the whole process and knowledge is, continuing on this metaphor, the necessary fuel to keep running.

2.1.2. The forces of the innovation

As discussed by Gomber et al. (2018), three aspects of the innovation constitute the determinants of the whole system: technological progress, process disruption, and services transformation. The following paragraphs will explain separately the three components.

Technological progress

Technological progress represents the core component of the Fintech Era. While before 2000 machines were only seen by the financial world only as computers *strictu sensu*, able to substitute the human intervention only for mechanical and repetitive activities, in recent times they demonstrated to be able to entail more complicated operations that were typically thought as human exclusive, thanks to developments in Artificial Intelligence (AI) and Machine Learning (ML). Specifically, these technological and computational innovations are the key to the development of fintech. These technological alternatives demonstrated to be advantageous also on the economic side: costs associated with hi-tech component follow a different, and more convenient, structure with respect to those of traditional components, requiring higher initial development costs but lower maintenance and control expenses. Moreover, the value generated by these components has been proved to be far superior. What is still sometimes argued is that, despite their high potential, ML algorithms combined with AI interfaces can (and will) replace humans only on the technical side and consequently will lead to a loss of all the psychological, social, and educational benefits attached to in-person services. It needs to be considered, conversely, that a correct exploitation of this tech components postulates a cooperation – rather than a substitution – between humans and machines, allowing, on one hand, humans to concentrate more on interpersonal and transversal features of the services and on those that require a high degree of personalization, while leaving, on the other hand, to machines all the activities that require standardized or deterministic approaches.

Process disruption

The whole financial industry experimented a significant disruption of its main processes and components, with the aim of reaching a more effective organizational setup. PwC (2019) theorized some of the present and future key disruptors of the fintech era: first of all, financial products will have a high degree of digitalization and will be distributed mainly through technological platforms. Also, the role of the blockchain will be expanded beyond cryptocurrencies, allowing people to store various different data and information. The AI will achieve newer results and its diffusion will allow firms to deliver a more specific and localized service. From the point of view of the profitability, customer intelligence is predicted to be destinated to become one of the most important drivers. Regulators will devote much more attention to these kinds of services and cybersecurity will become an absolute priority. Last, we can believe that sharing economy will gain much more importance in the financial industry and will be furtherly exploited to generate value for customers, and the fintech model will constitute the new approach of the sector.

Services transformation

Last but not least, when technological innovation and process disruption take place, it results obvious that the entire industry is subject to a deep transformation and everything becomes part of the innovation, from the services offered to control and management procedures. The result of such changes is, indeed, that financial services are no longer operating in the same way as before. And this occurs along various directions: in the previous state of the financial industry, few big players have mostly been in charge of how things worked, with delays in the transfer of funds, slow processes for opening accounts and costly trading opportunities (Gomber, et al., 2018). But now, pushed by the emergence of new faster and efficient firms, also these big companies were forced to revolution the way in which they delivered value to their clients. The advent of technology pushed in the direction of a sort of democratization and popularization of finance: thanks to sophisticated algorithms, brokerage services, for instance, can be performed without the need of a physical broker, digital infrastructures allows firms and people to access information and deliver their services at ease (and faster), and specialized visual, graphical, interactional and computational components enhance the customer experience contributing to a more efficient and effective result.

2.1.3. Evolution or Revolution?

We may speak of "evolution" of a sector as the gradual growth and transformation of that sector, considering all the changes that occur over time as a natural result of the self-enhancing process of the institutions. Speaking in terms of Darwinism, evolution can also be interpreted as a sort of "survival of the strongest" that in our context is represented by the biggest institutions that did not fail to adopt innovations and embraced fintech disruption with the proper timing. But, at that time, also the survival of these institutions was at stake: while they thought to have the necessary number of customers and an adequate degree of brand recognition to bind clients, customer inertia – that used to be one of the key components of service providing – was progressively becoming less and less relevant. Trust in the banking industry had radically changed after the 2008 crisis and clients were ready to switch from the old untrusted banks to newer, fresher, and more trustworthy tech companies. The reputation of the traditional banking industry was compromised, and a radical change was needed. It is still true that, while they encountered significant competition from the new "young" players of the banking industry, the older players saw only a partial erosion of their market shares. Moreover, we have already described how the services, procedures, and systems changed connotations, but in a quite radical way, resulting almost in a complete change of the industry itself. This, together with the fact that the innovation was not initiated by the actors already present in the industry, leads scholars to consider fintech as a hybrid event between an evolution and a revolution, but slightly more shifted towards the latter (Blakstad & Allen, 2018).

The following section will summarize the main services introduced with fintech revolution and will describe which services can be automated.

2.2. Which services can be digitalized?

As explained, the way of delivering value and offering services to customers radically changed, creating several new possibilities and opportunities (Phoon, 2018). After briefly analysing the new-born fintech industry, we intend to give to the reader an overview of the services that can be digitalized, discussing the advantages and disadvantages, and describing the new features and potentialities resulting from the digitalization of the service.

2.2.1. Automation vs. Digitalization

Automation can be defined as any machine or group of machines that perform predetermined or pre-programmed tasks. Depending on the level and characteristics of the automation we may distinguish between various types of robots (Collier, 1983): Fixed Sequence Robots (when they repetitively perform successive steps of certain operation on the basis of a predetermined sequence of information that cannot be easily modified), Variable Sequence Robots (when they repetitively perform successive steps of an activity on the basis of a sequence of information that can be easily modified), Playback Robots (when they perform actions from memory of previous operations performed under human control), Numerical Controlled Robots (when they perform actions on the basis of numerical inputs provided by switches, cards or tapes), Intelligent Robots (when they have their own decision making abilities and can detect changes in the environment utilizing for example tactile or visual sensors), Totally Automated Systems (when they perform all the physical and intellectual tasks required to realize a product or provide a service).

Digitalization, on the other hand, is a more general concept, and refers to the process of exploiting technology and digital interfaces when providing services or executing instructions with the goal of obtaining an enhanced experience, obtain more precise results or limit the execution and utilization time. In the following sub-section, the definition of non-fully automated services will be obtained residually, as the services that can be (and actually are) digitalized and partially automated but lack the requisite of complete automation as we defined it before.

2.2.2. Non-fully automated Services and Digital Financial Products

In the banking and finance sector, non-fully automated services are still diffused: while we already discussed the fact that the fintech advent marked an absolute revolution and a deep modification of the characteristics of services, we are still talking of an industry originating (or evolving) from one that had as a key determinant the physical interaction between customers and operators. Moreover, what we discussed in *Chapter 1* regarding the transition of roles of financial advisory from practical to psychological and behavioural roles can be extended to various other areas of finance such as insurance or risk management and also to business administration.

World Bank (2020) published a document summarizing the current state of advancement of integration of automation in the financial industry. They also describe some of the main services that exploit automation, dividing them depending on the need of the user: for example, in the field of payment services, various fintech solutions have been developed. Starting from most basic ones like electronic payment services and devices like PoS, to more complex ones like DLT-based Settlement and Virtual Currencies. While virtual currencies cannot be properly considered a “service” we may also consider the fact that the value of the currency is guaranteed by a system of mutual recognition of value that runs on the blockchain, and that, moreover, virtual currencies are issued and distributed almost only through digitalized platforms. Regarding the saving activities, a recent innovation is represented by digital piggy banks: through these services the user (the saver) can enhance the effectiveness of the activity by setting specific saving goals, by receiving personalized notifications and by, facultatively, setting automated recurrent money withdrawals. The latter option is quite interesting and innovative: the firm providing the service receives automatically fixed amounts of money at predetermined dates and stores them for the individual (while anyway keeping them available upon request). Another powerful functionality of such services, often delivered through smartphone or desktop applications or through websites, is to create a personalized saving plan for the user, after receiving as input the amount of money to be saved, the time horizon and the frequency of saving. Money saved can also be invested in various funds (typically managed by the service provider) in order to gain small financial returns and facilitate the saving activity for the customers. It is also worth to mention that some countries prohibit the pure detention of money to institutions different from banks and other specifically authorized entities, so many digital piggy banks may be forced to correspond a minimal interest and/or invest the funds received. Also, newer saving instruments have been created exploiting new technologies: blockchain bonds (also known as smart bonds) and mobile market funds are some examples of those instruments. Also, the activities of borrowing and lending money saw a deep revolution with the diffusion of P2P (peer to peer) lending and crowdfunding. While lending money was mainly a service that could be performed by specific entities, some new-born platforms allow users interested in investing their money to lend those to specific firms or start-ups to finance projects and obtain in exchange – besides moral gratification – financial interests, equity, or in-kind compensation. Last but not least, from the point of view of financial regulation, computerized algorithms can help firms and authorities monitor critical indices and to verify compliance with the requirements. These technologies are commonly referred to as RegTech and are divided in two main groups: Monitor-tech, that is used to process data in real time and monitor the financial situation, and Report-tech, periodically report to authorities about the activity of the institution. This kind of technologies lies in between the non-automated and automated services: it can either be seen just as a way of obtaining and processing data to be used by the institution for business and compliance purposes (so as a complement to the activity of the risk management area) or it can also be used as a completely automated way of reporting to authorities and signal eventual violations immediately to management or authorities.

2.2.3. Fully automated Services

Fully automated services are quite diffused in the financial industry and span from executing basic mechanical activities to providing advice. Automation in the financial services began back in the ‘30s with mechanical machines that could read and sort checks into a series of pockets, each containing checks for a particular bank (Collier, 1983). More recent examples comprehend also Automatic Teller Machines (ATMs), Electronic Funds Transfer Systems (EFTS) and others. Smart contracts also represent a recent innovation in the financial world: they can be defined as a computer programme or as a series of algorithms that facilitate the negotiation and conclusion of a contract, and, if opportunely set, ensure the correct execution and the respect of the obligation. They exploit the blockchain technology, are almost completely automated, and can refer both to standardized and personalized services. Examples of these smart contracts can be found in various areas: financial cryptography, management of intellectual property rights and even with inheritance and birth/death certificates.

Apart from this, the development of Artificial Intelligence and Machine Learning significantly increased the possibilities of the banking sector (Mehrotra, 2019): first of all, banks have started using AI-based virtual financial assistants that provide instantaneous service to customers. Automated Customer Support, more in general, is being increasingly employed to provide quick solutions to issues raised or encountered by clients, both by directing them to the right sections of websites or by connecting them with the relevant support staff. Moreover, through Natural Language Processing (NPL) chatbots can interact with customers providing support to queries, trying to recognize some pre-set keywords in the language of clients. These bots are completely automated and can provide customers with a fast service and avoid over-queueing of call centres’ lines for basic needs or pre-answered questions. Also, some banks are using smart cameras to detect facial expression of customers to generate instant feedbacks of their user experience. Insurance companies are also exploiting automated algorithms to generate policies and to underwrite them: the process of collecting and interpreting data to determine premiums and characteristics of the policies can be automated through Artificial Intelligence that have been proved to be able to conclude and settle an insurance contract in less than 3 seconds, performing multiple back-end processes and checks while interacting with clients and collecting all the information needed. Of course, all the previously described mechanical and repetitive activities are possible thanks to Robotic Process Automation (RPA) that enables the automation of cash deposit and withdrawal, cheque clearing, billing and statement generating. Credit Scoring is another activity that can be automated and enhanced easily: sometimes customers with no information or no credit history can be difficult to manage for credit institutions and banks, but AI can process alternate data like educational background, spending habits, location, age (etc.), and elaborate an estimated credit score and conclude the contract. Last but not least, getting financial advice and investment services are activities that can be automated through the usage of the so called robo-advisors and automated portfolio managers that exploit financial analysis algorithms to build and manage portfolios (*for further disclosure about robo-advisors and automated portfolio management see the following sections of this chapter*).

2.2.4. Traditional vs. Digitalized services

Digitalized services have for sure generated a significant change of market conditions and set a new standard in the quality of execution. Among the main advantages of digitalization there is the fact that the services can be provided faster: machines have execution times that are close to zero for most operations and take more than 3 or 4 seconds only when required to perform an extremely high number of computations. In this way results can be produced immediately, saving substantial amounts of time to the client and to the firm's personnel. Also, from the point of view of cost controlling, digitalized services are substantially advantageous: they require high utilization of resources only while developing the software or the application but then have approximately no marginal costs. Moreover, digitalized services allow a higher degree of transparency because of the way in which they are designed: machines operate only in a certain way and, unless programmed to do so, do not deviate from clients' and developers' instructions and their activity can be monitored easily. Access to digitalized services is easier and they can be exploited by a greater number of people, constituting an advantage both for firms and consumers. Last but not least, several risks linked to the traditional ways of delivering services can be completely eliminated with the usage of machines.

On the other hand, those who argue that digitalized services have also significant limitations, always point at the fact that automation eliminates any form of human contact and dangerously hinders the possibility of having services with a high degree of personalization because automated system often utilize standardized procedures to produce results. Furthermore, while it is true that digitalization allowed more people to access services and demolished many physical barriers, it is also important to consider that many behavioural biases against technology and other limitations may disincentive the participation of certain categories of users. Last but not least, technology raises many other important issues and exposes users to dangerous risk sources if not properly monitored, such as cyber-attacks or data breach problems (*see Chapter 3).*

2.3. What is Robo-Advisory? And how do Robo-Advisors work?

2.3.1. What is Robo-Advisory?

In the previous section we discussed the possibility of accessing certain services in a digital way, listing advantages and disadvantages. We also presented the existence of "automated" services – a step beyond the simple digitalization – mentioning the possibility of obtaining financial recommendations generated using an Artificial Intelligence, so through a completely (or, at least, partially) automated system. These Artificial Intelligences that provide automated financial advice take the name of Robo-Advisors. More precisely, we can define a Robo-Advisor as digital platforms comprising interactive and intelligent user assistance components (Maedche, et al., 2016) that use information technology to guide customers through an automated advisory process (Sironi, 2016; Ludden et al., 2015). Traditionally, financial advisory has been an activity based on human interaction and trust between advisor and clients (Torno, et al., 2021). Nonetheless, these robo-advisors have seen a growing popularity: in recent times, indeed, many robo-advisory firms have been entering the financial industry gaining relevant business results. Robo-advisors may be employed in any kind of industry (shopping advisor, health advisor, etc.) but the focus of this thesis will be mainly on robo-advisors applied to the provision of investment advice. To be fair, at the current state of the industry, the term almost exclusively refers to financial robo-advisors but the possibility to extend the platforms to other industries and services is currently being tested (Jung, et al., 2018).

Robo-Advisors were launched for the first time between 2008 and 2010, but started acquiring popularity only a few years later, in 2015, when several asset managers and banks started "delegating" their investment activities to these platforms (Narayanan, 2016). Actually, before robo-advisors, some online platform that provided some sort of financial advice already existed, but here the difference is substantial on several aspects. First of all, customer assessment procedures are much more detailed and specific and allow the client to obtain a personalized result. Moreover, current automated customer's portfolio management allows clients to modify the allocation and reconfigure or specify the portfolio (*see the following sub-sections for details on these two phases)*.

2.3.2. How do Robo-Advisors perform their services?

In *Section 1.1.* we described the various steps of the "traditional" advisory process, describing each phase and the actors involved in the process. The objective of this sub-section is to do the same for Robo-Advisors, highlighting the main differences with the traditional (human) advisory concepts.

With Robo-Advisors, the actors involved stay approximately the same, but change their connotations. First of all, the physical (human) advisor is replaced, at least partially, by the artificial intelligence that substitutes him/her in the portfolio building and data collecting phase. The adverb "partially" refers to the fact that in some cases human advisors are still present in the whole process but are paired with these platforms (*see Chapter 4*). The sales manager and the client remain unchanged, but the former is now conditioning things in a different way: while the provider of the service can decide the settings of the platform, the external influence is much more limited, and the usage of computerized advisors hedges significantly the problems highlighted by the agency theory.

The Robo-Advisory process

The phases of the Robo-Advisory process are quite similar to the ones of traditional advisory. We describe them below, following what suggested by Nussbaumer et al. (2012b).

The process begins with the "Configuration Phase". The configuration phase comprises the activities of initiation of the process, profiling, and risk assessment. Here, the Robo-Advisor and the client exchange information reducing the information asymmetry (Kilic, et al., 2015). Specifically, the client is informed about the functioning, capabilities and limitations of the platform and comes in contact with the interface. One first improvement of robo-advisors is that in this phase no screening or pre-selection can be made, so the target segment comprises all retail customers, independently from their wealth, financial literacy level or other factors. The customer is asked to register to the platform through an intuitive and simple registration process, where he/she is asked to provide some basic personal data like age, gender, marital status, and number of children. The client is then submitted with several questionnaires – that substitute the human advisors' questions – to assess financial preferences, investment goals and special interests (Tedesco, 2015). All these information is obtained with both direct and indirect questions, regarding aspects of everyday life and made-up situations where the client is asked to express a preference. The answers are then separated and used to build numerical indexes that will be used by the platform to determine the nature of the client and decide which instruments are appropriate in his/her situation (Faloon & Scherer, 2017). *Figure 2.1.* from Fein (2015) shows some examples of some questions that might be used by a robo-advisor to sage the clients' characteristics. These are only examples of questions and while they may seem quite generic and superficial, we need to keep in mind that between 2015 and 2023 many improvements have been made and that those questions, also thanks to regulatory intervention, have become much more specific and numerous, including, as said, newer transversal ways of collecting information indirectly; anyway, the list of *Figure 2.1.* still gives a general idea of how the assessment can be performed through computerized algorithms. More specific disclosure of the risk assessment phase will be made in the following paragraph.

- Are you saving (i) for retirement, (ii) to build an emergency fund, or (iii) to maintain my standard of living?
- Do you understand stocks, bonds and ETFs (i) a lot, (ii) somewhat, or (iii) not at all?
- When you hear "risk" related to your finances, do you (i) become worried, (ii) remain indifferent, or (iii) see opportunity?
- Have you ever lost 20% or more of your investments in one year?
- If you ever were to lose 20% or more of your investments in one year, would you (i) sell everything, (ii) do nothing, or (iii) buy more?
- When it comes to making important financial decisions, do you (i) avoid them, or (ii) make them?
- How much fluctuation are you confident your investment will encounter in the next year – (i) a lot, or (ii) not much?
- How long do you expect to keep your money invested?

Figure 2.1.: Example of questions that might be used by a robo-advisor to obtain information about the client. Source: Fein (2015)

The second phase of the process is called "Matching and Customization Phase" and includes the construction of a portfolio of investments performed by the platform that chooses instruments depending on the information gathered about the client. The novelty here is that the Artificial Intelligence can perform this operation in complete autonomy, without any single human intervention. The client typically receives multiple offers with various different options so that a higher degree of involvement can be reached. All the offers are associated with self-generated reports that explain the peculiarities and limitations of the portfolio, explaining costs and benefits associated. The client then can accept one of the offers or, if none of the recommendations is considered satisfactory, they can ask for newer options and reconfigure the risk/return profile. Of course, in the case in which the customer desires more information, many institutions providing Robo-Advisory services introduced the possibility to receive support from a human advisor that can explain things in a simpler way and help the client to modify their profile. Typically, the recommended instruments are mainly passive income instruments (common choices are ETFs and ETCs) that have been proven to provide adequate results, while actively managed products are typically avoided both because of their high costs and tendency to gain sub-optimal performances (Jung, et al., 2018).

After accepting (totally or partially) an offer or recommendation and forming the portfolio, the client can constantly monitor the results through a website or an application and decide whether the performances are satisfactory or not. This is called the "Monitoring Phase". Depending on the settings of the Robo-Advisor the client that is not satisfied can act in multiple ways. The so called "static allocation advisors", for example, do not allow the user to autonomously modify – not even minimally – the composition of the portfolio and require the authorization from the bank or even to close the advisory contract and start over. On the other hand, recently, less rigid Robo-Advisors, called "dynamic allocation advisors", have been growing in popularity: these advisors allow the client to make little adjustments directly to the portfolio but still remaining in pre-defined borders (to avoid excessive risk-taking by unexperienced people) or even to the risk preferences and investment goals. This flexible option is much more advantageous and less resource (time and money) consuming both for the provider of the advisory service and for the investor, because if the situation of a client changes (e.g., because they inherit money, they enter retirement, their family expands, etc.) the adjustments can be made quickly and efficiently, in some cases even without involving the bank's (or institution) personnel. Anyway, what remains unchanged is that the advice provider should constantly monitor the investments and automatically inform the client and adjust the portfolio when a misalignment between the needs and the recommendations verifies or when market conditions encounter substantial deviations.

Functioning of Robo-Advisors

We may analyse the functioning of Robo-Advisors along three different directories interaction with the client, risk and investment preference assessment, and portfolio building and monitoring.

Regarding the interaction with the client, typically, it happens through an application or a website, but in any case, by using a digitalized support. The interfaces of the first Robo-Advisors consisted in static, self-reporting menus where the client could select options and interact with the machine in a one-way design with a set number of clickable buttons and pre-defined choices. These interfaces were also provided with pop-ups that guided the client through possible issues and aimed at replacing the human touch of the traditional advisors. For example, some websites provided sporadically "behavioural" suggestions like the following: "Do you have debt? We recommend paying off high-interest debt before investing" (www.betterment.com). These suggestions and warnings could correct and complete the intentions of the customers and make up (at least in part) for the absence of a human expert. The advisors used to have a very formal language with no social cues and no signs of anthropomorphism (Hildebrand & Bergner, 2021). More recently, also because of the behavioural limitations evidenced by Robo-Advisory users (that will be discussed in *Chapter 3* together with the impact of anthropomorphism) more innovative and human-like platforms started diffusing. Specifically, conversational Robo-Advisors with chatbots (that exploit Natural Language Processing) have seen an increasing usage, sometimes improved with vocal and visual interaction with the Robo-Advisor which is often given even a name and a physical appearance through the usage of virtual avatars. Also, the use of a friendly and informal language with several social cues and dialogue-based turn-taking interactions represents a critical aspect of the new standard for Robo-Advisors. Independently from the design and features of the interactions, what remains a staple is the fact that the interface should be kept simple and intuitive and should allow the customer to feel an adequate degree of comfort and avoid uncertainty.

During client assessment the user interacts with the platform, alternatively through a multiple choice, one-way, classic questionnaire or with a conversation-based interaction where all the questions are proposed separately, and the user can reply directly by typing or with pre-set drop-down menus. Questionnaires, as said, start from basic questions to allow the user gain familiarity with the interface's functioning: gender, age, number of children, marital status, nationality, and other questions allow the Artificial Intelligence to draw a first socio-demographic image of the customer and then start the process of risk and financial objective assessment. What needs to be assessed is the general risk capability and possibility of bearing losses of the client, his/her financial literacy level, experience, and any additional risk factor. Financial data like income, wealth, liquidity needs and saving attitudes must also be collected and kept into consideration while building the portfolio. Typically, questions can be asked in various ways, directly and indirectly: for example, to assess how risk-averse a person is, one can decide either to ask them directly to give a measure of their risk-aversion on a scale, say, from 1 to 10 (direct approach), or one can ask different "transversal" questions like "When visiting a new city, will you be willing to visit low-income neighbourhoods or suburbs?" (indirect approach). Of course both ways present pros and cons, one suffering from the fact that the customer may not be completely aware on how to evaluate correctly a complex concept like "risk-aversion" and the other being imperfect because the risk-attitude of an individual may vary depending on the situation (in our case an individual might be more risk-averse when dealing with money and more risk-prone when dealing with personal safety issues, or viceversa). Moreover, when realizing questions, the firm should keep in mind that i) individuals may be reluctant to answer questions they feel are unnecessary, and that ii) too long questionnaires may lead to customer fatigue and disappointment (Tertilt & Scholz, 2018). Regarding the type of the questions, various different theories exist on the correct number of questions (not too high, not too low), tone of questions, and risk factors considered. Regarding the latter, So (2021) isolated 5 risk factors and reviewed more than 20 risk assessment questionnaires determining for each risk factor the most frequently category of questions used. *Table 2.1.* from So (2021) synthesizes the main types found in the analysis.

	Question Type	**Keywords Used in the Question**	**Keywords Used in the Option**	**Any Number or Percentage in the Option?**	**Any Graphs in the Option?**
1	Investment plan/goal and expected return from investment	Investment goal, investment objective, risk, and return	Capital preservation, capital growth, income generation, price fluctuation, inflation, and deposit rates	Few questionnaires provide return rate (%) in the options	No
2	Investment time horizon	Investment horizon and start withdrawing money	Less than, more than, and years	Most of the questionnaires have an option regarding investment time range in years	No
3	Description of investment knowledge and experience	Investment knowledge and experience	Limited, good, and extensive	Only some of the Hong Kong questionnaires have options regarding investment knowledge in year range	No
4	Description of product knowledge and trading experience	Stocks, bonds, funds, ETF, investment knowledge and experience	Stocks, equities, bonds, and funds	No	No
6	Description of the degree of risk willing to take in literal form	Risk, return, fluctuation, and attitude	Risk, return, growth, higher, more, long term, accept, and willing	No	No
7	Description of the degree of risk willing to take in quantitative form	Portfolio, fluctuation, comfortable, gain, and loss	Return, gain, loss, and fluctuation	Most of the questionnaires provide portfolio return rates (%) in the options	Yes *
9	Action would take when experiencing investment loss (hypothetical question)	Experience, decline, fall/fell, and loss/lost	Sell, buy, keep, and hold	No	No
10	Percentage of income/net worth for investment	Percentage, income, net worth, and investment	Less than and more than	All of the questionnaires display options in terms of percentage range	No
12	Financial health check and employment status	Liquid, asset, expenses, financial situation, and job status	Income and expenses	Only some of the Hong Kong questionnaires have options regarding time range to use up the reserves to cover expenses to meet unforeseeable events	No

Table 2.1.: Brief summary of question types. Source: So (2021)

The 5 factors isolated in the cited paper are the following:

- Factor I: Setting of realistic investment objectives/goals. To this purpose firms employ questions of types 1 and 2 from *Table 2.1.* above. Specifically, the first one is used to verify whether choices and expectations are realistic and the second one is used to validate the response of the client in relation to his/her willingness to take risks; it was also found that the number of questions pertaining to these two categories varied slightly depending on the institution and also on the geographical region where services were provided, even though setting of realistic investment goals often represent the category with the highest number of questions.

- Factor II: The Risk Appetite of the Investor. Questions of types 6 and 7 from *Table 2.1.* represent the most effective choice. The factor measures the degree of riskiness that an investor is intentioned to take, given his/her financial situation and investment goals, and will determine the aggressiveness of the strategy. The double assessment (literal and quantitative) is used to verify the coherence between the various responses of the client and overcome the eventual discrepancies that may originate when dealing with monetary/quantitative matters rather than with concrete/behavioural situations.
- Factor III: Understanding of Investment Risk According to Own Practical Experience and Knowledge. This factor assesses the experience and financial knowledge of the client both from a general financial and trading perspective and from a specific product-related perspective. Questions of types 3 and 4 refer to this factor and includes both self-evaluation measures (e.g., "How would you evaluate your degree of financial knowledge on a scale from 1 to 10?") and technical questions to have an objective measure of their knowledge (e.g., "When interest rates are raised, what happens to the price of a bond?"). The idea of this factor is to sage the investor knowledge and experience to verify whether he/she can understand correctly the risks involved and to decide which kind of instruments to recommend. These concepts, as said, are fundamental when evaluating an investor's risk preferences (Grable, 2000).
- Factor IV: Investor Behaviour when Suffering Investment Loss. Assessed through questions of type 9. The usefulness of the factor is pretty straightforward: it verifies how an investor would react when the portfolio is performing badly, and losses occur. This is a fundamental behavioural component that determines the attitude of the customer towards the advisory service. Indeed, customers that react negatively as soon as the first loss occurs should be given portfolios with stable investments that provide in most cases positive (even if often low) returns, while other customers can be matched with more rewarding investments that at some points may have negative returns.
- Factor V: Ability to take Risks. This is a factual information and refers to the capacity of the investor to bear risk and losses. Questions of types 10 and 12 belong to this factor and ascertain

the financial health of the investor together with the propensity of investing part of their income. The idea is to verify whether the individual has an adequate way of cushioning eventual losses and, on the basis of this, decide which kind of instruments to recommend and if they are in line with investment goals.

The cited research found six other types of questions, but they were far less popular and completely absent in some of the questionnaires. They are shown in *Table 2.2.* below.

	Type
5	Current asset allocation
8	Degree of risk tolerance when experiencing investment loss (hypothetical question)
11	Earning capacity of an investor
13	Age/education level of the investor
14	Confidence in making own investment decisions
15	Withdrawing money from investments to fill liquidity needs
	Total

Table 2.2.: Other question types. Source: So (2021)

Last but not least, regarding the rules used to build the portfolio, basically all the portfolio optimization models can, in theory, be utilized by the institutions providing advice. In practice, almost all the algorithms exploit the classic Markowitz mean-variance model (1952) or the more precise Black-Litterman Model (1990). Markowitz's model main principle is to assign a different weight to each asset class and then try to reach the highest possible return given the risk level or, vice versa, determine the less risky portfolio given the desired return. One of the main limitations of the mean-variance model is represented by the high sensitivity to input parameters and the fact that it does not allow the investor to include their personal views about specific assets in the determination of the portfolio. Black-Litterman model solves both this issues but requires a more complex analysis and while many scholars (see for example Idzorek, 2007; Fernandes et al., 2018) tried to apply the Black-Litterman allocation strategy obtaining satisfactory results, Markowitz optimization is still diffused in the provision of automate (and non-automated) advisory services. So, the obvious path of the Robo-Advisor will be to use the answer of the client to isolate a certain number of categories of instruments and determine the overall composition of the portfolio and then use a model to determine the precise allocation and proceed with the security selection. The monitoring phase will continue to use the same model to detect any deviation of the portfolio from the optimum and modify the allocation or, at least, inform the client about the issue. All these procedures are time-optimized and performed exoliting an Artificial Intelligence that will at any time instant determine the optimal composition and compare that with the actual composition of the portfolio.

2.4. Who uses Robo-Advisory services (and who does not)?

In *Chapter 1* we analysed in detail the demand of advisory services in general, with no distinction between traditional advisory users and investors who obtain advice through more technological and automated platforms. We also discussed the influence of some socio-demographic factors on the demand of financial advice, concluding with some evidence about the actual usage of these services in Italy. In the present section, the idea is to reproduce what we did before, this time concentrating specifically only on the demand of financial advice obtained from Robo-Advisors. Indeed, we should expect to obtain a different picture: some people may prefer not to rely on algorithms and impersonal recommendations when managing their finances. Conversely, some others may think of machines as more reliable and precise entities, because of their capacity to manage enormous amounts of data in a few seconds. This section will focus mainly on socio-demographic aspects like age, financial experience, wealth, and education level and will not deal with behavioural components or compare the two ways of obtaining financial advice (these aspects will be furtherly discussed in *Chapter 3*). At last, we will try to obtain some data about the usage of advisory services in Italy.

Before going through the actual discussion, anyway, a premise seems necessary: literature provided mixed evidence about the actual effect of some variables on the demand of Robo-Advisory services. For example, D’acunto et al. (2019) find that users of traditional advisory are not that different from users of Robo-Advisory services in terms of overall demographics; other scholars, on the other hand, found that some socio-demographic characteristics influence positively or negatively the actual demand of Robo-Advisory services, leaving the discussion on the topic still object of debate.

2.4.1. Traits influencing the demand of Robo-Advisory

Age

When we think about the users of Robo-Advisory we can imagine that, because of the way in which the recommendations are produced, they should have a certain understanding of how these platforms work, or at least a sort of IT knowledge. Customers that do not trust or that simply are not familiar with automated systems or technologies may be worried about the potential (unknown) risks and prefer to be assisted by a physical person that they can evaluate psychologically and observe in his/her actions. Using data from over 2,000 US investors over a time window of 12 months, Brenner and Meyll (2020) found a negative relationship between age and demand of Robo-Advisory services, possibly motivated by the scarcer IT knowledge of past generations and the higher faith in algorithms demonstrated by younger investors. The findings are confirmed also by Fan and Chatterjee (2020), who, anyway, used the same dataset as Brenner and Meyll, but a slightly different analysis technique.

Gender

The main reference in literature for the analysis of the impact of gender on the demand of Robo-Advisory is Warchlewska and Waliszewski (2020): they gathered data about 112 Polish investors and analysed the impact of socio-demographic variables on the demand of Robo-Advisory. Specifically, regarding gender, they found with an adequate degree of significance that men are typically more incline to use Robo-Advisors than women even though we should note that the sample they used was majorly composed by men (almost 86% of the respondents). Anyway, the finding is confirmed by other relevant research (see for example PwC, 2019) conducted with samples of investors with different nationalities. Figà-Talamanca et al. (2022), on the other hand, found that when considering samples only of highly educated investors these gender differences become almost completely irrelevant.

General Education and Financial Literacy

The role of education, referred to as general education level – so not specifically financial education – has been explored by Figà-Talamanca et al. (2022) and by Lourenco et al. (2020) that found a positive relationship between the level of education and the demand of financial advisory services. The rationale behind this may lie in the fact that more educated people are more aware about the potentialities of technology and have a more truthful image of the concrete risks incurred. More specifically, when the education pertains to financial/economic subjects the demand of Robo-Advisory services is furtherly increased (Fan & Chatterjee, 2020).

Investment Experience and Sophistication

The role of investment experience has been widely analysed. Mixed evidence has been obtained: Fulk et al., (2018), for example, found that more experienced investors tend to be more confident – here we refer to *confidence* and not to *overconfidence* – and less impulsive and more strategic in their decisions, leading to a greater usage of Robo-Advisory services. Robo-Advisory demand is also higher in those who had negative investment experiences (frauds with human advisors or just disappointing financial performances), possibly because of the faith in the impersonality and objectivity of the Robo-Advisor. Conversely, the effect of overconfidence (boosted by sophistication and investment experience) is more or less the same, reducing the demand of advice. This is slightly less relevant for Robo-Advisors than traditional human advisors, possibly because of its novelty (early adopter effect), given that in this situation overconfident people may consider themselves as innovators when adopting Robo-Advisory services. Moreover, the effect of overconfidence and better than average effect is less evident because of the lack of personal confrontation (the confrontation here would be with an algorithm). In conclusion, an interesting fact underlined by Reher and Sun (2020) is that investors with low levels of sophistication and, in particular, those who tend to possess less diversified and inefficient portfolios, showed a higher demand of Robo-Advisory services.

Risk Attitude

Another interesting finding by Fan and Chatterjee (2020) is related to the risk attitude of the investor: more risk tolerant investors show a higher demand of Robo-Advisory services. This may be a symptom of two different things: either the portfolios generated by Robo-Advisors tend to be (perceived as) riskier, or the investors that are aware of their high risk-propensity prefer to delegate investments to an automated system that account for their behaviour and pose an implicit limit on the actual volatility of the portfolio. No matter the reason, the finding is confirmed by many other scholars like Jung et al. (2018) and Fulk et al. (2018).

Family status

Again, Waliszewski and Warchlewska (2020) analysed the impact of family status on the demand of Robo-Advisory and found that married people were less incline to demand Robo-Advisory services, possibly because of the increase in the general level of income (see next paragraph), but then also found a positive relationship of the variable with the number of children, proving that households with more than one child tend to use more Robo-Advisory services.

Income and Net Worth

In conclusion, we are interested in understanding the role played by income and wealth in the demand of Robo-Advisory services. The great part of the research agrees on the fact that, because of the lower fees (and costs in general), Robo-Advisors should be more convenient for people with low income, that still wish to invest their money (D'Hondt, et al., 2020). Many Robo-Advisors, in fact, have no minimum investment amount and this is significantly advantageous with respect to traditional advisors. Data, supports the idea that Robo-Advisors are used mostly by low-income investors with lower capital and lower portfolio values (Fulk et al., 2018; Brenner and Meyll, 2020), but we need to consider the fact that Waliszewski and Warchlewska (2020) found that this is true only above a certain level of income and net worth. Regarding the composition of the net worth, Fulk et al. (2018) found that when the large part of the net worth was inherited, people were more likely to use the services of a traditional human advisor, possibly because of the sudden capital increase, that was not accompanied by a corresponding growth in education and financial literacy.

2.4.2. Usage of Robo-Advisory services in Italy

In the previous chapter, we have already analysed the condition of the Italian population with respect to the variables that we evidenced as relevant to determine the demand of advisory (robo and traditional) services. A few facts should be recalled from the analysis of *Chapter 1* before considering the actual diffusion of these services in Italy:

1. The Italian population suffered in the past years of a low level of financial literacy, but the situation is slowly improving;
2. Italians are great savers but not great investors: a big part of the wealth of Italian families is currently held in bank deposits and cash or in physical assets (mostly real estate);
3. Trust in the banking system in Italy has been challenged severely also because of the issues that followed the 2008 crisis and the pandemic;

Moreover, we need to consider that the market of Robo-Advisors is still quite in an early stage, so few data about the actual usage are available. Moreover, such data suffer from the fact that many people are not aware of the existence of such services and for this reason do not even consider the possibility of utilizing it.

After these obligatory premises, we can exploit reports and survey from Statista (2022) and PwC (2016) to obtain some data about the usage of robo advisory and some interpretation of it. First of all, the analysis shows that more than 45% of the interviewed subjects declares to be open to Robo-Advisory solutions. While the market is still small and only a few Italian players exist, the European regulation is increasingly favouring the diffusion of such services. Moreover, many well-known international providers offer those services also to the Italian population. Statista (2022) estimates that the current amount of asset under management of Robo-Advisors in Italy should be around 24bn of USD, and projects that to grow at a great rate and reach more than 30bn before 2027. Giving some raw numbers about the usage of these services, according to the cited reports, approximately 1.74 million people are estimated to use robo advisory services. The majority of those is constituted by males (58.5%) in the age group 18-34 (48.8%). Income seems to be less relevant because Robo-Advisory services are used by people with either low, medium, or high income. Among these, the targeted customers are mainly retail customers but in recent times also some B2B Robo-Advisory platforms started developing. In conclusion, the studies show that, as we briefly discussed before, the range of recommended products is broad, from equity to fixed income, but ETFs and other stable and profitable passive investments seem to be preferred.

2.5. Financial performances of Robo-Advisors: adequate or not?

After describing the characteristics, potentialities, and usages of Robo-Advisors, inevitably a question arises: are performances of Robo-Advisors satisfactory for clients? As we may imagine, because here the human advisor is replaced with an Artificial Intelligence, maintenance and utilizations costs for the clients are, on average, lower than the ones of traditional advisors. But if this is not paired with satisfactory financial results, the utilization of these advisors cannot be rationally explained. Again, being the market of Robo-Advisors still at an early stage of its development only few data is available. Moreover, the existing analysis use only a short time-window and long-term results cannot be evaluated yet. Keeping in mind these facts, we are ready to discuss if, at the current state, Robo-Advisors are financially sustainable.

2.5.1. Robo-Advisors portfolios

An interesting preliminary aspect to discuss, before talking about the financial performances of Robo-Advisors, is the composition of the portfolios that they recommend. We have already analysed the ways in which Robo-Advisors build portfolios for the clients. To briefly recall what we said, the Robo-Advisor gathers all the data about investment horizons, goals and risk attitude and determines first the proportions of the asset classes (asset allocation). This is the key phase because as many studies demonstrated, asset allocation can be considered one of the most important drivers of the overall performance of the portfolio. In this first phase, Robo-Advisors typically determine a mix of classes (typically between 5 and 15), ranging from stocks (both local and international) to corporate and government bonds (an adequate mix of emerging markets and developed markets) and money markets instruments that are (approximately) risk-free. Some Robo-Advisors also include more exotic asset classes like real estate, commodities, or inflation-protected securities but this is less frequent. To verify empirically the choice of asset classes, we may cite the work by Torno and Schildmann (2020) who analysed the composition of a set of portfolios recommended by Robo-Advisors and found the results shown in *Table 2.3.* below, where the first two letters in the category (Lo-Low, Me-Medium, Hi-High) describe the desired level of risk and the number (3, 15) represents the time horizon in years of the investment.

Asset class	Lo3 Avg.	Lo3 Min.	Lo3 Max.	Me3 Avg.	Me3 Min.	Me3 Max.	Hi3 Avg.	Hi3 Min.	Hi3 Max.
Equities	21.27	0	51	46.40	11	76	69.89	13	100
Cash	5.6	0	48	2.83	0	42	1.84	0	35
Gold	0.76	0	5	0.39	0	5	0.33	0	5
Commodities	0.65	0	7.5	1.3	0	6.1	1.45	0	12.5
Government Bonds	45.27	0	89	30.06	0	60	15.93	0	55
Corporate Bonds	25.38	0	80	17.36	0	36	8.94	0	30
Asset class	**Lo15 Avg.**	**Lo15 Min.**	**Lo15 Max.**	**Me15 Avg.**	**Me15 Min.**	**Me15 Max.**	**Hi15 Avg.**	**Hi15 Min.**	**Hi15 Max.**
Equities	25.01	0	79	53.14	30	84	80.84	39.59	100
Cash	4.33	0	48	1.55	0	10	0.82	0	6
Gold	0.76	0	5	0.39	0	6	0.33	0	5
Commodities	1.38	0	7.5	1.5	0	11	1.31	0	10
Government Bonds	42.79	0	89	25.33	0	60	7.68	0	33
Corporate Bonds	24.91	0	80	16.33	0	35	7.24	0	32

Table 2.3.: Asset allocation of various portfolios build by Robo-Advisors. Source: Torno and Schildmann (2020)

As we may observe, portfolios typically focus on Equity and Government/Corporate Bonds with just a small part of cash (especially in low-risk portfolios) and a minimal investment in gold and commodities to obtain a hedging effect and a stabilizer. The risk is mainly regulated by increasing/decreasing the proportion of equity even though we observe that some portfolios included 79% of equity even when low risk was demanded. Conversely, the proportion of government bonds never went above 55%. In short term portfolios the equity proportion is lower than in long term portfolios (equity is statistically less risky if kept for long time horizons). Also, the proportion between Government Bonds and Corporate Bonds stays the same for short term portfolios independently from the desired riskiness while it progressively approaches 1 for longer term investment as we increase the riskiness.

Regarding securities, one of the key rules used by Robo-Advisors is to choose mainly easily investable securities, mostly ETFs and mutual funds. Actively managed funds are typically avoided to preserve the low cost of the portfolios and also because, typically, complex strategies exploiting derivatives or investing in hedge funds require big capitals and are subject to high fluctuations that should be managed and observed constantly. The idea of the Robo-Advisor is different: to deliver a low-cost, easy-to-use service but at the same time that can provide customers with an appropriate financial assistance. Complex instruments, active strategies, and other out-of-reach asset classes are not suitable to this task. Only a few innovative and specific Robo-Advisors – especially those addressed to wealthier clients – allow clients to invest indirectly in some private equity funds (Phule, 2019). Then, in a second phase, the algorithm obtains data about the returns of the various asset classes and determines means, variances, and correlations between them. Using a predefined model, typically Markowitz optimization, Black-Litterman or some sort of Monte Carlo based optimization, the portfolios are built and compared. Last, among all the portfolios that have been composed, the machine selects a sub-group and then propose from one to a few portfolios to the client that then chooses the one that they prefer or decides to go back to the client assessment phase (Lam, 2016; Phule, 2016).

2.5.2. Performances of Robo-Advisors

After describing the composition of the portfolios created by Robo-Advisors we want to obtain some data about the actual financial performances of those portfolios.

Torno and Schildmann (2020) found in their analysis an average annualized return of 3.10%. If distinguished for riskiness, they found an average annualized return of 1.70% for low-risk portfolios, 3,22% for medium-risk portfolios, and 4.38% for high-risk portfolios. Sharpe ratios were respectively 0.22, 0.35, and 0.37, evidencing a slight advantage for high-risk portfolios but not relevantly different between medium and high-risk portfolios. No significant difference was found between short-term and long-term portfolios, evidencing a minor role of investment horizon in the recommendations of Robo-Advisors. They also compared those portfolios with three different benchmarks, each one representing one of the three major asset classes (equity, government bonds, corporate bonds) and found that in terms of Sharpe ratio, the portfolios were almost identical to the benchmark representing government bonds, slightly better than corporate bonds and significantly inferior to the Benchmark representing equity (in this case the MSCI World). In summary, the research proved that typically a higher risk-affinity leads to a higher performance per unit of risk.

Another study, conducted by Phule (2019), analysed performances of 5 German Robo-Advisors between 2015 and 2018 and proved that the average performance strongly varied between one advisor and one another. For example, the top performer in 2017 was SutorBank that has an annualised return of 5.7% while the worst performing (among the five advisors selected) was Fintego that yielded only 1.4%, less than a third of SutorBank. The advisors' results were also compared with a benchmark, built as an equally weighted portfolio consisting of the MSCI World Index and the Bloomberg Barclays Global Aggregate Total Return Index, and saw that the advisors significantly underperformed the benchmark both in terms of after fees returns and after fees Sharpe ratio: Sharpe ratio for the benchmark was approximately 0.20 while the highest among the Robo-Advisors (Vaamo) obtained a Sharpe ratio of 0.05. The main contribution of this study is to prove that the choice of the right Robo-Advisor is crucial and that performances may vary significantly from one to another advisor.

Last but not least, Tao et al. (2021) analysed the performances of some US Robo-Advisors and compared them with market indices like the S&P500, Nasdaq and DJIA. Conversely to previous research, they found some positive data for the Robo-Advisors, that obtained high Sharpe ratios (average Sharpe ratio for the robots in the period considered was approximately 1.41), and, when they compared the results with the indices, they found that in the period 2016-2019 Robo-Advisors outperformed the benchmarks significantly.

As we see evidence about the performances of Robo-Advisors is quite mixed and still a few research exists. It is still object of debate whether these performances are adequate and if they can be considered satisfactory. Hopefully, in the next years, the greater availability of data will generate more analysis and we will have a more complete view of the performances of Robo-Advisors. In any case, what needs to be kept in mind is the fact that Robo-Advisors are not thought as a way to exploit technology to "beat the market" or to obtain super-high returns, but rather as a way to provide people with an easily accessible service that enables them to invest money at a low cost, so the question "Do Robo-Advisors beat the market?" is quite misleading (while still interesting).

2.5.3. Robo vs. Traditional Advisory performances

We discussed from an absolute point of view the performances of Robo-Advisors and their comparison with some indices taken as benchmark for performance evaluation, finding mixed results. What can still be interesting is to compare the performances of automated advisors to the ones of traditional human advisors that, as we know, ask for higher fees, but provide the customer with an additional general psychological and behavioural assistance. We already said in *Chapter 1* that in recent times the core activity of human advisors shifted from financial planning to the general counselling of clients and that performances are not anymore, the focus of their existence. Also on this topic, as we may imagine, mixed evidence exists. Harrison and Samaddar (2020) conducted a simulated "contest" between a human advisor and a robo-advisor that were asked to build several portfolios for a series of clients aging from 30 to 70 and with different investment amounts. They back-tested the results of a time window of 17-months and forward-tested them over 6 months and found that the human advisor overperformed the robot in most of the portfolios, showing also a pretty standardized approach from the Robo-Advisor, pretty insensitive to the age of the client and investment amount. Of course, the methodology used is quite specific and some can argue that working with "laboratory-built" clients is quite different than working with real clients. Other research goes more or less in the same direction finding only in some isolated cases better performances for robots. Still, many scholars tend to believe in the potential of Robo-Advisors and are convinced that in the long run (for which we do not have enough data yet) robots will start to obtain better results and outperform traditional human advisors, completely revolutioning the market and the way to provide advisory services (Michael, 2019). Indeed, thanks to technological progress and better learning datasets that can be feed to the algorithms, we will obtain more accurate models and more refined procedures to manage clients' portfolios (Uhl & Rohner, 2018). As a conclusive remark, it is important to consider that while some researchers theorize a substitution between human and robo advisors, many others think of robo-advisors as a supportive instrument for wealth managers and traditional human advisors (see *Chapter 4* and following).

2.6. Robo-Advisors regulation in the European Union

At the current state of things, no specific regulations regarding Robo-Advisory exists. The present section will try to delineate the legal borders of Robo-Advisory activity and discuss how regulators decided to address the problem. Before going through the actual disclosure, a key aspect should be noted: the regulation of Fintech has not developed uniformly and currently we may find some differences among the national regulations of the various countries. This section will mainly address regulation at the European level and highlight the common aspects and principles highlighted by the communitarian regulators.

2.6.1. The technology neutrality principle and the issues of fintech regulation

A key principle that determines the nature of the existence of Robo-Advisors is contained in Regulation n. 283/2014 (guidelines for trans-European networks in the area of telecommunications infrastructure): the technology neutrality principle. The principle ensures "the freedom of individuals and organisations to choose the most appropriate and suitable technology for their needs. Products, services, or regulatory frameworks taking into account the principle of technology neutrality neither impose nor discriminate in favour of the use of a particular type of technology". This prescription is central in our discussion because if we interpret Robo-Advisory services only as a particular – technological – way of delivering an existing service (namely, provision of financial advice), then the whole general regulation of traditional financial advisory could be applied also to Robo-Advisory (Salo-Lahti, 2022). On the other hand, if we consider Robo-Advisory as a service that is too different from traditional advisory to be paired with it, a new specific regulation would be necessary.

To address the problem, Maume (2019) distinguished among four different categories of services that originate from innovation and that need to be regulated:

1. At the highest tier we fined business models where the innovation force is strong enough to determine the birth of a conceptual novelty, tapping into widely unregulated areas. These services need to be regulated because of the almost complete absence of laws that can ensure consumer protection and stability preservation. The question faced by policymakers is whether those innovations are sufficiently pressing to require immediate intervention, or they can be left unregulated for a while, to allow them to develop freely. An example of business model pertaining to this tier can be represented by the creation and usage of Distributed Ledger Technologies (DLT) that allow the existence of cryptocurrencies that are too different on too many aspects from financial instruments and, if not regulated, could have serious implications on illegal activities like money-laundering and tax evasion (Kiviat, 2015).
2. The second tier is represented by business models that could, in theory, be covered by current regulation, even though they do not fit in any existing category. Here the underlying technology does not operate a complete revolution of some existing services, but the mismatch would be so significant that regulators decide to create ad-hoc regulation. Often, having a specific regulation should be seen as advantageous both for clients and service providers: we need to remember that the main goals of regulation are for sure to ensure an adequate degree of protection for clients and limit hazardous activities but also to create an environment where new firms can proliferate and grow peacefully and freely. We may take as an example some of the new crowdsourcing campaigns that share some features of Initial Public Offerings (IPO) but that would at the same time be excessively limited if subject to IPOs regulation, because of their smaller scope and the heterogeneous group of investors (Pekmezovic & Walker, 2016).
3. The third tier is represented by activities and business models where the mismatch of regulation would still be present but is far smaller than the one of the previous tiers. Here regulators consider the effort to produce new specific regulation as unnecessary and suggest applying the current regulation of comparable similar activities, at most with some amendments and reinterpretations to facilitate the correct usage. In particular, experience tells us that in this category we find those activities for which existing regulation, if applied, would cover all the regulatory issues of the new phenomenon.
4. The last tier is represented by those activities where technological additions can be seen just ad efficiency improvements of the business and raise no regulatory concerns and for this reason need no further disclosure. Technological and automated screening for customers applying for loans online can be a good example.

Regarding Robo-Advisors, the thesis proposed by Maume (2019) is that they pertain to the third tier so they can be regulated applying the existing regulation for traditional "human" financial advisory with some simple reinterpretations, despite the light differences. This thesis is also the one that is supported by the majority of scholars and regulation experts. The following section will, for this reason, recall some of the key prescriptions contained in MiFID II (and previous documents) and analyse the possible adaptations of the regulation to track a generic framework of the legal environment in which Robo-Advisors operate.

2.6.2. MiFID II and Robo-Advisors

In *Chapter 1* we reviewed the main prescriptions contained in the MiFID II regarding financial advisory and their practical implications. For the whole discussion of this sub-section, we will refer to what has been said previously and we will try to reinterpret each prescription to adapt that to Robo-Advisors. Most of the considerations of this sub-section are derived by a scrupulous analysis of regulation and following the approach of Salo-Lahti (2022) that provided a complete review of the existing regulation and on the ways of reinterpreting such regulation to make it applicable to Robo-Advisors.

Customer and suitability assessment

According to MiFID II, advisors are responsible for the whole process of suitability and customer assessment: this phase of the advisory process is mandatory and fundamental for providing correct and adequate recommendations to the client. Robo-Advisors perform customer and suitability assessment through questionnaires that based on the answers match the profile of the client with a general category of financial products that has been pre-determined as suitable for a specific type of customer. This is particularly easy for those advisors that operate a pre-selection of customers and that use a different algorithm based on observable characteristics of the client (age, gender, family status). Regarding suitability assessment the MiFID II we have already gone through the general discipline for traditional advisors. ESMA released some guidelines about the features of a correct customer assessment and some of those are addressed to Robo-Advisors: specifically, in Robo-Advising clients it is particularly important to i) give a "very clear explanation" on whether there is human involvement or not, and ii) inform the client on how each answer will impact on the suitability assessment. Moreover, the client must be made aware on how the information will be utilized to form the recommendation and on the frequency with which the information will be updated. ESMA also proposed some key requirements for the questionnaires:

- attention should be paid on clarity exhaustiveness and comprehensibility, avoiding any kind of opaque, misleading, or confusing information;

- the layout, font, and line spacing should be selected in such a way to make clients comfortable with the design, and all the questions should be clear in their graphical appearance;
- colours must not create any kind of mental distraction or confusion in the clients and neutral tones should be preferred;
- the robo-advisor should be able to provide practical examples and supplementary explanations when needed;
- the client should be informed also about the possibility to interact with a human while filling the questionnaire and about the eventual costs of this service;
- procedures that notify inconsistent answer should be included in the algorithms.

Disclosure duties

Disclosure duties are another key aspect of advisory discipline: MiFID II states that all the information provided should be fair, clear, and not misleading. Moreover, information about the products, rights and duties, nature of the service and any other relevant aspect should be provided to the customers. Typically, this happens through paper-documentation that is consequently summarized by the human advisor. When dealing with a robot or a website in general, this phase is executed through online documentation that is typically long and full of technicalities. People tend to "agree" and confirm that they have read the terms and conditions without even visualising a single line of the documentation (probably because of its length). As many scholars have noted, this risk is particularly relevant for online documents because people tend to be less scrupulous when clicking and checking a box rather than when manually sign or check a box with pen and paper. And this becomes crucial when we talk about Robo-Advisors that are, as may imagine, delivered through computerized platforms, and have no pen and paper involved. In this regard, we may suppose that Robo-Advisors should anyway have a way to inform the client about the rights, costs, and duties in the most precise and clear way possible. Also, the information to be provided are different because when dealing with a Robo-Advisor, information about the functioning of the platform and about the governing algorithms must be made available to the client.

Responsibility and conflict of interest

Conflict of interest are a minor problem when we talk about robo advisors, at least on the advisor-client side. Conflict of interest are still present anyway on the firm-client side because the algorithms may be programmed in such a way to recommend specific kind of products or when the products offered are issued by specific subjects. The MiFID II prescriptions that state that the client should be informed of all the steps to avoid conflict of interest (and when this is not possible at least informed about the presence of such conflicts) apply also to Robo-Advisors. Clients, indeed, should be made aware of any of the presence of any conflictual circumstance and should be able to consider this when comparing different advisors. Regarding the algorithms, ESMA stated that they should be regularly reviewed, updated, and monitored to prevent any kind of damage to customers. Moreover, documentation about the construction, programming and scope of the algorithms should be kept and updated constantly. Last but not least, procedures to detect and verify the presence of computational or visualisation errors should be in place and such errors must be corrected without hesitation, keeping track of all the measures taken.

2.6.3. Cybersecurity aspects

What need to be still considered is the matter of cybersecurity and use of personal data: traditional human advisors face the former issue only marginally, and have stringent regulation for the latter, but for robo-advisors this represents a crucial aspect. All the data collected by the advisory is managed through algorithms and clients interact with their portfolios through mobile applications and web pages, exposing themselves to various cyber-risks and privacy concerns that can severely hinder the financial (and psychological) condition of clients. Moreover, for firms, failing to include in the platforms some processes that can grant an adequate protection for the clients against cyber risks would result in relevant legal and reputational damages (ESAs, 2016). On the other hand, the management of these data through algorithms that can manage high volumes of data at the same time (Big Data) is extremely advantageous: it can bring better tailored products and services and more effective risk management processes. And this is true also for Robo-Advisors that can manage complex and dynamic data to be used for the portfolio analysis (Sanz Bayòn & Garvìa Vega, 2018). In order to protect customers authorities stressed that the regulation applied to the general protection of consumer data should be applied also to fintech industries and that customers must be always informed about the use of their personal data (Report on FinTech: The Influence of Technology on the Future of the Financial Sector, 2016). Specifically, we need to consider part of the discipline contained in the GDPR (General Data Protection Regulation, EU 2016/679): clients hold the complete right to be forgotten (art. 17) and should be informed about the existence of any automated system managing their data (art. 13). As noted by Salo-Lahti (2022) and by the Centre for Data Innovation the discipline of the GDPR, and in particular art. 17, may create some non-ignorable issues to Artificial Intelligence-based algorithms that typically work with training database that are hardly modifiable ex-post. Anyway, the ESAs stressed that this becomes irrelevant and that, in order to comply with regulation, the processing of data should be transparent and clearly communicated.

Regarding cyber-risks, to preserve adequately consumer faith and confidence in the functioning of financial markets, the ESMA stated that "if investment services are provided through online tools, special attention should be paid to the risks of malicious cyber activity" and that "firms should have procedures to mitigate such risks" (ESMA, 2015). To this purpose, for example, we may recall that the Cybersecurity Act (EU) 2019/881, introduced the so called "certification of Information and Communication Technology" that ensured the efficiency and correct and safe functioning of technologies. The presence of the certification can be a powerful instrument for the trust-building process. Last but not least, EBA has issued guidelines on the usage and security risk management for financial institutions using ICTs (EBA, 2019).

2.6.4. Conclusive remarks

Regulatory discipline of Robo-Advisors is still quite fragmented and only a few specific prescriptions for Robo-Advisors exist. Possibly, in the following years, steps in this direction will be taken and some specific regulation (or at least a uniformed framework with some standards) will be introduced to address all the inconsistencies that occur when applying current regulation to Robo-Advisors. Moreover, some issues arise also on the non-regulatory side: while Robo-Advisors seem to be a good solution for many of the problems that typically affect the interaction between clients and human advisors, they suffer from strong critiques on several aspects like excessive simplicity, over-standardization, and the lack of behavioural contributions. Also, we should note that Robo-Advisors are not completely immune from psychological biases and distortion of some procedures. The next chapter will examine those behavioural biases and the other problems that affect traditional and robotic advisory.

CHAPTER 3: BEHAVIOURAL (AND NON-BEHAVIOURAL) ISSUES RELATED TO THE USAGE OF ADVISORY SERVICES

In the previous chapters we described in detail the main features of traditional human advisory and robotic advisory. Anyway, we haven't discussed yet all the behavioural (and non-behavioural) obstacles to the adoption of each type of advisory. In fact, the possibility of conflict of interest, the issues related to personal trust, and many other concepts are significantly relevant in this context. For example, a customer that strongly fears the possibility that advisors may be part of big conflicts of interest and other organized scams will probably be reluctant to utilize such services. While one can correctly think that, in this sense, Robo-Advisors might be a great solution, we should also consider the fact that other behavioural biases and obstacles will join the scene if we decide to utilize Robo-Advisors: for example, some users might be sceptical about the fairness and functioning of automated services. As we will see, this is especially relevant for those who value preciously the human interaction and that consider advisory as a mainly human activity.

Specifically, the first section discusses the main issues related to the usage of traditional human advisory services. Then the possibility of using Robo-Advisory as a solution to this will be investigated and we will see whether robotic advisors are immune to the issues related to traditional advisory described in *Section 3.1.*. The third section analyses whether the usage of an automated advisor raises other, newer behavioural (and non) issues that might constitute an obstacle. In conclusion, the aspects that can facilitate the adoption of Robo-Advisory services will be discussed.

3.1. Issues related to the usage of traditional advisory services

3.1.1. The role of trust between advisee and advisor

Before going through the actual role of trust in the relationship between advisors and clients, we should give a definition of trust. Gambetta (2000) defines trust as the expectation that another person (physical or juridical) will perform actions that are beneficial (or at least non detrimental) to us, regardless of our monitoring capacity on these actions. This general definition of trust that can be applied in all contexts (social, financial, political, etc.) and is one of the key drivers of our everyday activity: we trust our politicians with their promises, we trust our friends when we tell them our personal issues and when we share our lives with them, we trust our family, and, more in general, all the people we voluntarily interact with.

Moreover, trust is fundamental for the correct functioning of financial markets in general. People, indeed, depart with their money in exchange for increased financial returns and other promises, relying strongly on trust issues, because of the volatile nature of those returns (Guiso, et al., 2018).

And this is true also in other economic contexts: when we concede a payment dilation we are "trusting" our counterparty and we expect them to pay at the scheduled dates; when a bank decides to lend money, they trust the borrower, that should repay the debt with no delays; when we invest our money in a new-born firm, we trust the underlying business idea and the firm's managers behaviour. Trust affects people's financial behaviour also in an indirect way: for example, various studies (see for example Guiso et al., 2004; Georgarakos & Pasini, 2011) demonstrated how individuals that tend to trust less other people, are less willing to buy stocks.

Specifically, regarding our field of analysis, in the previous chapters we only mentioned the role played by trust in the relationship between the financial advisor and the client. But we need to be aware that it represents a key factor that we should consider in our analysis. A low level of trust in the advisor can be a serious obstacle for the correct functioning of the advisory process. Indeed, without an adequate degree of trust, clients would be reluctant to give their money to an advisor. If we recall what we said in *Chapter 1* about the role of the advisors, we see that they have become a sort of guarantor of an "internal peace of mind" of the client that, having his/her money safely managed and monitored by an expert, can focus on other aspects of their lives, and avoid most of the psychological stress originating from financial and economic issues (Gennaioli, et al., 2015). When trust is missing, the peace of mind is not guaranteed anymore and, in some cases, it transforms into an additional preoccupation source. Trust is a key factor also in the evaluation of the performances of an advisor. Sometimes, indeed, financial returns and other measures may be too difficult to be comprehended and objectively evaluated by unexperienced clients, resulting in the fact that most of the positive or negative evaluation of the advisor is determined by the level of trust. For example, a client that does not trust his/her advisor would for sure struggle when trying to follow the recommendations obtained, and will probably evaluate results with prejudice, concentrating on negative events (confirmation bias) and interpreting positive results mainly as lucky coincidences, with this leading to an almost guaranteed early termination of the advisory relationship. Trust influences also the intention of people to follow and implement the recommendations obtained: Pauls et al. (2016) and Lachance & Tang (2012), among the others, found a significative link between people's willingness to implement financial advice and the perception of how trustworthy the advisor is. Last but not least, trust becomes relevant also for other non-financial reasons. In *Chapter* 1, we stressed how clients, after commencing the relationship mainly driven by financial needs, they start to discuss with the advisor personal, behavioural, and even spiritual or sentimental problems. We cannot imagine an individual sharing his/her problems with a person they do not trust.

To conclude we should consider that trust between advisors and clients can be developed only during time, with frequent interactions, effective advertisement, and tangible results. In this sense, many factors can influence the trust-building process between advisor and client: scholars analysed that, while a subjective component exists for sure, for example, the fact of having some neighbours, colleagues or relatives that we trust, already following the recommendation of a specific advisor generally increases the initial and general level of trust (Cruciani, et al., 2018). Jargon and technicalities should be avoided when dealing with unexperienced clients, and an adequate time should be dedicated at collecting information and listening to the client needs. Communications should be as consistent as possible, and a high level of transparency must be kept. For some clients, also the use of sarcasm and irony, while still keeping a professional attitude, to create a friendly, informal, and familiar environment may significantly increase the speed of the trust-building process (Bergeron & Vachon, 2008). Anyway, a more precise and detailed model of the trust building process and an analysis of the impact of various factors on the level of trust has been developed by Cruciani et al. (2021).

3.1.2. Conflicts of interest

Another key issue, that often constitutes a partial obstacle to the usage of financial advisory services, is represented by the presence of conflicts of interest. We have already discussed the agency theory and its implications, verifying that principal-agent relationships are typically prone to conflicts of interest. Before continuing the discussion, to give a precise meaning to this phrase, we might say that professionals face conflicts of interest when they have a personal (e.g., financial) interest in giving biased advice (Sah & Loewenstein, 2014). Of course, conflicts of interest are present in every kind of human interaction: for example, when someone asks for a nice place to eat and we recommend them a place owned by a close friend even though there might have been better places that we could suggest, we are having a conflict of interest. In the financial industry, and in particular for advice-based services – such as financial advisory – conflicts of interest may be extremely dangerous. Conflicts of interest originate mainly in two ways: first, the advisor might be conditioned by the institution for which he/she works for; alternatively, advisors might be directly involved in conflicts, resulting from corruption, frauds or promises of extra compensation. In the first case, the bank, the sales manager, or the general responsible forces or basically “pushes” advisors to recommend a particular kind of financial instrument, typically issued by a friend institution or by an institution that the bank is interested in obtaining a relationship with. Here the advisor faces a tough choice: abide to their supervisors and give biased advice or stick to honesty but, on the other hand, incur in the risk of ruining the internal employer-employee relationship. Also, the systems used to evaluate the advisor might originate biased recommendations. Suppose that the activity of an advisor is evaluated based on the number of clients that obtained positive returns after a certain amount of time, independently by the average amount of these returns: in this situation an advisor might decide to recommend only low risk instruments that produce with a high probability only positive returns, maybe ignoring the actual risk preferences of customers. If not pushed by the mother institution, advisors may intentionally incur in conflicts of interest: external agents might try to promise specific compensations to advisors that recommend a certain kind of instrument (e.g., the stocks of a specific firm, instruments issued by a specific bank, etc.). Scholars have widely also analysed the way in which the different compensation models affect the presence of conflicts of interest. “Commission only” schemes (that are possible only for non-independent financial advisors) provide that the advisor compensation is based on the number of products that they sell and on the number of clients that they serve. Here the client does not directly pay the advisor, but rather pays the general service provided by the institution that will consequently remunerate the advisor. These schemes are quite risky because the involvement of the firm is strong and the risk of incurring in externally-forced biased recommendations is high. We should note that in this form of compensation the commission must not depend on specific characteristics of the instrument sold, to avoid the risk of influencing the judgement of the advisor that might be tempted to recommend instruments that earn a higher commission (Robinson, 2007). For independent financial advisors we find various fee-only schemes. Some advisors for example charge a fee based on the total amount of asset under management. In this case, conflicts of interest are less frequent, but this has another negative implication: advisors that obtain fees based on the amount of money that the manage will be induced to cater primarily to high-net-worth clients (Dean & Finke, 2011). Some advisors adopt “flat fees” schemes where the client pays a fixed fee for each recommendation or plan received, independently from the actual decision to follow the recommendation and to entrust the money to the advisor. This scheme, again, is less prone to originating conflicts of interest but is by far the one where prices are the most salient, with this resulting in a decrease in the demand of the service. Another widely used options is represented by the “hourly fees”, where the amount of the fee depends on the time spent on a specific plan or in a specific meeting. This scheme might have positive consequences but also some dangerous outcomes: when the fee is time-based the advisor will try to spend as much time as possible with the client to increase his/her own payoff; on the other hand, the client will try to obtain as much information as he/she can in the shortest time possible, with the risk of concluding meetings earlier to save money, sacrificing full comprehension of information or avoiding asking for questions and clarifications (Robinson, 2007). Last but not least, schemes where the advisor earns a fixed minimum fee plus a percentage of the return generated are problematic because will induce the advisor to be more “reckless” with the client money trying to earn superior returns. Mixed schemes – with both commission and fees or with multiple types of fees – are also a possibility (Cheng, 2016).

While regulation punishes severely this kind of conflicts and many norms about conflicts avoidance and disclosure exist, some conflicts are still present and hidden by advisors. Moreover, as argued by many scholars (see for example Ben-Shahar & Schneider, 2011; Verracchia, 2001) consumers, often, do not know how to respond to conflicts of interest’s disclosures and tend to either ignore them (Hampson, et al., 2006) or discount the advice obtained insufficiently (Cain, et al., 2005). Disclosure might also have an effect on the advisor that will probably feel licensed to offer biased recommendations (Monin & Miller, 2001).

Last, we need to note that the presence of conflicts of interest undermines significantly also the overall level of trust in the financial system and advisory services in general, contributing to furtherly obstacle the demand.

3.1.3. Misleading advertisements

The way in which independent advisors and firms advertise themselves can become misleading for clients when they need to choose between one advisor and the other. Regulation prescribes that any form of advertisement should be based on real (documented) facts and that every information given should be clear and not misleading. But no limitations are imposed on the choice of such information. For example, an advisor that advertise himself/herself saying that “more than a hundred clients obtained positive returns when following his/her recommendations” maybe is using a documented and real information, but the information can be only partial. If we suppose that the advisor had in his/her career more than a thousand different clients, we see that the relative number of customers that obtained positive performances is a mere 10%. We might argue that such a practice is quite diffused among all financial services and can be considered as one of the bases of the advertisement doctrine. Nonetheless, this represents a problem because customers that are aware of this might be reluctant to trust the information they read in advertisements or become suspicious. On the contrary, those who ignore the risks implied in this “biased” or “partial” information will probably make an incorrect choice when deciding between advisors. This process leads naturally to a damage to the overall reputation of the financial industry and to the trustworthiness of the figure of the financial advisor. Moreover, in a world where every advisor advertise himself/herself only on certain positive facts, clients will struggle to distinguish between “trusted advisors” and mere “salespeople”. Fortunately, regulation has addressed in some ways this problem: the “best-interest” rule and all the transparency duties imposed by current regulation of financial services acts exactly in the direction of protecting clients from this kind of damages, trying to ensure that, independently of how the advisor advertised the service, all actions are performed in the best interest of the client and all the information provided is as transparent as possible. This anyway offers only a light protection against "biased" advertisement because still it does not allow clients to distinguish between "good" and "bad" advisors.

In recent times, indeed, the way in which advisors advertise themselves has changed: rather than on past performances, advisors tend to promote their services playing on their trustworthiness, experience, and dependability (Mullainathan, et al., 2008). This is aligned with the fact that the role of the financial advisor has evolved the last years, shifting from a financial planner – that would have rationally advertised the service highlighting positive past performances – to a behavioural and psychological counsellor that advertises himself/herself on behavioural and personal characteristics. Anyway, we should note that these aspects are less objective and measuring them objectively can be difficult: for example, how can we measure trustworthiness? How can we determine the actual experience of an advisor? The number of years of activity is a good proxy of experience but many years of work do not guarantee a high degree of experience: experience depends also on the variety of instruments they know and recommended in the past, on the number of clients and on the type of services that they provided in the past (financial planning, brokerage, independent vs. firm-dependent advisory). To this purpose, advisors also tend to use some tactics to portray themselves as trustworthy in the eyes of customers. Hauptman and Roper (2017) conducted an analysis, reviewing more than 25 websites of advisory firms, broker-dealer firms, and insurance companies and isolated three main tactics used to advertise services and increasing the perceived trust. First, the use of titles and adjectives that convey the impression that they are providing expert investment advice like "chartered" or "certified". These adjectives and titles like "advisor" or "consultant" are sometimes used also by some brokers and salesmen, to create the impression that the activity advertised is a real advice providing rather than mere financial instrument sale. This is particularly dangerous for the profession of the advisor because it creates confusion in the mind of the customers, hindering the image of the service. While many regulations have norms to limit such practices, many firms try to employ some tricks to get round these regulations, often resulting in expansive court claims that furtherly damage the general reputation of the financial industry. Another widely used tactic is to describe the work in such a way to convey the impression that the advice offered is precisely thought to meet individual needs, even if many times the recommendations are pretty standardized and only lightly adapted or varied depending on the actual risk preferences of clients. The third tactic highlighted in this study is to use in the websites messages, slogans and images that generate in the clients the impression of trust and reliance: phrases like "Our clients always come first" (Raymond James) or "A relationship you can trust, close to home" (Schwab), images representing acts of kindness and cooperation, and similar structures are often used by firms and advisors to advertise themselves and always are inserted in capital letters and bright colours.

3.1.4. Other behavioural limitations of traditional advisors

We have already discussed how factors like overconfidence, experience, and other behavioural components shown by clients influence the individual demand of advisory services. This sub-section deals with the various psychological biases that directly affect the activity of the advisor and that can possibly obstacle the effectiveness of the service, reducing the willingness of clients to hire an advisor. We know that investors, regardless of their experience and sophistication, are subject to various biases when managing their portfolios. Even though, in *Chapter 1*, we said that one of the main roles of the financial advisor is nowadays bias management, financial advisors are all but immune from these biases and sometimes are even more prone to them. Specifically, we will go through the main irrational behaviours that people show when investing and analyse how (and if) they may affect financial advisors. Experience and awareness of this biases may surely help to limit or avoid them, but because they are a result of some inner mental processes and structures, supposing a total immunity from them would be utopistic.

While describing the Bias Management function of the advisor, in *Section 1.2.*, we already talked about how overconfidence and disposition effect affect professionals. Specifically, we documented that scholars agree on the fact that financial advisors are both more confident and overconfident (Van de Venter & Michayluk, 2008). This results in a slight tendency of initiating a great number of trades, with negative outcomes on the net returns. Interestingly enough, advisors are anyway able to correct this behaviour in their clients, educating them to a correct decision-making process and emotion management (Campbell & Viceira, 2003). Anyway, overconfidence leads to less underdiversification problems in portfolios created or managed by advisors than in clients' self-managed portfolios. The disposition effect, on the other hand, seems to be quite mitigated, even though we should note that advisors tend to be sort of optimistic about their decisions, with this leading to a general "hold" strategy in the portfolios. Optimism is in some ways implied in the relationship between the advisor and the client: an advisor that is too pessimistic (or too realistic when the market is "bear") will probably scare and cause negative feelings and peeve the client. About herding behaviour, the evidence is quite mixed: for example, Venezia et al. (2011) found that financial advisors – differently from analysts – tend to herd less, while in the analysis conducted by Garduno (2022), a sample of 21 advisors declared that herding was one of the factors that mostly influenced their recommendations. Financial advisors, also, tend to use standardized base-set of instruments for all the clients, typically those which earned positive results in the past. Furthermore, Ahmad (2021) notes that advisors (because of experience and knowledge) tend also to be less affected by all the biases deriving from the availability heuristic but not completely immune. Last but not least, some studies evidenced how advisors tend to be reluctant to modify excessively the portfolios they build, depending on the market outcomes. This might depend on two reasons: first, it can be determined by the fact that modifying a portfolio excessively could be perceived by the client as a sign of incertitude and consequently hinder the image of the advisor in the eyes of the customer. Another explanation lies in the confirmation bias: advisors that include a certain group of stock in their clients' portfolios will then conduct constant research on the stocks and monitor the results constantly. In this process, pushed by a mixture of overconfidence and emotional processes, advisors may pay more attention to news and estimates confirming their initial hypothesis.

3.2. Are Robo-Advisors the perfect solution?

3.2.1. Human-Machine trust dynamics in the context of Robo-Advisors

Sub-section 3.1.1. described in depth the dynamics of the trust-based relationship between the financial advisor and the client. Trust, as we said, is a concept inherent to the human nature and determines the nature of all the human interactions. When we deal with a human advisor, to understand that trust represents a key issue is quite easy: but when the advisor is a machine? Of course, the dynamics of trust and of the trust-building process are different from the traditional ones. We said that human advisors gain trust by their clients through various processes: frequent meetings help; professionality and informal language, together with the avoidance of complicated jargon can make the client more comfortable and help him/her feel in a more familiar context; positive financial and behavioural results complete the job. But how can machines do this? Frequent meetings with a machine are unreasonable because the answers provided are (should be) always the same and they are not programmed to give psychological assistance to clients. Moreover, machines do not have the ability to decide whether in a specific situation is preferrable to adopt a formal and professional tone or to use informal language (yet). Financial results can be provided but no (or just minimal) behavioural contributions are included in the deal. For our purposes, in the relationship between advisees and Robo-Advisors this is quite problematic. The difficulty of creating trust, indeed, is one of the main vulnerabilities of robotic advisory (Scherer & Lehner, 2022). Nonetheless, the decision of adopting or not Robo-Advisory solutions is strongly related to trust as it is in many other services, and in particular for those that employ advanced technologies (Reichheld & Schefter, 2000). But trust in a machine can depend on many factors, and this varies significantly among individuals: the identity and reputation of the developers, the context in which it operates, the activity performed, the design and perceived safety and many other factors. The idea of this sub-section is to try to analyse the main determinants of trust in the context of Robo-Advisory services.

Trust in automation

Robo-Advisors provide an automated service. Automated machines, and in particular those which are used to provide services, have precise trust dynamics related to what we can call "Trust in automation". Indeed, the factors that determine trust in automated services are not identical to those that regulate trust in services delivered through the intervention of a human being.

First of all, experience-related dynamics are not relevant for Robo-Advisors. Or at least they are relevant in a different sense: for a human being, experience is a fundamental factor, but machines do not gain experience and we cannot compare the machine's "learning" process to the human experience gaining. The closest concept would probably be represented by technological progress, intended as the gradual improvement of machines' performances due to technological and architectural changes. Anyway, we may argue that once an improvement in a technology is made, the obsolete procedures progressively disappear, and the machine is substituted. Moreover, often, people are not able to correctly evaluate the state of the technological progress. In this sense, more than actual progress (that will naturally occur), what will determine an increase in the level of trust would probably be the diffusion over time and growth in popularity.

This is furtherly confirmed by the theories of various scholars, that often call into action the so called "Trust Transfer Theory". Trust transfer is a cognitive process in which trust is transferred from one domain to another. In particular, the theory works along two directories: between different domains and between peers. The former says that the trust in one domain has a strong influence on the trust in another related domain (Lu, et al., 2011). For example, according to the theory, if I trust a vocal assistant on my smartphone (e.g., Siri, Cortana) this should have a positive influence on my perceived trustworthiness of home virtual assistants (e.g., Alexa). To apply that to our context, we might say that people who use and trust similar services and use artificial intelligences in their everyday routines should trust more Robo-Advisors. The other formulation of the theory says that trust can be transferred from person to person: basically, if a relative, colleague, or friend of mine trusts someone, my level of trust in that person should be influenced positively (Strub & Priest, 1976). This has been proved to work also when our peers trust a service, a product, or a company. Again, for us, this would mean that if someone we trust trusts Robo-Advisors, we would probably trust more Robo-Advisors in our turn. The existence of this mechanisms also in the context of Robo-Advisors has been tested by Cheng et al. (2019) with encouraging results. The theory, as said, furtherly supports the fact that with time and with a growth in the popularity of Robo-Advisors, trust towards them will probably reach a general higher level: indeed, when more people will start using Robo-Advisors the trust transfer mechanism will have an even stronger effect.

Cheng et al. (2019) also analysed another key determinant of the trust building process: supervisory control. We can define supervisory control as the human monitoring of the performance of an automated system in case of emergencies (Ngo-Ye, et al., 2018). Of course, when we deal with automated systems, human supervision is fundamental to prevent bugs or malfunctioning from damaging the utilizers of that system. In the human-machine relationship supervisory control can determine an increase in the level of trust of the user, that will probably feel safer (Muir, 1994). Analysing a sample of 230 investors, Cheng et al. (2019) confirmed the existence of the positive relationship between trust in Robo-Advisors and the degree of supervisory control.

Another fundamental contribution is the one from Körber (2019). He established a model with six dimensions (five explanatory variables and trust in automation itself) to measure the level of trust in automation. Starting from the approach proposed by Mayer et al. (1995) of organisational trust - adapted to the features of trust in automation – and combining it with the theoretical account by Lee and See (2004) he theorized the determinants of trust in automation proposed in his model. First, he included three determinants that were already present in the model by Lee and See (2004), but dividing them into more detailed facets: Competence/Reliability, intended as a measure of the perceived probability of errors and malfunctioning and perceived capacity of the system of taking over complicated tasks correctly (rationally, a system with only few mistakes and high capability should be more trustworthy); Understandability/Predictability, representing the degree to which an individual is capable of understanding and predicting the actions of the system, based on the inputs (again a predictable and understandable system should be seen as more trustworthy); Intention of Developers, as a measure of reliability of the developers of the system (if developers are recognized as competent and interested in the client's well-being then the system is obviously considered more trustworthy). Then, considering the fact that typically trust exhibits an individual component (Körber, 2018), he added a fourth dimension, Propensity to Trust, that accounts for the individual willingness *a priori* of a person to trust other people, technology, and services. As the fifth and last factor, Familiarity, was considered: to be fair, Familiarity is thought to affect trust in automation only indirectly, by increasing the degree to which the other variables exert their influence.

Trust and adoption of a new technology

Last but not least, Robo-Advisors, more than automated services, are also a technological innovation. Since the 90s many scholars started working on developing models to explain the process of acceptance of new technologies and innovations.

One the first contributions comes from Rogers (2003) that in the book "Diffusion of Innovations" developed the well-known model called "Innovation Adoption Curve". He theorized that when a new product or service is launched, the curve that describes the adoption of the product is a gaussian, or more in general a bell-shaped curve (see *Figure 3.1*).

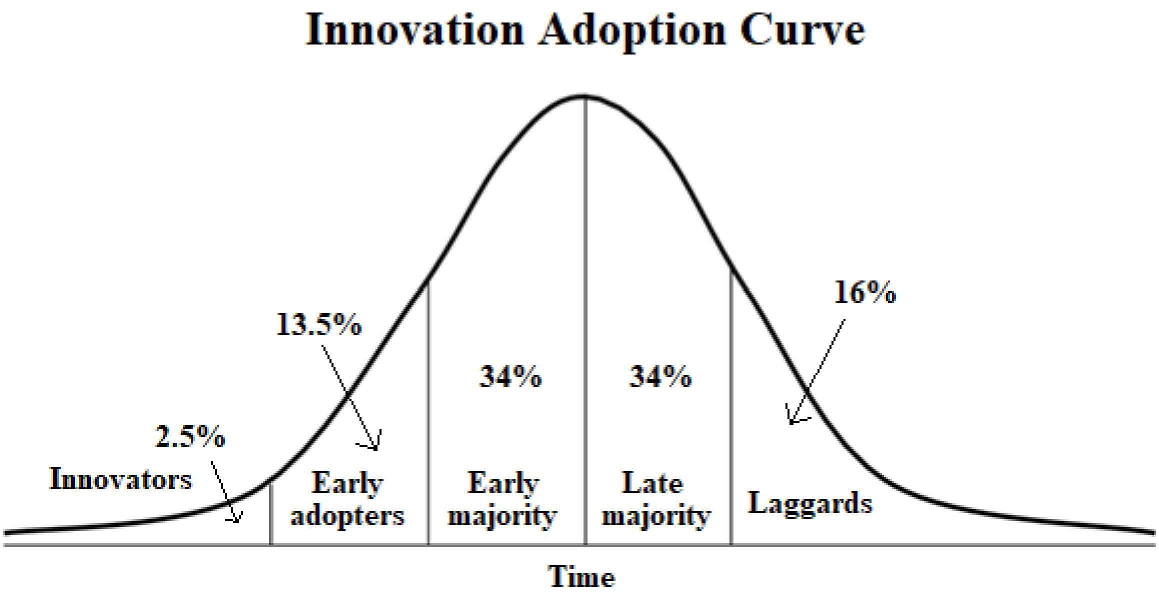

Figure 3. 1.: Rogers' Innovation Adoption Curve. Source: personal elaboration.

Specifically, Rogers divided adopters into 5 categories:

- Innovators: this category comprises people that are willing to experience new ideas and bear the risk of spending their time and money on unsuccessful products. They typically have technical knowledge about the product and play the role of "gatekeepers" for innovations, giving initial feedbacks that are useful for the developers to improve (or completely abandon) the project. They account for about 2.5% of the total adopters.
- Early adopters: more limited from the technical point of view with respect to innovators, early adopters are willing to try new products but only when a short "testing" period has gone. They play a key social role in the diffusion of the innovation because, if they are satisfied, they will start to "spread the news" and more users will start adopting the new product/service. We might say that they "put their stamp of approval on a new idea by adopting it" (Rogers, 2003, p.283). This category contains almost 13.5% of the users.
- Early majority: this is the group that contains about a third of the population (34%). They are deliberate with adopting new products and services, but they do not want to be neither the first ones nor the last ones. Their response to innovations is not sluggish but takes more time than it did in the previous categories.

- Late majority: quite similarly to the previous group they account for another third of the users (34%). These people need more time to accept innovations than the "early majority" and are willing to try new products and services only when almost half of the population already uses them. They cannot be considered as "reluctant" to innovation, but at the same time they cannot afford the risk of wasting money and time on "failed inventions".
- Laggards: the last category contains all the users that are typically sceptical about innovations. They struggle to accept new ideas and are extremely tied to traditional products and services. This group will embrace innovations only when a considerable amount of time has passed, and they can be sure of the functionality of the new product/service. They account for almost 16% of the population.

Currently, in the field of Robo-Advisory, we might say that we are still in the "Early adopters" phase, with a few companies providing these services and a small (but not minimal) proportion of the population using Robo-Advisors.

More recently, specific models and theories for technological innovations have been developed. One of the most used and well known is the "Unified Theory of Acceptance and Use of Technology" (UTAUT) by Venkatesh et al. (2003). UTAUT tries to integrate all the pre-existing models and tries to explain the intention to use and adopt a new technology with a series of behavioural and psychological factors. Specifically, they identified four factors that affect the intention (referred to as "Behavioural Intention") and use behaviours (referred to as "Use Behaviour"). The first factor included is the "Performance Expectancy" 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) and comes from a synthesis of five factors existing in the previous models, namely, "perceived usefulness" from the Technology Acceptance Model 1 and 2 and the Theory of Planned Behaviour (TAM 1/2 and TPB), "extrinsic motivation" from the Motivational Model (MM), "job-fit" from the Model of Personal Computer Utilization (MPCU), "relative advantage" from the Innovation Diffusion Theory (IDT), and "outcome expectation" from the Social Cognitive Theory (SCT). This is the strongest predictor of the Behavioural Intention, but the relationship between performance expectation and intention is moderated by age (younger people are more interested in the performances of a new technology than older people) and gender (this predictor is likely to be especially salient to men). The second predictor is represented by "Effort Expectancy" defined as "degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). This construct is again obtained by merging three factors of previous models, namely, the "perceived ease of use" (TAM 1/2), "complexity" (MPCU), and "ease of use" (IDT). This factor influences the Behavioural

Intention and is moderated by gender (stronger influence for women), age (younger people give considerable importance to this factor) and experience (more relevant at early stages of experience). The last factor that influences the Behavioural Intention is the “Social Influence”, 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, p.451). It was represented in the previous models by three different objects: “subjective norm” (TAM 1/2), “social factors” (MPCU) and “image” (IDT). The effect of social influence is moderated by gender (more important for women), age (interestingly enough, stronger for older people), voluntariness of adoption (more relevant when the adoption is mandatory) and experience (again, more relevant in early stages). The last factor included in the model is the only one that directly affects the Use Behaviour of a new technology and is represented by the presence of “Facilitating Conditions”. The factor can be 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). This synthesizes three constructs of the previous models: “perceived behavioural control” (TPB), “facilitating conditions” (MPCU) and “compatibility” (IDT). The effect of this factor is moderated in the model by age (more relevant for older people) and experience (stronger for people with more experience). According to the model, the degree of acceptance and adoption of a new technology depends largely on the correct balance of these four constructs, adjusted on the moderating variables. *Figure 3.2.* from Venkatesh et al. (2003) is a graphical representation of the model.

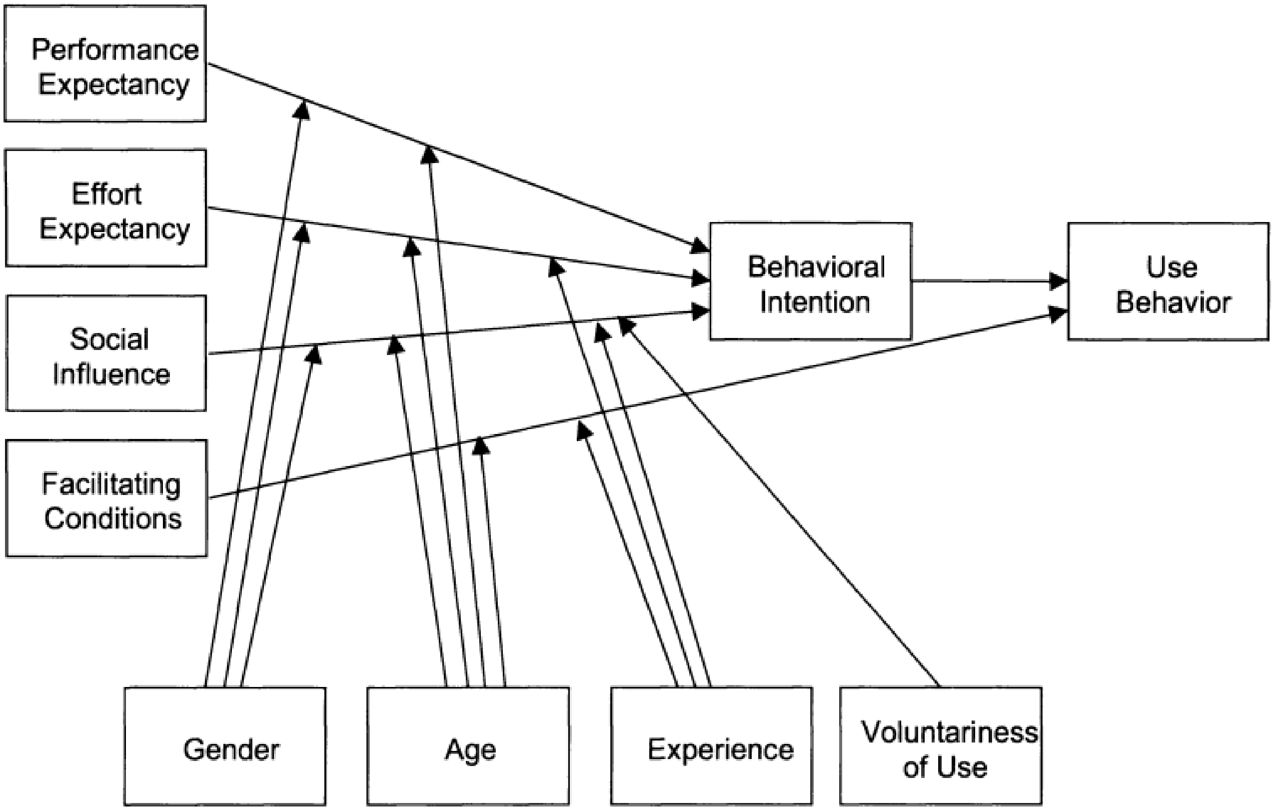

Figure 3. 2.: graphical representation of the model of the Unified Theory of Acceptance and Use of Technology (UTAUT). Source: Venkatesh et al. (2003).

Regarding specifically Robo-Advisors, the current state of the four constructs is still not completely satisfactory: performance expectations are quite high, because of the hype posed on artificial intelligence, while the actual performances of Robo-Advisors are significantly volatile; effort expectancy and facilitating conditions are quite fine, because using Robo-Advisors is easy and, as said in the previous chapter, also the service is accessible to all categories of individuals, from low to high income; the social influence of Robo-Advisors is, on the contrary, still scarce because of the novelty of the service and also in light of what we said previously about the current stage of the innovation adoption curve for Robo-Advisors.

3.2.2. Are Robo-Advisors immune from conflicts of interest?

One of the main arguments of those who support the idea that Robo-Advisors are better than human advisors, consists in the fact that Robo-Advisors are immune to conflicts of interest. But is this really true? The short answer to the question is: yes. Robo-Advisors are indeed influenced only marginally by conflicts of interest. The longer answer would start with: it depends. Of course, Robo-Advisors are artificial intelligences and for this reason they cannot have any kind of personal interest in giving incorrect advice or in recommending a specific product rather than another one. Conflicts of interest are a concept that is naturally linked to the limitations of the human mind and is rooted in the inner egoistic tendency of persons and institutions. Machines do not have minds (despite the fact that we call them “intelligences”) and are neither selfish nor altruistic, so they cannot be corrupted with money or benefits and cannot be psychologically persuaded or blackmailed to do a specific action. Machines will do exactly what they are programmed to do. And the problem lies exactly here. Robo-Advisors work on the basis of their algorithms, that are coded by humans. For a bank it would practically be quite easy to set a Robo-Advisors so that it recommends specific products or uses a specific broker to conclude transactions. A report from the Financial Industry Regulatory Authority (2016) in the U.S. specified that Robo-Advisory services are not completely immune from conflicts of interest and that clients that utilize such services must be aware of the fact that the conflicts of interest of Robo-Advisors might be similar to the ones of traditional human advisory services. In this regard we may cite Fein (2015) who found that a lot of Robo-Advisors, in providing recommendations to their customers, used affiliated brokers and specific clearing firms from which the bank received a compensation, or even some banks directly used their own products for the recommendations. Having an affiliated broker can be advantageous and can help to control the monitoring costs. Moreover, it ensures a high degree of stability and transparency. On the other hand, this choice makes the process inefficient because a certain broker can charge prices that are not always the most favourable ones for the clients. Also, Lam (2016) found some conflicts of interest when analysing Schwab Intelligent Portfolio: observing the recommendations of the Robo-Advisor they found that it typically recommended an unusually large proportion of the portfolio to be invested in money markets funds of the Schwab Bank. He argued that this allowed Schwab Bank to use the cash to profit from the interest rate difference between the lending interest rates charged and the rate paid to investors.

Anyway, more recent Robo-Advisors seem, also thanks to regulation, to have mitigated these tendencies but still some conflicts are present and disclosed in accordance with transparency regulation. Nevertheless, with a correct monitoring of the programming activity from authorities and with mandatory disclosure duties, most conflicts of interest can be avoided thanks to Robo-Advisors.

3.2.3. Biased Robo-Advisors

Another argument often used in favour of Robo-Advisors is that they could help to mitigate behavioural biases that affect all kinds of investors. Understanding whether Robo-Advisors can provide clients with unbiased advice is fundamental because, as proved by Gurun et al. (2018) and by Bhattacharya et al. (2012), this feature (unbiased advice) represents an important determinant of advisees’ trust towards advisory services. As we discussed before, while unexperienced investors are subject to a wide variety of biases when they invest money, professionals, and more experienced investors (like advisors) are for sure less subject to them and are able to recognize the presence of such biases, but at the same time they are not completely immune from them, and their results are often hindered by these behavioural limitations. But to mitigate the negative effect of biases, Robo-Advisors have to be immune from biases themselves (Edwards, 2018).

Cognitive biases, for example, are linked to the presence of a cognitive system that machines, for obvious reasons, do not possess. This would make them (almost) immune from such biases. The same holds for most of the other behavioural biases that typically affect investors. Indeed, behavioural biases depend on the behaviour of the individual, but algorithms do not behave subjectively, they cannot be influenced by friends and colleagues and they do not pose more attention to a particular piece of information rather than to another one; they do not have emotional feelings and they do not feel neither anxiety nor regret; they are not scared of losses and they sell and buy instruments when they are told to or when the market reaches particular conditions. But what we said about conflicts of interest hold also for biases: because Robo-Advisors follow instructions coded by humans, these biases might be hidden inside the algorithms. For example, given that machines do not have yet the computational power to analyse with an adequate timing all the existing securities, a certain choice on the universe of securities to consider has to be made. This exposes Robo-Advisors to the risk of incurring in the so called "Home Bias" – the tendency of including in portfolios high shares of domestic securities possibly because of a perceived informational advantage or because of an affective feeling – losing most of the benefits coming from geographical diversification (Bekaert & Wang, 2009). More than home bias, the tendency to recommend in most cases a specific basket of instruments is frequent in Robo-Advisors. Excluding the already cited cases of conflicts of interest, the reason underlying might be more or less the same: programmers need to make a choice among the huge variety of securities existing and thus Robo-Advisors will explore only a limited (even if wide) selection of instruments and with a high probability recommend in most cases the same ones (because of better performances, lower volatility, or more favourable conditions). This can be interpreted as a sort of bias towards these sub-group of securities, even though not caused by a proper cognitive limitation, but rather from a technical-computational limitation. A great contribution comes from Bhatia et al. (2020) that, through a qualitative study of Robo-Advisory services offered in the Indian context, found some biases also in Robo-Advisors. Specifically, they distinguish between two categories of biases found, both of them resulting mainly from the fact that automated systems are programmed by (biased) humans: biases in the assessment questionnaires and biases in the architecture of the advisor. Regarding the first category, they argued that when questionnaires are developed without supervision from behavioural experts, it often results in biased questionnaires, where a significant amount of non-effective data is collected and used to incorrectly assess the clients risk attitudes and financial goals, or again, questions that are not relevant nor applicable to make investment decisions are asked repeatedly, consuming the client's time. The combined effect of these issues inevitably leads to sub-optimal performances in terms of perceived quality of the service. Regarding biases in the architecture of the advisors, certain codes, as said, typically result in specific patterns and the use of just sub-groups of instruments. Basically, automated advisors work on *if-else* structures to determine the universe of securities or percentage to recommend to a specific client. For example, if a Robo-Advisors if programmed to recommend a percentage of equity going, say, from 10% to 20% of the portfolio for highly risk-averse customers, then, when the advisor gains the view that the client is highly risk-averse, then the recommended proportion of equity cannot be altered in any way (neither reduced nor increased), at least at the preliminary recommendation stage.

On the other hand, to conclude, we should note that other biases like disposition effect and trend chasing, as said, are extremely mitigated, as demonstrated by a great number of studies (see for example D'Acunto et al., 2019). Also, decision inertia of customers can be substantially mitigated by including specific features in the design of Robo-Advisors (Jung, et al., 2018). And this holds for many other biases. So, again, the argument of immunity (at least partial) from biases and the theory that argues that Robo-Advisors help clients mitigating the effect of behavioural biases is, in principle, valid – even though with some exceptions – and makes Robo-Advisors a valid solution against these irrational behaviours (World Bank, 2019).

3.3. Additional issues affecting the usage of Robo-Advisory services

3.3.1. Excessive standardization of risk profiles and lack of individualization

Among the most criticized aspects of Robo-Advisory we find the fact that the portfolios created are often too standardized and thus they are not able to precisely capture the clients' specific objectives and risk preferences. Before discussing the issue, we briefly recall what we said about the way in which portfolios are built. First of all, the system collects information about the client and combines them to obtain an overview of the actual financial situation, investment goals and risk preferences. The information is used to classify and categorize the client and then to determine the asset allocation of the portfolios. The system then builds a series of portfolios using mostly passive instruments, like ETFs, and offers them to the client that can decide to obtain/refute the portfolios or make small changes. All choices are made according to a specific portfolio optimization model, typically mean-variance optimization, or similar models.

Let's start from a technical and objective consideration: risk assessment questionnaires comprehend a fixed set of questions that, of course, must be pre-determined. Even though through sophisticate programming we may be able to build an adaptive questionnaire where the information requested and the questions asked at a certain point of the procedure vary depending on the answers provided to the previous questions, these questions come from a predefined pool. Of course, because of this implicit limitation, the degree of individualization of the service is lower than the one of traditional advisors. FINRA (2015) warned investors that sometimes the portfolios built by Robo-Advisors may resent of extremely standardized questionnaires, where the risk capacity is assessed using only a part of the information provided and that risk evaluations may be based on incorrect or unprecise assumption. To be fair, from 2015 relevant changes occurred in the standards of Robo-Advisors, leading to a general improvement of the performances and an increase in the possibilities of individualisation, but this issue is still present (even if in a lighter way) in most Robo-Advisors. Also, Tan (2020) argues that through Robo-Advisors, investors are rendered passive, and this results in miniaml differences in the portfolios recommended. Another key issue, highlighted by many scholars (see for example Au & Krahnhof, 2020), is related to the lack of individualization and the impossibility to personalize portfolios: for instance, clients that rely only on Robo-Advisors are not able to take part to the stock picking phase and clients cannot express preferences for specific types of investments (e.g., sustainable investments vs. traditional investments) nor exclude certain categories of firms. This issue, of course, while it impacts only marginally the financial returns (given that a correct portfolio construction has been made), dangerously hinders the demand of Robo-Advisory services from those investors that may be interested in the ethical side of their investments.

3.3.2. De-humanization and lack of human contact

The (almost) total lack of human contact represents another aspect that is often criticized by those who contest Robo-Advisors. We will go through some of the main implications of the use of algorithms to provide services in the following sub-section but some of the considerations we made about the features of trust relationship between humans and machines made in *Section 3.2* should be kept in mind. While the absence of a human being can be seen as an advantage (Jung, et al., 2019) from the point of view of the bank – or more in general from a cost-reduction perspective – we should also consider the implications of this on the quality of the service provided: understanding the risk capacity of clients, listening to their preferences, worries, and ideas constitutes a key phase of the advisory activity and helps the trust-building process to develop smoothly. Clients that are listened and assisted in their problems will, indeed, feel more comfortable with the context and the situation, even when they are not used to. Even though we can argue that many clients may feel a similar degree of comfort when interacting with an Artificial Intelligence, we cannot ignore the problem. Independently from the client’s expectations, attitudes and behaviour, a human advisor will typically (at least in theory) have the necessary psychological flexibility and empathy to correctly comprehend and interpret them; robots are unlikely to be able to do the exact same on their own (Dolata & Schwabe, 2017).

Machines for sure are protected from most of the problems that arise as a consequence of the behavioural limitations of human advisors, but we should ask ourselves if a completely impersonal advice providing, with all its advantages and disadvantages, is what clients really want (Jung, et al., 2018). Especially in situation of financial distress and when losses are likely to occur, what clients need is someone that reassures them and that can give them support to psychologically overcome the situation. Moreover, we discussed extensively the fact that advisors are now working as behavioural consultants and play the role of educators, psychological counsellors, and bias managers. Advisors can help people to manage correctly also difficult emotional situations that have to do with their finances (e.g., divorce, marriage, death of a relative, inheritance management). Of course, these activities cannot be performed by a machine. Cocca (2016) gives us an example of this: "a customer may feel more willing to talk about the consequences of the sudden passing away of their wife when the long-time advisor of the family addresses this delicate issue with due care, whereas a robo-advisor might send a change of text of the testament contract by e-mail on the basis of the calculated probability of such a scenario" (Cocca, 2016, p. 48). It is clear that some situations cannot be managed properly and with the right degree of touch by machines because they cannot adopt any form of sympathy. Nevertheless, not all investors use advisors for the behavioural contributions that they can provide, but sometimes they are still hired as mere financial planners: for these customers a pure robotic environment may have the right characteristics to satisfy their demand of the advisory service. Anyway, the lack of human touch and the de-humanization of the service constitute a relevant obstacle for the diffusion of Robo-Advisors.

3.3.3. Algorithmic aversion

In the previous section we explored in depth the dynamics of the trust relationship between humans and machines, highlighting the main determinants and considering the various differences between human-human trust and human-machine trust. We documented how a low degree of trust towards machines aliments negatively people's feeling for Robo-Advisors and dangerously hinders their image and diffusion. Going deeper in the analysis of such issues – the ones that influence the adoption of these services – we find the so called "algorithmic aversion". Often, trust in automation and algorithmic aversion are phrases used as synonyms while, despite being closely related, they describe two different concepts. We already defined trust in automation. Regarding algorithmic aversion, we might define it as a behavioural anomaly and, more precisely, as "the behaviour of neglecting algorithmic decisions in favour of one's own decisions or other's decisions, either consciously or unconsciously" (Mahmud, et al., 2022, p. 1). Algorithmic aversion is considered irrational because if we prove that algorithm-based decisions are better – more efficient and more precise – than human decisions, then deciding to refute them is illogical and leads to a reduction of individual's expected utility (Dietvorst, et al., 2015). Algorithmic aversion becomes a central problem in the field of Robo-Advisors: we extensively remarked the fact that the portfolios and recommendations are formed using an Artificial Intelligence, and clients are aware of this, paving the way for algorithmic-aversion-related issues. Specifically, Niszczota & Kaszàs (2020) conducted a study analysing formally whether the phenomenon was also relevant for Robo-Advisors. Conducting five different experiments on a pool of 3,828 subjects they found that algorithmic aversion extends also to the financial industry and represents a relevant obstacle for the adoption of Robo-Advisors and, more generally, for most services of the Fintech realm. This was furtherly confirmed by Filiz et al. (2022), that conducted an experiment on a pool of 160 students. Each student was asked to perform a series of tasks and each time they had the possibility to perform the task on their own or to delegate the task to a Robo-Advisor. The advisors were programmed to perform the task in the most efficient way possible and return the highest payoff obtainable (subjects were not aware of this). Nevertheless, most students chose to perform the task on their own, and delegate the task only in 40% of cases, highlighting a common sense of algorithmic aversion towards Robo-Advisors. To conclude, it is worth to mention that some scholars argue that the reason that undermines the usage of Robo-Advisory services is a preference for humans, rather than algorithmic aversion and that this becomes particularly relevant in the fields where a specific individual has more expertise or in those pertaining to domains that the individual cares most about (Morewedge, 2022).

Factors influencing algorithmic aversion

Once we stated that algorithmic aversion – or preference for humans – represents a fundamental issue in the field of Robo-Advisors, it would be useful to isolate factors that influence and cause the feeling of aversion towards algorithms. Starting from the cited contribution of Morewedge (2022), he proposes a theoretical framework where individuals would prefer humans in activities where the evaluative criteria are ambiguous and when the perceived relevance of identity was high. This is relevant in our context because it raises a fundamental question: to what extent financial advisory can be considered an activity with a high degree of identity-relevance? Morewedge (2022) makes a direct reference to financial advisory and considers it as an activity with a low degree of ambiguity and identity relevance, suggesting that algorithmic aversion is not the main determinant of the low demand for Robo-Advisors services, contradicting other previous studies. To support the thesis, he cites the work of Castelo et al. (2019) that conducted various experiments: specifically, one of the experiments considered the number of clicks on Facebook ads and compared the number of clicks on ads containing advice based on human recommendations and on ads containing advice based on algorithmic recommendations. They found that in the field of "dating advice" people clicked more on recommendations made by humans than on the ones made by algorithms, while the amounts of clicks on ads for financial advice seemed to be uninfluenced by the fact that recommendations were provided by humans or machines. The reason individuated by Castelo et al. (2019) is the higher objectivity of the evaluation criteria in the domain of financial advice (performances). In this sense, we discussed deeply how financial advisory has changed, shifting from being a substantial financial planning activity, based on results and financial performance, to a real behavioural and psychological counselling. With this new definition, the objectivity of the evaluation criteria of this activity are questioned. Morewedge (2022) takes, instead, as examples of high identity-relevance activities those where the subject perceives uniqueness of his/her individuality, like gift recommendations – activity that currently is extensively performed also by algorithms – or hiring/firing employees, and sentiment-based activities like poetry and painting. In the healthcare domain, the tendency to prefer human solutions when the individual's own health conditions are perceived as unique is confirmed in a study conducted by Longoni et al. (2019). Again, a question arises: do individuals feel themselves as unique with reference to their risk preferences and financial needs? Interestingly enough, in the cited framework, activities like advice receiving and healthcare are perceived as activities with a lower degree of identity relevance when the advice is addressed to other people, evidencing a sort of deindividualization effect. Another relevant question would be whether this tendency is unmotivated: if everyone feels to be unique but that other patients may not be unique, the actual concept and reliability of the self-assessed degree of uniqueness is again questioned.

Another important factor, cited in the work of Morewedge (2022) and analysed in depth by Logg et al. (2019) is the relevance of expertise in the activity, and thus the social distance from it. Specifically, conducting several experiments, they found that experienced professionals in a specific field, for example forecasters, rely less on algorithm-based forecasts and prefer to use their own analysis. This might be pushed both by an aversion motivated by technical reasons (professionals are aware of the limitations of algorithms in their field and know how to overcome them) or by a sort of refute of machines depending on a fear-like emotion (they are scared that machines can substitute them) or cognitive dissonance (if machines perform better than me then I would be useless; because I do not feel useless it means that machines' performances must have some drawbacks). Determining the real reason underlying this effect is fundamental because it would have serious implications on the use of big data and, in our domain of interest, on the possibilities of cooperation between Robo-Advisors and human advisors. If we look at the experience of the service provider with the eyes of the service recipient another interesting tendency is revealed: Madhaven & Weigmann (2007) found that when they asked people to choose between experienced human agents and consolidated and largely used algorithms, respondents said that they would prefer the human agent. On the contrary, when they compared novice human agents and machines framed as "new" in the corresponding field, most subjects preferred to rely on the results of the machine.

The weight given to the mistakes of robots is another key element that must be considered. We might think that individuals weight mistakes equally when made by algorithms or by humans. But this is not true. Research by Dietvorst et al. (2015) proved that people lose confidence more quickly in machines than in human beings when they observe them making the same mistake. This finding is crucial, especially in fields where the definition of mistake is not clear like financial advisory. How can we give a definition of mistake in a context where the outcomes are not predictable *a priori*. For example, a negative performance of a portfolio cannot be considered a mistake and the same holds in the case of several negative performances. This tendency to overweight algorithms mistakes could probably by determined by the higher expectations that we pose on machines' performances. And this is not completely unreasonable: machines exist with the aim of providing the humankind with a way of obtaining near-perfect and efficient solutions to mechanical tasks or high-demanding computational problems. While algorithms are still far from being perfect, it is a common opinion that their outcomes should be, in a certain way, superior and this constitutes a possible explanation of this mistake-overweighting effect.

The last group of factors that we need to consider is represented by socio-demographic variables like gender, age, and level of education. Exploiting the literature review on this topic by Mahmud et al. (2022) we might obtain some interesting insights. Educational level affects algorithm aversion positively: people that are more educated tend to give more credit to decision taken by robots. On the contrary, less educated people, and in particular those who declared to feel uncomfortable with numbers, tend to be more sceptical and pose less trust in algorithms (Thurman, et al., 2019). Regarding gender, several studies in various fields (e.g., health, justice) have found that females are less interested in recommendations generated by algorithms (Araujo, et al., 2020). However, in other fields of analysis, this gender discrepancy disappears (Workman, 2005). Last but not least, regarding age, research found different results, depending on the context. In particular, on one hand, older people perceive algorithmic decisions as less useful and they consequently pose less trust in them (Lourenco, et al., 2020). On the other hand, when older people had to choose between their own decisions and decisions made by machines, they relied more on the latter (Ho, et al., 2005). Younger people, on the contrary, showed the exact opposite behaviour, posing a high degree of reliance in machines, but preferring their own decisions to external algorithmic suggestions.

3.4. What else can (and will) facilitate the adoption of Robo-Advisory solutions?

We discussed the various factors that may reduce the intention of investors to adopt Robo-Advisory solutions. Trying not to be redundant, in this section we will only explore factors that possibly can facilitate Robo-Advisory adoption, excluding those that have been considered as obstacles in the previous sections. Of course, to facilitate the diffusion of this way of delivering advisory services, the idea would be to work on the factors that we cited as obstacles (social distance, excessive standardization, etc.), aiming at reducing their negative impact. In this section, a different perspective will be taken and other factors that can (and, hopefully, will in the recent future) boost Robo-Advisory adoption will be investigated.

3.4.1. Anthropomorphising Robo-Advisors

We explored in the previous section one of the main critiques that Robo-Advisors receive: the lack of human touch and the complete de-humanization of the service. While the first Robo-Advisors were quite basic and consisted mainly in recommendations generated on the basis of answers to one-way non-interactive questionnaires, recently, the newer platforms started including chatbots that can dialogue and create an interactive environment, increasing the involvement degree of the customer. Moreover, many services that use chatbots, including Robo-Advisors, often integrate this by giving the bot a real identity and personality, including a name, a specific voice, catchphrases and sometimes even a physical-virtual appearance. This phenomenon can be called "anthropomorphism", that we may define more specifically as "attributing capacities that people tend to think of as distinctly human to nonhuman agents" (Waytz, et al., 2014, p. 221). Anthropomorphism can be applied to a multitude of entities – robots, deities, animals, nature forces and so on – but our focus will be on anthropomorphising machines. In the context of anthropomorphising robots, each different feature has a different impact on the intention of clients to adopt Robo-Advisory services and delegate decisions. Specifically, humanising automated services and Artificial Intelligences has been proven to have positive effects on the acceptance of some services. Anyway, currently, few studies have confronted the problem directly in the field of Robo-Advisors and more in general regarding the provision of financial advice (Hodge, et al., 2021) and the question on whether some features actually can increase the positive feelings and acceptance of this new technology remains open. For example, Back et al. (2021) analysed the effect of anthropomorphising Robo-Advisors on the disposition effect of investors. While they found that, as confirmed by previous research, Robo-Advisors in general help clients mitigating the negative outcomes of the disposition effect, they also found that giving human features to Robo-Advisors has two indirect consequences that offset each other: in their experiments, anthropomorphising the system lead to an increase in the socialness towards the machine and thus the propensity to follow the recommendations once provided, but at the same time reduced the willingness of individuals to seek in the first place such recommendations. In another study, Morana et al. (2020) found that anthropomorphism has no direct influence on the willingness to follow recommendations of Robo-Advisors but at the same time it may have an indirect influence on this, via influencing the general trust level towards Robo-Advisors. These findings constitute only the starting point of a future series of necessary studies on the impact of this features on the demand of Robo-Advisory services: because many providers are now integrating their robotic advisors with human characteristics, determining whether this has a positive effect or not is fundamental for the correct and prosperous development of this market.

In the following paragraphs we will go through the main features that typically are used to increase machines' human-likeness (name, voice, physical appearance) and for each one we will discuss the main implications and briefly analyse the existing literature.

Naming your Robo-Advisor

Persuasion theories say that when an advisor provides his/her name and other personal information, the clients perceive him/her as more trustworthy and then they are more inclined to follow the recommendations obtained. Some studies suggest that naming an Artificial Intelligence – and more in general a bot – increases the perceived degree of humanlike appearance (LaFrance, 2014) and leads to an increase in the positive feelings of users towards the technology (Burgoon, et al., 2000). We might suppose that this should apply also to automated financial advice providing. Mixed evidence on this topic actually exists. Some studies have analysed, indeed, that naming a technology can help people to perceive it as more trustworthy and thus start to rely on its performances more frequently. This might of course be true but other, undesired, effects can result from humanising a technology. Riegelsberger et al. (2005), indeed, argued that naming a technology will result in an increase in the perceived trustworthiness but at the same time will give the impression that the machine is less complex and thus less able to perform complex tasks. This might have some dangerous consequences, as we said that the perceived capacity to manage complex tasks strongly influences the level of trust in automation. Specifically, the effect of naming the Robo-Advisor has been tested by Hodge et al. (2021) conducting two different experiments on a pool of 108 MBA students, comparing named and unnamed human and robotic advisors. Specifically, in the first experiment they proved that the subjects were more willing to rely on human advisors when they know their personal information (in this case the name) but conversely were more likely to rely on recommendations provided by unnamed Robo-Advisors, highlighting a negative effect of humanisation. In the second experiment they furtherly confirmed the cited findings of Riegelsberger et al. (2005), finding that participants were more likely to rely on the named Robo-Advisor when they needed to perform a simple task and more likely to rely on the unnamed machine for more complex activities. According to the mixed results obtained by research, naming Robo-Advisors will result in a variable effect on the willingness of delegating decisions to it, that depends also on the perceived complexity of the decision at issue.

Voice of the Robo-Advisor

Some Artificial Intelligences that interact with users providing information and assistance based on Natural Language Processing (NPL), substitute and/or integrate the classical chat-based dialogue with proper vocal interaction. Everyday examples of this are represented by vocal assistants of many smartphones (e.g., Siri, Cortana, etc.) and house assistants like Amazon Alexa. They can interact with the user without the need of typing or clicking buttons, but just based on vocal inputs. Compared to written chat-based interaction, vocal interaction is often considered as more natural because of its more sequential processing, more colloquial tone and language (Dennis, et al., 2008) and absence of the unnatural pauses typical of written communication (Rubin, et al., 2000).

The tendency of providing robots with voices exists in many fields, including Robo-Advisory, but is fully established and completely accepted only in certain specific contexts (smartphones and home assistants). For sure we may imagine that, if just the fact of naming a machine can become a powerful tool to increase its perceived human-likeness, providing it with its own voice will have only better outcomes; anyway, the indirect and non-intended consequences must be analysed before deciding whether to equip your robot with a voice. Again, many findings confirm that benefits resulting from vocal interaction regard (and decrease) mainly the social distance of an individual from the robots, increasing the perceived trustworthiness of the machine, increasing behavioural intentions. Specifically, Chèrif & Lemoine (2019) compared the impact of human voices vs. robotic voices: they found that robots with human voices gave a stronger impression of social presence than robots with synthetic voices. Moreover, they also proved that human voices help the trust-building process between individuals and machines. Anyway, the experiments by Chèrif and Lemoine (2019) were conducted considering virtual vocal assistants. Virtual vocal assistants like Alexa and Siri are different in a key aspect from other kinds of automated assitants (like Robo-Advisors): they can be seen as a sort of shortcut to activities that can be performed successfully by the individual. For example, when I ask to my smarphone's virtual assitance to find a restaurant near me, I'm just using it to facilitate my work or because I cannot type directly with my hands at the moment: indeed, I would be completely able to type that by myself on any search engine and find the information desired. The same holds for most activities performed by home assitants like setting a timer, opening/closing windows, reproducing some music, etc.. These activites are less complex than obtaining customer assitance from a company or receiving financial advice. On the function and characteristic of vocal interaction in general wide research exist, in particular addressing voice design and the structure of the vocal interacation (to have a more precise view see the literature review on the topic realized by Schmitt et al., 2021) but, to the best of our knowledge, few to no studies have analysed directly whether the complexity effect discussed in the previous paragraph (and also the other features of voice) may play a role also for voice-provided robots in the field of Robo-Advisory, while it is true that vocalized automated financial advisory is starting to diffuse. Hildebrand & Bergner (2021), for instance, analysed how conversational Robo-Advisors can alter positively the perfection of trust, the feeling towards the service and the financial decision making process, but they considered a text-based interaction where the phrases used and answers provided by the Robo-Advisors were more informal and the interaction was substantially dialogue based. Also the cited research by Morana et al. (2020), analysed various types of anthropomorphised robotic advisors, each one with an increasing degree of anthropomorphisation but they argued that one main limitation of their study was based on the fact that the taks that had to be performed by the Robo-Advisors of their experiments had a low degree of complexity. Morover, in line with other scholars (see for example also Hodge et al., 2021, p. 784) they suggested that more research on the effect of conversational user interfaces has to be done, in particular regarding, for example, voice-based conversational agents. The nearest contribution to our analysis would be the one from Kim et al. (2020) that analysed the effect of different kinds of anthropomorphism (e.g., visual, uditive, etc.) and found that only the visual anthropomorphism can have an effect on the propensity to continue to use a certain Robo-Advisor. Anyway, specific and extensive research about the role of voice still needs to be produced.

Giving physical appearance to Robo-Advisors: avatars

The most recent innovation frontier in the field of humanizing machines is represented by the tendency of giving them a face or even, in some cases, a complete physical appearance (facial expressions, simulated body language, gestures and identification marks). All these features are combined to form an avatar. First of all, an avatar can be defined as "the physical representation of the self in virtual reality" (Castronova, 2003, p. 3) where the self becomes, in our context, the personified Robo-Advisor. Providing a virtual entity with an avatar can be considered as a high degree of anthropomorphisation because here most of the features coexist: avatars often have, beyond a physical appearance, a name, specific catchphrases and sometimes they can even interact vocally. Various studies have observed how human-like embodiment through avatars can influence trust significantly and contribute to creating social bonds with the virtual agents (Qiu & Benbasat, 2009). Specifically, in economic contexts we find, among the others, the study by Holzwarth et al. (2006) that found a positive effect of the avatar on websites of companies, that can increase the pleasure to use the website and the attitude towards the product, with this resulting in a higher purchase intention behaviour. Moreover, differently from what we said for vocal interaction, many studies addressed the possible effects of equipping your Robo-Advisors with an avatar. The cited contribution from Kim et al. (2020), proved for instance that only this kind of anthropomorphism (visual anthropomorphism) can increase the level of propensity to continue using the Robo-Advisor. Martin et al. (2019) investigated the role of anthropomorphism by using an avatar-provided Robo-Advisor and found a significant effect of this kind of humanization on the overall investment volumes and found aso that avatars can indirectly increase the volumes via their direct effect on the perceived social presence. Last but not least, relevant results have been achieved by Ganbold et al. (2022) that found that using avatars can significantly reduce the overall level of algorithm aversion – with this resulting in significant benefits on the intention to utilize Robo-Advisory – and, depending on the facial appearance of the avatar, can also enhance reliance on the advice provided by the automated advisor. Specifically, the latter effect was more evident and pronounced when the avatar's face and other characteristics exhibited a higher level of competence.

3.4.2. The degree of financial and technological literacy

We briefly mentioned the direct impact of financial literacy on the intention to use financial advisory (robotic and human) services. Anyway, we believe that financial and technological literacy might have also indirect impacts on our matter. Regarding the latter, we should imagine that a higher degree of technological literacy, will positively influence the perceived familiarity with automated services and thus increase the level of trust in automation. Moreover, understanding and knowing the potentialities of technology can possibly limit the negative effects of algorithm aversion and, transitively, boost again the level of trust in the automated process. Understanding the functioning of those algorithms can also help clients to correctly evaluate the risks related to the usage of specific technologies and avoid overestimation of such risks (Alexander et al., 2018; Prahl & Von Swol, 2017).

Anyway, Burton et al. (2019) argue that technological and algorithmic literacy would have a limited impact because most studies that prove the existence of algorithmic aversion are conducted on university students that are presumably quite informed and familiar with such topics. On the other hand, the effect of technological literacy on the adoption of Robo-Advisors and similar services has only few to no analysis and we may suppose technological literacy to have a stronger effect on those coming from older generations. Last but not least, technological literacy, may help to have a more correct image of how machines evolve and perform. Reich et al. (2022), deepening the cited research by Dietvorst et al. (2015) on the role played by machines errors on the degree of algorithm aversion, found that consumers are often reluctant in adopting algorithm-based services also because they think that machines cannot improve their behaviour and correct their mistakes, while this is not the case. Specifically, they sustain the fact that by highlighting machines' ability to learn, this tendency can be reduced; this, of course, can also be achieved by increasing the general level of technological literacy and general education of individuals.

On the other hand, regarding financial literacy, we already discussed the mixed direct effect that it might have on Robo-Advisory acceptance. Scholars analysed anyway the indirect effects of this variable. Specifically, Litterscheidt & Streich (2020) studied the effect of financial education interventions on the intention and propensity of individuals to delegate to a Robo-Advisors (and more in general, a digital asset management tool) their own financial decision-making process. They found that financial education (and though also specific interventions) increases the willingness to delegate financial decisions to Robo-Advisors. The main explanation might be related to the fact that through education, individuals become more aware of the principles of financial investing and, understanding the complexity of the decision, they understand that a correct and well-built financial strategy can be extremely beneficial and thus start to demand more advisory services (and thus also more Robo-Advisory services). Robo-Advisory adoption on its own is boosted by the fact that education also increases the understanding of the main rules on which the algorithms are based, with this having a powerful positive role in reducing algorithm aversion (Dietvorst, et al., 2015). Moreover, through financial education clients become more aware of the existence and functioning of financial technologies: pairing this with the cited understanding of the complexity of the decision, algorithms become a powerful solution in the eyes of educated investors (Litterscheidt & Streich, 2020).

3.4.3. Regulatory advancements

Regulation can have a significant impact on innovation. Well-designed regulation helps services to diffuse, creating an adequate environment that can allow them to proliferate (Pelkmans & Renda, 2014). In particular, by removing and imposing entry barriers, for example, regulators can ensure efficiency and stability of industries. Moreover, regulation must ensure the presence of an adequate degree of protection for clients, that will consequently feel safer and thus will be more incline to exploit the regulated services and products. The dark side of the matter, on the other hand, is represented by the fact that an excessively strict and severe regulation does not allow industries to grow peacefully, reducing opportunities of improvement and discouraging new industries from entering the market. This has been for decades (and it still is nowadays) a major issue in the financial industry. The fast pace with which financial services are developing constitutes an important challenge for regulators that need to address timely but adequately the duty of disciplining new trends and technologies. Regarding Robo-Advisors, as we said before, there is no specific regulation, but rather some guidelines on their structuring and functioning, paired with various informative reports that aim at making customers aware of risks and potentialities of these services. In the next year, when Robo-Advisors will gain more popularity and diffusion, probably we can expect legislators to produce ad-hoc regulation that will precisely and scrupulously address the various issues specifically related to the usage of Robo-Advisory services (cybersecurity, responsibility in case of misconduct and errors, data privacy, etc.). Proper regulation will be, indeed, a fundamental factor conditioning the success of Robo-Advisors (World Bank, 2019): when clients will feel completely and adequately protected their level of trust toward Robo-Advisors will grow relevantly and we should expect the industry to proliferate quicklier. Moreover, scholars are convinced that also policymakers will benefit from introducing more transparency, appropriateness, and good practice standards also for Robo-Advisors (Baker & Dellaert, 2018).

In the next and last chapter of the first part of the thesis, we will discuss, in light of the existing literature, the various possibilities of cooperation and substitution between human advisors and Robo-Advisors and revise theories and ideas proposed by scholars.

CHAPTER 4: CONFLICT AND COOPERATION BETWEEN ROBO-ADVISORS AND HUMAN ADVISORS: A LITERATURE REVIEW

The last chapter of the first part of this thesis contains a brief review of the existing literature about the cooperation and conflict between human and robotic advisors. The idea is to summarize the main findings and theories of all the previous research on the topic to constitute a solid theoretical base on which we can successively build our experimental discussion. Scholars have historically been divided between those who theorize a future substitution effect between traditional and robotic advisory, considering the force of the progress as too disruptive and strong, and those who support the idea of a cooperation scenario, where the machine operates as a calculator of optimal portfolios and data collector and the human advisor continues to cover the role of behavioural and financial counsellor, rather than the old role of financial planner. To be fair, more recently, the great majority of research started to agree on the latter occurrence, where a future cooperation of the two kinds of advisors is hypothesized. Anyway, our intention is to review both the older and newer literature on the topic to give a complete view of the current environment and on how it developed.

Specifically, the chapter is divided in three sections: the first one gives an overview of the papers addressing and discussing the possible substitution effect between the two types of advisory. The second section explores the current (and more recent) literature that analyses the possible cooperation frontiers. The chapter concludes with some general remarks about the reviewed literature and introduces the second part of the thesis.

4.1. Is Robo-Advisory a threat for human advisors? Robo-Advisory as a substitute to human financial advisory

We all have heard at least once the phrase: “at a certain point, technology and Artificial Intelligences will replace us completely”. While we do not want to express any opinion on the long-term consequences and reliability of this phrase, we should take into account the fact that in the last years many jobs and works ceased their existence because of technological developments. And this is a thing that is as old as humanity. For example, back in the XIX and XX century, the “knocker-up” was “a person whose job was to go from house to house in the early morning and wake up workers by tapping on the bedroom window with a long pole” (Pospelova, et al., 2021, p. 2). At the time, alarm clocks were not reliable nor cheap but, as soon as they improved and became more available, these professionals completely disappeared. Through history we may find a huge variety of examples. Technological innovation and replacement of sub-optimal mechanisms are concepts strictly related one to each other and embedded in the human nature: we might interpret this as a sort of efficiency oriented “Darwinistic” tendency. Indeed, when an activity can be performed by a machine, obtaining the exact same (or even better) results and maybe while even reducing costs, there is no reason – other than ethical and moral considerations – to stick to human performances.

Anyway, the matter is different when the performances of robots cannot perfectly match human-based outcomes or can improve just certain aspects reducing performances on other sides. This is exactly the case of Robo-Advisors. In this sense, the trade-off between the extreme cost-efficiency (and computational power) of robots and the refined and highly adaptive – while less efficient – performances of humans may become a central issue. As we said in the introduction to this chapter, part the older literature and some isolated papers support the idea of a substitution effect between human advisors and Robo-Advisors. For example, Tokic (2018) analysed BlackRock's Robo-Advisor 4.0 and its potential to replace the human intervention in financial decision-making. The Robo-Adivosor 4.0 was at the time the most advanced example of usage of Artificial Intelligence in financial advisory. Compared to predecessors, the new Robo-Advisors had significant improvements: it could easily perform various kinds of activities, like enhanced information processing and fundamental investing. As argued by Tokic (2018) after observing and analysing the structures of this system, the robot was able to carry out complex analysis using top-down and bottom-up valuation approaches. Moreover, it could autonomously perform SWOT (strengths, weaknesses, opportunities, threats) analysis of firms, it could be used and modified for capital budgeting purposes and even to compute the estimated net present value of capital investment projects. While this Robo-Advisor needs to be considered as a different kind of advisor whit respect to the ones that we have been majorly discussing, it represented one of the first attempts to fully substitute the human discretionary decision making, tendency that can easily spread to other industries. Anyway, again, we should note that the paper focuses mostly on the practical and performance-oriented aspects but does not treat extensively other limitations of robotic advice. Brenner and Meyll (2020) investigated the relationship between the adoption of automated advisory and the potential reduction in the demand for traditional financial services. Using representative data from the 2015 National Financial Capability Investor Survey (NFCS-IS) they analysed the matter and found a strong negative correlation between the demands of the two services and showed how this effect was even stronger for those investors particularly worried about investment frauds and conflicts of interest. Anyway, they also argue that, independently from the findings, banks and other firms should continue in their effort to provide trust-based high-quality advisory services (regardless of the current advising method) to lead the financial industry to finally reach the perfect complement between human and robotic advisor. This last reminder highlights how, while the substitution effect exists and might in some cases negatively influence the demand of traditional advisory services, the integration of the two advisory systems may result in a powerful arrow in the quiver of banks and advisory firms to gain substantial improvements in the provision of advisory services. Also, Terlit and Scholz (2018) argued that, while a complete substitution seems unplausible at the current state of the art of Robo-Advisors, if and when they evolve, their existence will severely hinder the competitiveness of traditional advisors. Uhl and Rohner (2019) share the same view. They estimated and compared the costs and performances of Robo-Advisors vs. traditional advisors on three different levels of analysis: rebalancing and access of a passive investment strategy, efficient implementation of diversified asset allocation, and management of psychological biases. They verified how Robo-Advisors result superior in all three levels and argue that this cost efficiency will, in the long-term, become determinant for the demand of advisory services. Chia (2019) analysed the recent introduction of Deep Learning (DL) techniques in the field of Robo-Advisory: He focuses, in particular, on the possible risks and potentialities of deep-learning-based Robo-Advisors and argues that while, on one hand, they might be seen as a perfect solution and as a substitute for human advisors because of their immunity from any kind of conflict or greedy intention and also thanks to their enormous computational capabilities, they might, on the other hand, pose some non-trivial challenges from the point of view of regulation. Deep learning processes, indeed, are always seen as a "black box" in the domains of information technology and artificial intelligence, with an opaque decision-making process that can be hardly monitored and controlled even by those who developed it (Chia, 2019).

Research has also focused on specific factors, users, and aspects for which Robo-Advisors might be able to replace humans. Krahnhof and Au (2020) investigated the role of Robo-Advisors in the German banking market by analysing data of a quantitative database and by conducting semi-structured expert interviews: Exploiting their findings, they argue that Robo-Advisors represent a powerful instrument that can replace traditional advisors by providing a cost-efficient and digitalized – thus more accessible and inclusive – solution to customers. On the other hand, they also notice that Robo-Advisors have currently a non-ignorable number of limitations and that, even though technological improvement will progressively contribute to reduce the potential disadvantages of Robo-Advisors, experts support the idea that due to their standardized nature (together with the issues related to the completed absence of sympathy) they will never be able to fully replace human advisors. This substitution effect might also be more relevant for younger investors: because of their more limited availability of funds to invest and thanks to their higher level of technological savviness, young people tend to be more interested in robotic financial advisory (Fisch, et al., 2019). Also, younger individuals might be less interested in the other behavioural and psychological benefits that can be obtained through human financial advisors – while we should note that this largely depends on their life stage rather than their age – and this is caused probably by the diffused distrust of young people towards traditional financial institutions (Nourallah & Ohman, 2021), and also because of the ease with which they can access financial education through digital platforms. Anyway, regarding this topic, few studies have analysed in depth the differences between what young people look for when they decide to hire (or not to hire) a financial advisor and what older people desire.

Also, other authors analysed the possible substitution between human advisors and Robo-Advisors but most of them, in the end, argued that a substitution between robots and human is still far from being a real threat and evidenced the main factors on which human advisors will not be substituted and the main deficiencies of Robo-Advisors. Apart from the contribution of Fein (2015), that we extensively discussed in the previous chapters, we might find various examples. O'Mary (2017), for instance, argued that Robo-Advisors lack the "complete view" of the situation and while they might be a powerful solution to boost the investment activity, they will never substitute experience and the "solid understanding of the big picture" (O'Mary, 2017, p. 2) that only humans can have. Wong (2021) analysed in a short paper the main factors in which Robo-Advisors can replace and overperform humans. The author specifically argues that, while the debate on which kind of advisory should be preferred strongly depends on socio-demographic characteristics of the evaluator and on his/her financial condition, robotic advisory cannot perfectly replicate the activity of the human advisor and thus will never become the unique solution. Also, Zhang et al. (2021) conducted three experiments to investigate the differences in consumer's perceptions of Robo-Advisory. Their results suggested that consumers tend, in general, to prefer human experienced advisors to Robo-Advisors, with this furtherly supporting the idea that a substitution between the two kind of advisory is unlikely to happen. Last but not least, we may cite the contribution of Metzler et al. (2022), that states how customer needs cannot be perfectly satisfied by using only automated advisory services: conducting a case study across US Robo-Advisory firms, they provide support for the hypothesis. In general, most of the scholars that argue that a complete substitution effect is unplausible, always cite the possibility of having a hybrid service, where human advisors exploit the computational power of machines to deliver extra value to clients and to limit the potential costs related to the service.

4.2. Human-Machine cooperation: Robo-Advisors as a complement to human financial advisors

Recent frontiers of innovation in the field of Robo-Advisory consist in the usage of human advisors and Robo-Advisors not as alternatives but rather as two complements that can provide a complete and client-oriented service. Scholars have been theorizing this sort of cooperation between robots and machines in the field of financial advisory for a few years now and have explored various ways in which this hybrid service could be offered to clients. Intention of this section is to briefly review such literature and provide an overview of this phenomenon of cooperation.

One of the oldest studies addressing the cooperation between robots and human in the context of financial advice is the one by Singh & Kaur (2017). They developed their argument with a theoretical discussion, gathering opinions and conclusions of many scholars and financial industry professionals from conferences, journals, articles on periodicals and books and summarized the state of the art of Robo-Advisors for the time, highlighting limitations and potentialities. Specifically, among the limitations they listed substantially what we discussed in *Chapter 3*, but focusing in particular on the fact that they fail to provide personal assistance and guidance and fail to assist investors on non-monetary matters. While the do not directly express an opinion on the matter, they report how some firms were starting at the time to introduce these Robo-Advisors in hybrid models, where human advisors were paired with these algorithms that could enhance their performances. Moreover, in the conclusion of the cited paper, Robo-Advisors are depicted as “a valuable complementary resource to investors” (Singh & Kaur, 2017, p. 41). In the same year, Dimitrios et al. (2017) analysed the impact of robots on the wealth management industry (a scope a bit broader than financial advisory on its own, but still relevant). Again, with a theoretical discussion and analysis, they investigated in particular the frontiers of cooperation between robots and humans: they argue the diffused idea of the necessity of a choice between one of the two models of advisory and pose the attention on hybrid advisory, as a solution in which machine capabilities are merged with human’s sympathy and ability to manage complex emotional situations to increase the total value delivered to customers. Indeed, they discuss the fact that the core of the advisory is (and must be) in most cases the trust-based human relationship between advisor and advisee, but that machines can surely be determinant in the analysis of portfolios and in the effort and cost reduction of both providers of the service and receivers. What is their main conclusion is substantially that cooperation, in the form of hybrid models, would help to reach all kinds of customers and to provide a complete service. The tendency to prefer hybrid models is confirmed also by some marketing studies conducted by MyPrivateBanking (2017) and Business Insider (2017) that revealed how people show a nice degree of openness to Robo-Advisory solutions but remain reluctant to accept the full automated model. The two insights evidenced how investors are still needing human confrontation, and this becomes particularly relevant in moments of crisis where a high degree of uncertainty exists, and people are worried about their financial situation’s stability. Indeed, as explained by Jung et al. (2018), Robo-Advisory should not be seen as a threat to human advisory and to those clients that need in-person assistance, but rather, represents a great service-enhancement opportunity both for clients and businesses.

Jung et al. (2018) tried also to develop some principles and rules to build a Robo-Advisor specifically for those who are more risk-averse and have limited funds. They conducted a study by analysing available data and by collecting new data on a pool of through various methods (questionnaires, interviews, click-stream analysis, and screen recording) and found that most of the subjects analysed declared that they would in conclusion invest through Robo-Advisors but only after speaking – one or more times – with a human advisor that could convince them about the trustworthiness of the institution and of the service. In their study, social presence of robots was found, indeed, as an important factor that can reduce (but not eliminate) the need for prior human confrontation. Risk-averse customers, they conclude, might not be the adapt kind of consumers to start with first-time automated investing, for the high relevance that they pose on trustworthiness: for this reason, they advise banks and institutions to develop hybrid plans that begin with the interaction with a human advisor and then progressively introduce and integrate the Robo-Advisor. Otherwise, they argue, "these customers are likely to prefer the status quo, either investing nothing or relying on [pure] human advisory" (Jung, et al., 2018, p. 378). The opinions of experts of the industry were also gathered by Coombs & Redman (2018): they conducted exploratory research on the possible interaction of human advisors and robots, with a substantially qualitative approach. They conducted structured interviews on five advisors form WealthCo. They explored in depth the features of their services, starting by asking to describe the first interactions with clients and then progressively introducing the idea of a supportive platform and robotic advice. Collecting and interpreting the answers of the interviewed subjects they concluded that automated advisory is more likely to enhance the service provided by human advisors, rather than substituting it.

More recently, scholars started focusing directly on the reasons that push people to choose one or the other kind of advisory (or a combination of the two). Waliszewski & Zieba-Szklarska (2020), to this purpose, repeated the SWOT analysis of Robo-Advisors, obtaining similar, but renewed, conclusions to the ones of Jung et al. (2018). Moreover, analysing data provided by a study on Robo-Advisory acceptance conducted by Wells Fargo/Gallup (2016) on US investors, they concluded that, because of the fact that while Robo-Advisors are perceived mostly as a way to save money and obtain assistance by paying lower fees, the hybrid models remain the more realistic ones. On this conclusion agrees also Merkle (2020) that argues that hybrid advisory is the future of delegated investments. To sustain this thesis, he avers that, while the potentialities of robots in financial advisory are undoubted, Robo-Advisors lack some of the fundamental characteristics that people look for in financial advisors; he also cites recent studies to show how the human touch is highly valued by younger generations, like millennials, implying that the effect will not disappear just by the passage of time. Anyway, we should note that this last argument has still to be verified for newer generations, because of the lack of data and because of the (still) scarce interest shown by the older components of the most tech-savvy generation, Generation Z. Indeed, the development of technology and the new globalized and interconnected environment in which components of Generation Z are growing is likely to have a strong impact, significantly increasing the differences between them and the previous generation's components and thus possibly changing the studied paradigms of human-machine interaction acceptance. Ruhr (2020) conducted another interesting study, by collecting data from a survey conducted on 148 university students. One of the main contributions of the paper is to prove that the effect of the degree of automation of the service on the intention to use a Robo-Advisor follows an inverse U-shaped curve, meaning that it increases gradually until it reaches a peak and then starts dropping. As argued, in the paper, this point towards the usage of hybrid Robo-Advisory models, where automation is present but still supervised and accompanied by a human being.

Looking from the perspective of institutions providing the service, Beketov et al. (2018) analysed the matter from a different perspective: the methods used to build portfolios and manage wealth. This contribution is interesting because poses the attention on the possibility of substitution of old methods (like the well-known mean-variance framework) with newer ones, with important computational needs. Analysing more than 200 existing Robo-Advisors they found that substantially the methods of the robots, at the time, did not contemplate a pure substitution of the "old" methods but rather augmented them, by means of allowing a higher number of data to be managed simultaneously. On the other hand, they argue, robots have the capability to employ new, more precise, and more "solid" approaches, enhancing again the activity of the human advisor, but not substituting him. To be fair, from the point of view of the advisors and wealth managers, one of the first studies to analyse the possibilities of integration between traditional human advisors and Robo-Advisors is the one by Gauthier et al. (2015). Specifically, they argue that robots in financial management could be beneficial for traditional institutions that had no availability or interest to develop their own Robo-Advisor: indeed, banks could outsource the portfolio building services, so that wealth managers could sell the portfolios of robots (saving time and money) and the robot provider firm could profit monetarily by obtaining shares of the profits obtained selling those portfolios and reputationally, by the interaction with the bank that could expose them to new customers. While we should note that this study was developed in 2015 and that this cooperation between banks and Robo-Advisory firms had also some negative consequences (conflicts of interest, etc.), with proper regulation and monitoring it is clear that the integration of traditional advisors and robotic advisors might be beneficial also for the established, old, traditional institutions.

Research has also analysed the possibility of providing through Robo-Advisors a more complete service, that could range from the simple portfolio building and investment recommendations, to other classes of advice. At the current state of the art, Robo-Advisors are mostly domain-specific, meaning that a specific robotic advisor is designed to address a specific class of problems. For example, Robo-

Advisors that provide recommendations and assistance for retirement saving purposes, are not able to provide assistance on other domains, like mortgage uptake, tax-harvesting, loan management, etc. (D'Acunto & Rossi, 2020). Human advisors, on the other hand, cover exactly this function. With a human advisor, while obtaining recommendations on investments and portfolios, you can easily discuss your financial choices and obtain expert advice. Some scholars tried to investigate the possibilities of developing the so called "holistic" Robo-Advisors, that would represent a revolution in the industry and probably become a powerful and disruptive instrument in the hands of financial institutions. Anyway, as suggested by the two studies by D'Acunto & Rossi (2020) and D'Acunto & Rossi (2021) on the topic, developing and implementing such forms of Robo-Advisory would be extremely complicated and resource consuming and would require wide research on both the theoretical and practical side. Thus, we may consider again, cooperation between robots and humans as a viable solution, where the robot is specialized in a few domains and the human advisor provides support on the other, non-covered domains. Moreover, the presence of a human advisor may help clients to express more precisely their needs, when they do not feel comfortable with the machine, and even override the allocations proposed by the system and turn them into more specific and client-oriented allocations.

4.3. Concluding remarks

While new options and solutions for clients are being continuously theorized and developed, hand in hand with technological advancements, the industry is making huge steps in the direction of offering a broad and inclusive service.

The ideas and theories that we reviewed in this first part of the thesis constitute only the solid ground on which we will build an empirical and experimental analysis. Indeed, a cooperation between robots and humans may surely lead to an optimized and high-quality service, but it would probably have some inevitable drawbacks with respect to pure types of advisory, one for all being a slight increase in costs, motivated by the additional value obtained through the intervention of the human advisor. Even if this extra-cost might appear strongly convenient, given the additional (although non-monetary) return obtained, it might not be suitable (nor affordable) for those with minimal financial availabilities, or for those that are only interested in receiving financial planning assistance, and that are not interested in interacting with a human to obtain psychological and behavioural value. Different models of advisory (pure-human, pure-robot, hybrid) might be suitable, for example, for different categories of investors with different needs and goals. Offering more than one option helps firms and autonomous advisors to differentiate the supply of this service and though reach a broader panorama of clients, even though we still need to keep in mind the well-known trade-off between specialization and differentiation that exists when providing services or offering products.

CHAPTER 5: DEVELOPMENT OF A QUESTIONNAIRE TO TEST RELIANCE ON ROBO-ADVISORS' RECOMMENDATIONS

5.1. Introduction to the study and theoretical considerations

5.1.1. Study introduction

The chapter of the thesis deals with an issue that we treated from the theorical point of view in the previous chapters: reliance on recommendations and utilization of Robo-Advisors. Understanding the determinants and characteristics of this phenomenon is fundamental for the prosperous development of automated advisory services. Indeed, a service that is not utilized, no matter the underlying motives, is fated to disappear quickly. People are not fully rational and will not weight their own mental processes of acceptance or refusal of a service. They will simply decide to use it or not while the market's implicit rules will complete the job by getting rid of non-efficient businesses. The same will presumably happen when the service is used but then the recommendations are not followed: progressively investors will realize this, and will stop using robotic advisory, at least in the scope of its original purpose. Of course, Robo-Advisors, we may suppose, exist to offer a high-quality service, and to broaden the spectrum of individuals that can obtain financial advice. Broadly speaking, we may say that one of the long-run goals of most services is to increase the quality of life of people and reduce some of the social gaps that characterize our society. While this is quite pretentious and, in some ways, "philosophical", at least there is no doubt on the fact that Robo-Advisors are not here to turn into mere information providers for investors.

In this sense, the idea of the empirical study that we include in this dissertation is to develop a questionnaire to test the degree to which people decide to rely on investment recommendations provided by automated advisors. We believe, considering our own experience and basing our opinion also on the cited literature, that many factors may influence the acceptance of robotic advice.

The questionnaire(s) used are available, on request, from the author.

5.1.2. Theoretical considerations and literature review

Various aspects may have an effect on the phenomenon at issue. In the first part of the thesis, we underlined some key findings of scholars about the role of variables like gender, age, education, and wealth. In addition to this, we reviewed the main theories about acceptance of technology and discussed the determinants of trust in automation and algorithm aversion, two fundamental concepts that, for obvious reasons, act as protagonists in our analysis.

To make a brief review, we may start from the variables influencing the usage of advisory services in general. Regarding socio-demographic variables we have discussed how gender makes a difference only for people that have not attained a high level of financial education (deductible from Bucher-Koenen et al., 2017), in the sense that females tend to be more incline to obtain and follow financial recommendations (see for example Hacketal et al., 2012 or Chatterjee & Zahirovic-Herbert, 2010), even though we should note that plenty of literature with mixed results exists on the role of gender (Bhattacharya et al., 2012, found the exact opposite; Hung and Yoong, 2010, found no differences between men and woman), so the debate remains open. This might be motivated by differences in overconfidence (Calcagno & Monticone, 2015), in the level of financial literacy (Lusardi & Mitchell, 2007), and in the level of risk-aversion (Bernasek & Shwiff, 2001). The conclusion that we deducted from Bucher-Koenen et al. (2017) is closely related to this. Indeed, for highly financial educated individuals, no differences in the overall risk-aversion related to gender are exhibited (Hibbert, et al., 2013). Moreover, we should note that at higher ages the discrepancy between males and females in demand of advisory services tends to disappear (Reiter-Gavish, et al., 2021). Along this line, we should consider that the age of a subject plays an important role: older people tend to resort more to their financial advisors when they have to decide on investments (Hackethal, et al., 2012). This might be motivated both by an indirect effect of the higher wealth level (wealthier people use more advisory services according to Collins, 2012), by the fact that they tend to have bigger families (more children and being married increase the demand according to Bertocchi at al., 2011) or by an exogenous independent effect. Also, some literature highlights that gender bias, trusting more the advice coming from an advisor of a specific gender (according to Klein et al., 2021, male advisors are trusted more), and confirmation bias, trusting more recommendations and advisors that confirm the individual's prior beliefs (demonstrated by Cheng, 2019), may also play a role in the ex-post degree of satisfaction with the service.

Concentrating on Robo-Advisory, we reported that the majority of the users is constituted by males (Warchlewska & Waliszewski, 2020). The difference with females disappears only when we consider a pool of highly educated investors (Figà-Talamanca, et al., 2022). Education, in general, reduces the overall level of algorithm aversion (Thurman, et al., 2019). This last consideration is fundamental when we analyse the results of an experimental study because many researchers use mostly university students (sometimes with finance/economics background) as subjects for the experiments, thus we should hypothesize this kind of pools of respondents to be part of the "highly educated" group. Anyway, apart for those that are highly educated, the differences between men and women might be determined both by inner psychological factors (overconfidence, emotional traits, confidence, etc.) but also by what we said about the determinants of algorithm aversion and trust in automation. For example, reviewing the models that describe acceptance of technological innovations by Venkatesh et al. (2003), we saw how females perceive as more important and relevant in their decision the social distance from the innovation and the easiness of use of a new technology. On the contrary, men put more weight on the expectations on the performance of the technology. Age influences for sure the acceptance of the recommendations of Robo-Advisors: while young people, if compared to older people, tend to use more the Robo-Advisory services (with this being possibly motivated by the lower degree of trust in the traditional financial system shown by younger generations) it is also true that they tend to receive the recommendations but then decide on their own. Older people, on the contrary, trust more the traditional human advisors (Lourenco, et al., 2020) but when they decide to use algorithm-based decisional systems they tend to follow the recommendations more than young people, instead of deciding on their own (Ho, et al., 2005). Regarding trust in automation and algorithm aversion determinants, research have shown that younger people pose more importance on the performance expectation and easiness of use, while older people weight more the social presence and by the existence of facilitating conditions for the access to the system. Algorithmic aversion, moreover, is influenced by some additional factors: first of all, the self-assessed uniqueness of the own financial situation – indeed when individuals feel unique with respect to their problems and need assistance, they tend to prefer humans – as demonstrated by Longoni et al. (2019); but also, the perceived importance of personality traits and identity in the activity plays an important role, being negatively correlated with the algorithmic aversion (Morewedge, 2022).

A correct interpretation of the balance of each determinant of acceptance of Robo-Advisory services is fundamental to draw any kind of conclusion on the research idea.

5.2. Description of the research idea and methodology

5.2.1. Research idea

The research idea originates from a study that focuses on the degree of reliance on robotic recommendation of Italian investors, realized by Alemanni et al. (2020). The original research, titled "Do investors rely on robots? Evidence from an experimental study" has been published by Consob in September 2020. Substantially, the idea of the cited paper was to investigate the behaviours and traits that may influence the propensity of people to rely on the advice provided by a robotic entity: they tried to verify, specifically, whether recommendations originated by human advisors were perceived as more reliable than recommendations originated by Robo-Advisors. To do this they realized a five-stage experiment and submitted the survey to 178 students at an Italian university located in Rome. In the first phase of the experiments, the subjects, after reading instructions, were given a hypothetical amount of money, and were asked to invest this sum in one (only one) of six pre-built portfolios, each one with a different risk-return pattern. The portfolios were represented with the distribution of their expected returns, specifying only the average return (M) and the 68%

confidence interval (A and B), with no other attached information about the composition or about the mathematical properties of the distribution, analogously to what is represented in *Figure 5.1.*, taken from the paper at issue.

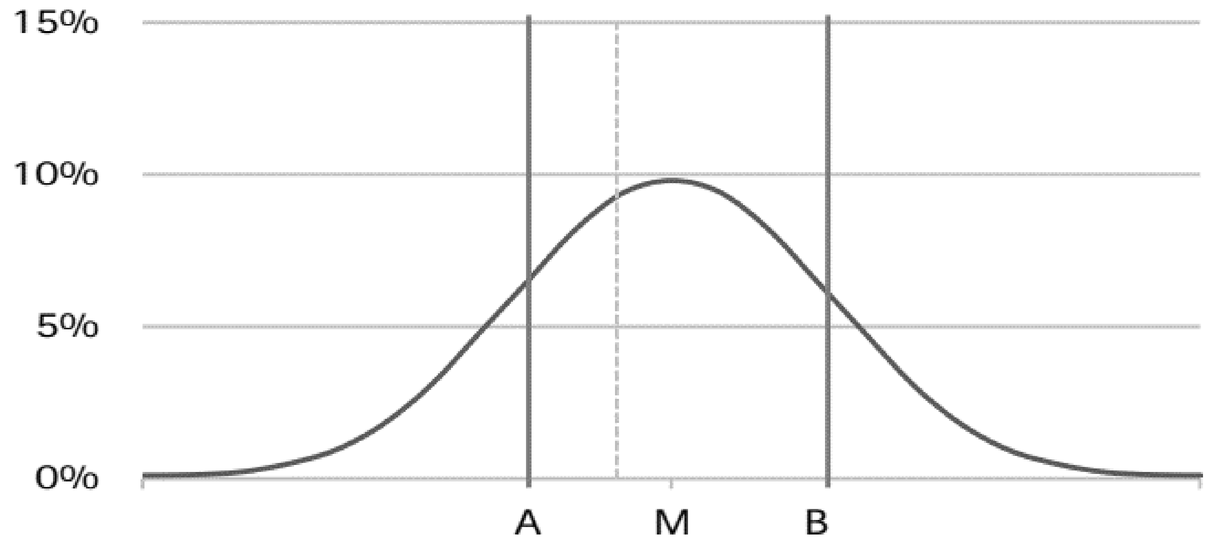

Figure 5.1.: Representation of portfolios in the paper by Alemanni et al. (2020). The dashed line represents the zero return and A and B mark the area of the 68% of the distribution. Source: Alemanni et al. (2020).

After making the initial portfolio choice, each subject filled a risk-assessment questionnaire, composed by the 13 questions of the classical Grable and Lytton’s Risk Tolerance Quiz (2003) and some other questions taken from Robo-Advisor’s risk-assessment questionnaires. Calculating a risk-score based mainly on the answers provided to the Grable and Lytton’s Risk Tolerance Quiz, for each participant the optimal recommendation was elaborated. The second phase of the experiment consisted in receiving an investment recommendation: in a between-subjects experiments, participants were divided in two groups, each one with a different treatment. Participants in the first group had the “Treatment H”, human recommendations, and participants from the other group had “Treatment R", robotic recommendation. Independently from the treatment to which they were assigned, recommendations were formed in the exact same way. Participants undergoing “Treatment H” were seated in an isolated room where a human advisor (randomly male or female) gave them a printed investment recommendation and verbally communicating to them which of the six original portfolios was identified and most suitable and thus recommended. Emphasis should be put on the sentence used that contained the following first-person statement: “On the basis of your risk profile, stemming from your answers in the questionnaire, I elaborated the present recommendation...”. Participants had no possibility to ask clarifications or other information to the human advisor. Participants undergoing the robotic treatment, on the other hand, were seated in a room with a computer that showed a message containing the recommendation. The communication contained the following, this time impersonal, statement: “On the basis of your risk profile, stemming from your answers in the questionnaire, the computer elaborated the present recommendation…". Participants in each group were not aware of the existence of the other treatment. After receiving the recommendation, in the third phase of the experiment, the subjects were seated in front of a computer and had to decide whether they wanted to change their original choice made in Phase 1 or wanted to keep the portfolio originally chosen. After making the choice they had to answer some tasks and other questions to obtain data about their risk attitudes, about the overall level of financial literacy, digital literacy, self-assessed financial literacy, and socio-demographic characteristics. Each participant received a variable payoff, ranging between 0.30€ and 8.5€, randomly determined. The main conclusions that researchers derive from this experimental study are mostly related to what can be called "confirmation bias": they argue that the probability of following the obtained recommendation did not depend on the nature (human vs. robot) of the advisor and neither on their characteristics (male vs. female) but rather on the difference between the recommendation obtained and the initial choice. Between those who received a recommendation that was different from their initial choice, the experiment showed a grater propensity to follow the human recommendation. Just a little influence of the "gender bias" was shown in female investors, that seemed to be more inclined to follow the recommendation of the human advisor when the advisor was a female.

Based on the characteristics of the study we evidenced some key limitations, some of them already highlighted by the authors, that in our view could have shifted slightly the empirical results obtained. First of all, we argue that the questionnaire lacks some key questions and sections that might have been useful for the identification of specific risk-profiles and to gain a better understanding on the reasons underlying each choice. For example, we agree on the choice of representing portfolios only through the distribution of their returns, but we also contest the fact that we cannot know whether investors understood the graphs. While on a pool of highly sophisticated investors we may also consider this question as useless and assume a complete (or at least a sufficient) understanding of the situation, when we use a pool of students and workers with various backgrounds and specializations, we cannot be sure of the correct understanding of the features of the investment. The paper draws some conclusions based on the difference in riskiness between the initial choice and the final choice without anyway verifying whether subjects correctly perceived the riskiness of the portfolio. In this sense, for instance, an investor might have considered "Portfolio 1" to be the riskiest of them all and choose it in line with his "gambler" personality and result completely stunned when the recommendation provided by the advisor contained "Portfolio 6" that, although it was actually the riskier, was probably perceived as the safest. Moreover, while assessment performances of the Grable & Litton Risk Tolerance Quiz (2003) are undoubted, a subjective and self-assessed measure of risk-aversion might have also been useful to test the prior beliefs of participants and to verify whether the differences in the recommendation and initial choice could possibly be motivated by an incorrect perception of own risk-aversion. Another limitation that we detect in the paper is related to the main conclusion of the whole work, the role of "confirmation bias". While, on one hand, confirmation bias is in our view (and in literature) a fundamental factor that needs to be considered, we recognize a limitation in the way used to assess the presence of this cognitive bias. As said, the paper considers the proportion of people that accepted the recommendation because it was equal to their initial choice. We argue that it seems unreasonable, at least for the majority of people, to change our initial preference after receiving confirming feedback from an expert. For instance, suppose that you chose as your initial portfolio, say, "Portfolio 2" because you believe that it represented the most appropriate choice. Then, a financial advisor (robotic or human), after collecting information about your risk-attitude and personality, tells you that your choice is appropriate and that he would have chosen the same portfolio for you. It is hard to believe that a rational individual would then change his mind about the initial choice and select another portfolio. In this sense we propose to add a new measure of satisfaction and future intention to follow recommendations to obtain data also on subjects that obtained a recommendation that matched the original choice. We also notice that, in our opinion, the questions used to gather data about the personality of the individual are quite broad and confusing, even though they are taken from actual Robo-Advisors' questionnaires. In the first part of the thesis, we already discussed both the advantages and disadvantages of such questions: specifically, in this context, we contest the fact that questions like "What would you do if you felt hungry while travelling?" do not perfectly capture the actual personality of the individual. Indeed, answers might be related to the specific context created by the question (e.g., travelling): for example, answering to the reported question, I may decide to enter the first restaurant I see not because I am impulsive or impatient but rather because I just think that it is advisable to travel with full energy. On the contrary, I may decide to buy ingredients in a supermarket and make myself lunch only because I do not want to spend more money on a restaurant meal. While the questions are voluntarily thought in this way because we expect subject to hypothesize a situation and answer based on their emotions and not on the concrete situation, subjects typically struggle to adopt such a behaviour and when they do they answer based on how they want to look rather than on how they really look. The paper, furthermore, does not consider any measure of psychological traits of individuals, for example related to overconfidence. Overconfident people might, indeed, show negative feelings towards recommendations that contradict them, and this might influence the willingness to accept or refute a recommendation. In addition, we argue that digital literacy is assessed using a self-evaluative questionnaire: asking subjects how good they do know some concepts with a Likert-scale is a good starting point, but such a measure is prone to deviations due to miscalibration or overconfidence. We advise for this reason to include some multiple-choice test-like questions to also obtain an objective measure of digital literacy. In conclusion, one of the biggest scopes for improvement of the experiment is that it misses the opportunity to include any form of assessment of individuals' levels of interpersonal trust in general and trust in automation. These factors might be fundamental to sage, in light of what we said about the role of trust both in human advisory (personal trust) and Robo-Advisory (trust in automation). Indeed, some individuals might show a certain behaviour independently from the recommendation obtained and on his/her psychological and socio-demographic characteristics, but just depending on the low degree of interpersonal trust and trust in automation.

The idea of our first research is to replicate the analysis performed in the cited paper, integrating the experiment with new sections, and slightly modifying the approach and the setting of the experiment, trying to work on the various ways to improve the predictive validity of the results. Our aim is not to revolution completely the original experiment, thus we will try to correct only a part of the limitations detected. Anyway, following the conclusions of the paper and considering the reviewed literature, we formulated some *a-priori* research hypotheses. First of all, we expect to confirm the hypothesis of the existence of a confirmation effect (bias) that increases, rather than the propensity to follow the recommendations, the overall immediate satisfaction deriving from the service obtained and thus the perceived quality of the recommendation and the propensity to continue using the service and follow eventual future recommendations:

H1: When subjects receive a recommendation that confirms their initial choice, independently from the appropriateness of such recommendation, they perceive the quality of the recommendation as higher and thus they become also more prone to utilize it in the future.

Anyway, we believe a key determinant of the willingness to use again the Robo-Advisors to be, other than "Confirmation Bias", the level of trust in automation (and eventually the level of trust in general towards professionals delivering services):

H2: The main determinants of the willingness to use Robo-Advisors and accept their recommendations is represented by the level of trust in automation.

Moreover, because of the structure of our experimental setting, we may hypothesize a slightly preference for the more human-like advisor's recommendations. In the following sub-section, we will present the structure of our experiment and the recommendation providing procedure and explain how we will proxy our "human" advisor:

H3: There is a preference for human (human-like) advisor's recommendations and thus an increased probability of rating the quality of the service as high for those who receive it.

Last but not least, with respect to possible gender bias, we believe Robo-Advisors to be a nice way to neutralize any kind of effect and thus we expect to observe no differences between the perceived quality of recommendations coming from male advisors or female advisors.

H4: The gender of the advisor delivering the human (human-like) recommendation has no influence on the perceived quality of the recommendation and nor does the eventual gender correspondence/difference between investor and advisor.

5.2.2. Methodology

Given the scope for improvement offered by the structure of the cited study, we propose a series of new questions and integrations to improve the predictive validity of the experiment. For each additional information that we desired to obtain from the subjects we inserted a new section in the experiment. Depending on the characteristics of the new sections we either used a standardized and largely validated, well-known, approach or we autonomously validated our new features and questions on a pool of university students before implementing them in the final questionnaire. Anyway, before modifying substantially the core structures of the experiment (confirmation bias assessment, gender bias, recommendation providing, etc.) we conducted a pilot experiment with a preliminary version of our (improved) questionnaire on a pool of university students, to verify whether we could find the same conclusions using the same approach. The content of this preliminary version is described in *Subsection 5.3.2.* but, in summary, it substantially reproduced the original questionnaire in the paper by Alemanni et al. (2020) adding the new measures, but without changing the assessment methods. Indeed, before revolutionizing the questionnaire, we wanted to understand the main features and limitations from a more concrete point of view. The idea is to verify whether the main conclusions of the paper may still be valid in the new financial environment and also if the experimental setting may work in the same way on our pool of subjects.

After conducting this pilot test, we improved our validation of the part regarding "trust in automation" and we developed a final set of questions and sections for the experiment. The only key difference between our setting and the original one, lies in the way in which the human advisor's recommendation is delivered: while the original experiment used a physical person to communicate the "human" recommendation, given that we had no availability for physical structures to be used for the experiment, we substituted the physical person with a pre-recorded video that shows a person (not a real financial advisor but a person identified to subjects as a financial advisor) that reads the recommendation. In the concluding results we need to keep this into consideration.

5.3. Experiment structure and development

5.3.1. Introducing new measures: choice and discussion

This sub-section aims at describing how we propose to correct the detected limitations: each limitation was amended either by using a consolidated approach taken from the literature (and thus without validating it) or by introducing new sets of questions. For these new sets of questions, we discuss how we developed or chose them. Specifically, with respect to the analysis of "trust in automation", we utilize an approach proposed in literature (see Körber, 2019) but not sufficiently established yet. For this reason, in the pilot test the 19 questions proposed by the author are all included. Indeed, we should note that the 19 questions of the cited paper were originally used in a different context and thus we ned to verify whether they could be appropriate to employ it also for our purposes. To this purpose, before including them in the final questionnaire, we validated the scale, conducting an Exploratory Factor Analysis on the data obtained to eventually adapt the approach to our context.

Verifying correctness of subjects' perception of the riskiness of portfolios

The first limitation that we noticed is related to the absence of a way of distinguishing between subjects who understood the information about the riskiness of the portfolios and those who did not. Our proposed remedy is quite simple: we can introduce a question in the section testing financial literacy, showing again the distributions of the portfolio's returns, asking subjects to order them from the safest to the riskiest. Because of the structure of the graphs, a logical ordering based just on the shapes of the gaussian curves (visually evaluating the aspect through kurtosis) exists. *Figure 5.2.* shows an example of this fact: given the three graphs, it is pretty intuitive also for someone that is not trained in statistics (or related fields) that the correct order (riskiest to safest) must be either A-B-C or C-B-A, but deciding correctly between these two combinations requires either knowledge or luck. The fact is that unexperienced subjects had no way to determine whether the one with the heaviest tails was the riskiest or the safest. We should presumably expect subjects who cannot distinguish distributions to order them either correctly or completely reversed with an almost equal probability. Though some subjects may have a correct awareness of their risk-preferences but chose the wrong portfolio because they misinterpreted the nature of the portfolios, and thus eventually refute the recommendation. To be fair, because of what we said about the existence of a logical ordering of portfolios, just introducing a single question along the line of "Which of the following portfolios is the riskiest?" may be enough. Again, also asking how subjects perceived the riskiness of the portfolio they chose may be an option, using a phrasing similar to "Do you think that the portfolio you chose is a high-risk, medium-risk, or low-risk portfolio, if compared to the other portfolios you were offered?". Each of the possibilities has pros and cons: we opt for introducing, at least in the preliminary experiment, the question with all the portfolios, asking subjects to order them from the safest to the riskiest. In this way we can insert a more dynamic task in the experiment and use the answers to obtain a proxy of the degree of attention and use of logic of each respondent. Because the new introduction is minimal (even though crucial) and the utilization is pretty straightforward, validation is not necessary.

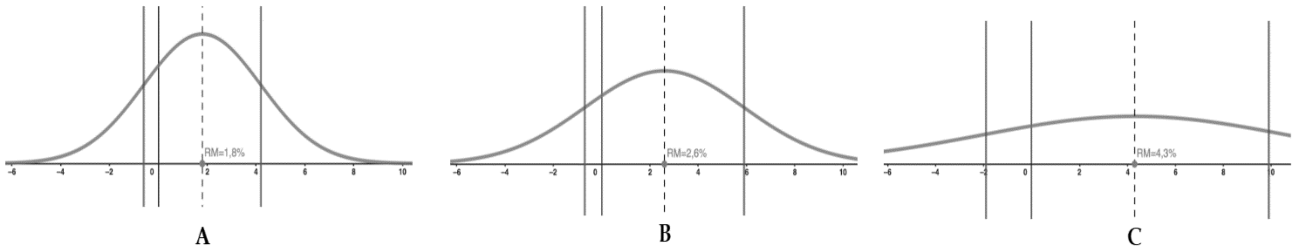

Figure 5.2.: three portfolios that must be ordered from riskiest to safest. It is clear that the correct order is either A-B-C or C-B-A. Source: personal elaboration.

Introducing a measure of self-assessed risk-aversion

We also discussed the convenience of having a question or two that assessed the self-evaluated risk aversion of participants. While this is only a minor limitation, such measures are always useful to gather interesting data about participants. Indeed, if we ask people to evaluate their risk aversion, we might obtain a further explanation of the eventual discrepancies between the initial choice and the recommendation received. Someone that perceives himself/herself as a highly risk-averse person but then answers to the Grable & Lytton Risk Tolerance Quiz (2003) and reveals to be a real risk-lover is a symptom of some cognitive issues in their choices and perception of hum/herself. We propose two questions to verify the self-assessed risk-aversion. The first one should be something like: "When investing, you consider yourself to be risk-averse, risk-neutral or a risk-lover?". This question assesses the risk-aversion of participants when we deal with investments. Anyway, in this regard, we should note that people that answer the questions may have no experience with investments and thus their judgement may reflect unrealistic and hypothetical ideas. The other question is used to obtain information about the general risk-aversion of subjects, independently from the context. We propose something along the line of "In your everyday life you consider yourself to be a real gambler, someone that weights risks and opportunities before making a decision, or someone who avoids risks completely?". This question is quite similar to the first question of the Grable and Lytton Risk Tolerance Quiz (2003) but has a substantial difference of focus. This question regards a self-assessment while the Grable & Lytton's one focuses on an external (best friend's) evaluation of risk (even though many times people tend to answer to this question based on their own self-perception). Anyway, for simplicity purposes, one can even decide to use only the first question and avoid the risk of asking two very similar questions (even though theoretically different). In theory, many different approaches, and not necessarily the ones we propose, can be used to obtain information about the self-assessed risk-aversion of subjects. Anyway, independently from the choice of using one or two questions, using our approach or introducing a personalized set of questions to evaluate the self-assessed risk-aversion, we recommend generating the questionnaire randomizing the order of the two risk-assessment sections to avoid and neutralize any kind of order effect. Specifically, we suggest distributing the questionnaire so that half of the subjects see first the self-assessed risk-tolerance question and then the Grable & Lytton's quiz; the other half should answer first the Grable & Lytton's questions and then self-evaluate risk-aversion.

Analysing confirmation bias

Confirmation bias plays another important role in our experiment. We discussed that people might be more satisfied with an advisory service when it confirms their prior beliefs. Anyway, detecting and testing confirmation bias is not easy: using the measure that is used in the paper has surely a good potential but raises some non-negligible issues. In particular, it is impossible to distinguish those that decided to choose the same portfolio as their initial choice because they trust the recommendation more (confirmation bias) or just because someone confirmed their initial decision and they saw no reason to change their mind. Moreover, we have no way to verify whether the reason underlying the refute of an individual is related to confirmation bias (the recommendation is different and thus I do not accept that) or just to the fact that they believe that the initial choice was better. What we suggest is to ask an additional set of questions. For example, subjects can be asked to evaluate the overall quality of the service received on a scale from, say, 1 to 10. In this way we can compare the median score of those that had a recommendation identical to their initial choice and the median score of those that obtained a different portfolio and obtain a comparable measure of the effect of confirmation bias. Another idea, that can be combined with the proposed Likert-scale, is represented by a question that asks to the respondent whether he/she would be interested in using again a similar system or, anyway, whether he/she may be intentioned to use similar systems in the future. The main drawback of this questions is that subjects may be influenced by the simplified setting of the experiment. We need to remember that everything is simulated, and a highly simplified choice is required to participants: indeed, they might be willing to use again a simple system like the one we presented but if they were in the same situation with a real robotic advisor and with real money, their answers may be different. This is partially confirmed by what we said about the complexity effect on algorithm aversion: when the task required is particularly simple, algorithm aversion is reduced, and this results in an increase in the general level of acceptance of the service. Nonetheless, such an approach may help us obtain interesting insights about the possible role of confirmation bias and allow us to determine its influence more precisely.

Personality traits

We already argued in depth the possible ways to improve the predictive validity of the experiment and enlarge the scope of our analysis in order to obtain more (and more precise) information about the personality traits of individuals. This information is not used for determining the recommended portfolio but rather as an ex-post measure to verify the reasons underlying a specific acceptance or refute choice. What the questions aim to do is to use an indirect way to gather some data about openness to new experiences, extraversion, agreeableness, and other traits. The idea is to ask transversal questions and simulate situations in which respondents need to make a choice. Depending on the choice we may deduct some factors about the personality of individuals. In our opinion, the questions anyway resent of the fact that the situations used may generate some feelings into the subjects that may answer depending strictly on the simulated situation. Another example, different from the one that we reported before, might be the following: when we answer to the question “You are alone in the woods and you hear a loud scream, what do you do?”, our answer may reflect our personality but also our experience with being alone in the woods or even our knowledge and feelings towards nature and animals. In place of these questions, we suggest using another, largely validated, approach: the TIPI (Ten Item Personality Inventory). This approach was proposed by Gosling et al. (2013) and consists in a very simple but effective task. Subjects are asked to rate themselves on a Likert-scale from 1 to 7 for various emotional and personality traits. In total we have ten different items that are subsequently combined into five constructs that represent the various traits of the individuals. The five constructs, often referred to as “Big Five”, are the following: extraversion, agreeableness, consciousness, emotional stability, and openness to experiences. For each construct we use two items, one direct and one reverse, to check also for consistency between answers. The approach is solid, simple to interpret and widely used in similar contexts, so we strongly recommend using this. As argued by the creators of the approach, this approach might be inferior if compared with some multi-item instruments but becomes optimal when it is needed a short and effective personality measure and especially when personality traits are not the primary topic of the analysis. *Figure 5.3.* is a representation of the TIPI structure, taken from the original paper by Gosling et al. (2013).

Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which *you agree or disagree with that statement*. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

Disagree strongly	Disagree moderately	Disagree a little	Neither agree nor disagree	Agree a little	Agree moderately	Agree strongly
1	2	3	4	5	6	7

I see myself as:

1. _____ Extraverted, enthusiastic.
2. _____ Critical, quarrelsome.
3. _____ Dependable, self-disciplined.
4. _____ Anxious, easily upset.
5. _____ Open to new experiences, complex.
6. _____ Reserved, quiet.
7. _____ Sympathetic, warm.
8. _____ Disorganized, careless.
9. _____ Calm, emotionally stable.
10. _____ Conventional, uncreative.

TIPI scale scoring ("R" denotes reverse-scored items): Extraversion: 1, 6R; Agreeableness: 2R, 7; Conscientiousness; 3, 8R; Emotional Stability: 4R, 9; Openness to Experiences: 5, 10R.

Figure 5.3.: TIPI scale and scoring. Source: Gosling et al. (2013)

A measure of overconfidence

Overconfidence is a psychological factor that might become very relevant when we analyse the willingness of subjects to accept an external recommendation different from their own beliefs. Indeed, overconfident people will be reluctant to accept a solution developed by someone else, especially when this is in contrast with the original idea of the individual. For this reason, our suggestion is to include a section that measures overconfidence of participants through a simple task. Overconfidence is typically though to manifest in four different ways: miscalibration (overestimation of own abilities and of the precision of information possessed), better than average effect (considering yourself as better than others, on average), excessive optimism (being too optimistic), illusion of control (thinking to have more control on things than it can actually be true). While all these manifestations might have an implication on the probability to accept or refute a recommendation, the most interesting one is for sure miscalibration. Subjects that consider themselves as good enough to self-determine the correct portfolio choice will give scarce credit to any external suggestion, independently from the source. One of the main approaches typically used is to conduct a “miscalibration test”. The idea, proposed by Alpert & Raiffa (1982), consists in asking participants to perform a simple task: they are given a series of measures (e.g., height of mount Everest, number of Countries in the European Union, etc.) and are asked for each one to provide an estimate of the limits of a confidence interval where the required precision of the confidence interval should be computed as $\frac{n-1}{n}$ where n represents the number of measures (typical values for n are 3,4,5 or 10). If participants give are asked to provide, for example, a 90% confidence interval for 10 measures, they should, in theory, realize 9 intervals that correctly contain the measure and one that does not. Subjects that score 9 out of 10 are said to be correctly calibrated; subjects that score less than 9 out of 10 are said to be miscalibrated and overconfident (more overconfident the more mistakes); subjects that score 10 out of 10 are underconfident. This is a consequence of the fact that when we overestimate our abilities (in this case our estimation abilities) we tend to give intervals that are too narrow. The authors also suggest including questions of different difficulties: people typically manifest underconfidence for hard questions and overconfidence for easy questions. This approach has, anyway, some drawbacks: it strongly depends on the difficulty of the questions, that is a subjective attribute. For example, if we choose a pool of questions that is “difficult” for participants, we will always obtain intervals that are either extremely wide or too narrow because completely mispositioned. For example, if we ask participants to estimate “the average number of bacteria on the surface of the human body”, for which the correct answer would be a number “between 30 and 39 trillion”, we are going to obtain with a high probability either infinitely wide intervals or intervals that are wide enough but result miscalibrated because of the completely misunderstood order of magnitude of the measure. Another limitation of such test is represented by the fact that people often do not have a clear understanding of what a “90% confidence interval” is and tend to generate intervals that they think are reasonably containing the measure, without considering the required precision of the interval. Last but not least, in such tests, people tend to try to guess the correct measure with narrow intervals, for the own personal sake of guessing it correctly, altering in this way the predictive validity of the task. For high number of subjects anyway we recommend using this task both for its simplicity and straightforwardness.

Interpersonal trust and trust in automation

Finally, we argued that the original experiment lacked a way to assess respondents’ level of interpersonal trust and trust in automation. These two concepts are fundamental in the relationship between advisee and advisors (human or robot) and are thought to be the key variable that determines the intention of customers to accept and follow recommendations provided by professionals. We treated this extensively in *Chapter 3*.

We start from interpersonal trust in the relationship between respondents and the human advisor. Of course, in an experimental design similar to the one presented it is quite difficult to assess the level of trust towards the human advisor, because participants had no previous contacts with him/her and, moreover, could not ask any kind of question or clarification about the service. Anyway, obtaining a measure that captures individuals' general trust attitudes is, in our opinion, fundamental. In particular, we are interested in distinguishing between subjects that are sceptical *a priori* about trusting other people, and thus will probably be more likely to refute the recommendation "in general", and those that typically trust other people, for whom eventual refusals of the recommendation might be attributed to other causes. Moreover, although minimal, trust towards experimenters may also be thought to play a role. To this purpose, we propose again a largely validated approach, taken from the existing literature. In particular, we suggest using the questions contained in the World Value Survey. The approach, taken from the World Value Survey paper by Haerpfer et al. (2022), is simple and intuitive and requires subjects to answer to a series of simple questions and rate how much they trust various categories of people. *Figure 5.4.*, from the cited paper, shows the questions that we suggest using. As we see, trust in different groups of people is analysed: we are mostly interested in understanding the general level of trust (question above) and the level of trust towards people you meet for the first time. This constitutes the best proxy for our human advisor. Anyway, other categories are still interesting to assess the general willingness to trust people of individuals.

Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people? (*Code one answer*):

1 Most people can be trusted
2 Need to be very careful

I'd like to ask you how much you trust people from various groups. Could you tell me for each whether you trust people from this group completely, somewhat, not very much or not at all? (*Read out and code one answer for each*):

	Trust completely	Trust somewhat	Do not trust very much	Do not trust at all
Your family	1	2	3	4
Your neighborhood	1	2	3	4
People you know personally	1	2	3	4
People you meet for the first time	1	2	3	4
People of another religion	1	2	3	4
People of another nationality	1	2	3	4

Figure 5.4.: Questions used to assess the general level of interpersonal trust. Source: Haerpfer et al. (2022)

Regarding, on the other hand, trust in automation we propose a new approach, taken from Körber (2018), who proposed a questionnaire that can be used to assess the individual's level of trust in automation (for specific discussion on the model see *Section 3.2.*). The cited framework of analysis, anyway, is used and validated on a different context: Automated Driving Systems (ADS). While some contact points can be found between Robo-Advisors and Automated Driving Systems we found it convenient to perform a validation of the questionnaire also in our domain. Anyway, because of the limited diffusion of Robo-Advisors, using directly a Robo-Advisor as the object of the questionnaire would have been quite problematic. Instead, we opted for using something that could be similar to Robo-Advisors but more well-known, in light of the cited implications of the "Trust Transfer Theory". Specifically, we tried two different options: vocal assistants (Siri, Cortana, etc.) and chatbots. After conducting two separated analysis and discussing pros and cons of each one we decided to opt for chatbots because of two main facts: first of all, as said, vocal assistants represent a sort of shortcut for people, to perform actions that they could perfectly perform on their own; Robo-Advisors, on the other hand, provide investment services that we suppose people not to be able to perform on their own, at least with the same results. The other key reason is represented by the wide diffusion of vocal assistants, that generates in people a higher degree of acceptance. On the contrary, chatbots, as well as Robo-Advisors are still seen with a bit of reluctance on their performances and require a sort of minimum level of trustworthiness to be exploited for certain actions. For example, some European banks offer customers the possibility to open new saving accounts through a chatbot when they cannot do that on their own. Of course, people may also request in-person or telephone help from a human being when they do not feel comfortable with the chatbot or when they do not trust it. Clearly, while this assistance is completely cost-free, clients will need to wait some time before a human assistant is available and thus they may not be able to open new accounts during night hours or during holiday periods.

The questionnaire consists in 19 Likert-scale questions (items) that are used to measure various constructs that are thought to influence trust in automation. The five constructs are the ones explained in *Section 3.2.*, represented in *Figure 5.5.* that shows the structure of the model proposed by the author. Specifically, we see that some factors are thought to influence indirectly trust in automation and some others are thought to be direct factors.

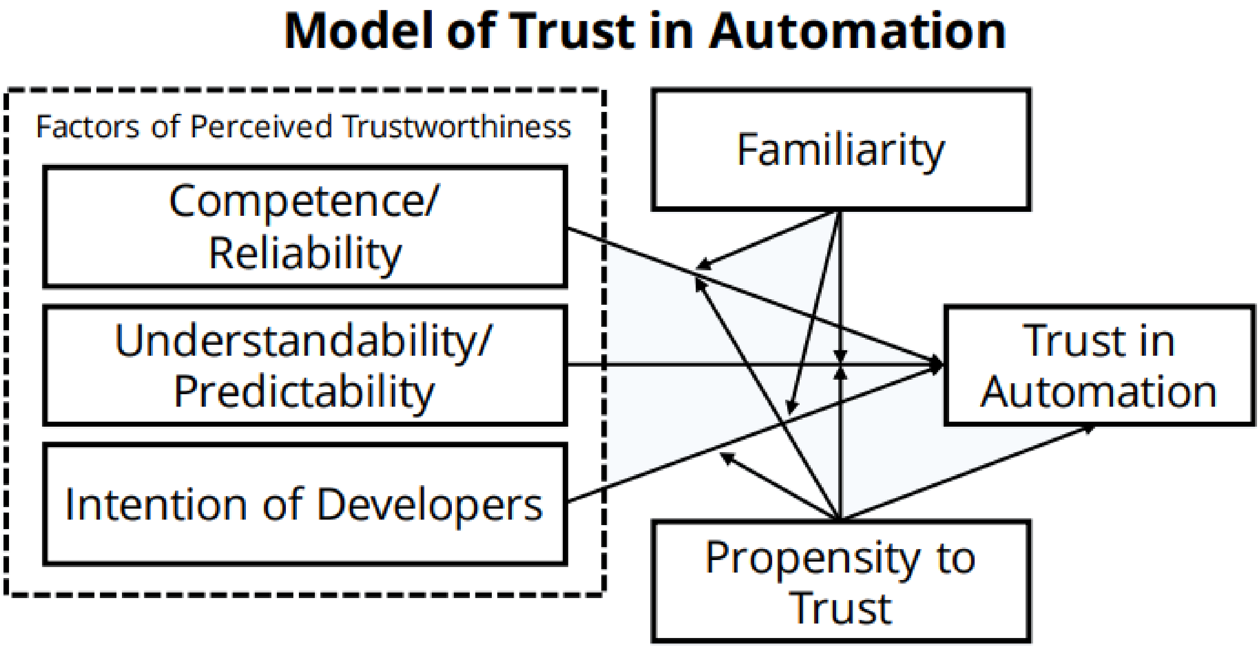

Figure 5.5.: Model of trust in automation. Source: Korber (2019)

To verify the validity of the model for our purposes, after the pilot questionnaire, we intend to conduct an Exploratory Factor Analysis (EFA), to verify the eventual redundance of items, and then, if the factors are similar enough to the ones of Korber (2019) a Confirmatory Factor Analysis (CFA) on the model presented above. The questionnaire contained the 19 items of the model (see *Figure 5.6.*) and some other questions to sage participants experience and comfort with chatbots. Specifically, in the additional questions, we described five different categories of chatbots (bank, clothes shop, public service, transportation service, household appliances retail and maintenance assistance) and for each one we asked whether participants had ever interacted with a similar chatbot and how comfortable they feel (or would feel) when interacting with it. These additional preliminary questions are used to partition the dataset and analyse separately those who had previous experiences with chatbots and those who did not.

		Strongly disagree	Rather disagree	Neither disagree nor agree	Rather agree	Strongly agree	No response
1	The system is capable of interpreting situations correctly.	①	②	③	④	⑤	○
2	The system state was always clear to me.	①	②	③	④	⑤	○
3	I already know similar systems.	①	②	③	④	⑤	○
4	The developers are trustworthy.	①	②	③	④	⑤	○
5	One should be careful with unfamiliar automated systems.	①	②	③	④	⑤	○
6	The system works reliably.	①	②	③	④	⑤	○
7	The system reacts unpredictably.	①	②	③	④	⑤	○
8	The developers take my well-being seriously.	①	②	③	④	⑤	○
9	I trust the system.	①	②	③	④	⑤	○
10	A system malfunction is likely.	①	②	③	④	⑤	○
11	I was able to understand why things happened.	①	②	③	④	⑤	○
12	I rather trust a system than I mistrust it.	①	②	③	④	⑤	○
13	The system is capable of taking over complicated tasks.	①	②	③	④	⑤	○
14	I can rely on the system.	①	②	③	④	⑤	○
15	The system might make sporadic errors.	①	②	③	④	⑤	○
16	It's difficult to identify what the system will do next.	①	②	③	④	⑤	○
17	I have already used similar systems.	①	②	③	④	⑤	○
18	Automated systems generally work well.	①	②	③	④	⑤	○
19	I am confident about the system's capabilities.	①	②	③	④	⑤	○

Figure 5.6.: Questions of the original questionnaire by Korber (2019). Source: Korber (2019)

5.3.2. Pilot Questionnaire: repeating the original experiment

Initially we repeat the experiment using the original setting with only some slight modifications. In this pilot questionnaire we try only to insert the new sections and use the same assessment method as in the original study. Using a similar sample size, we try to reproduce the results obtained by Alemanni et al. (2020). Specifically, we submitted the questionnaire to a group of university students from graduate and undergraduate courses from the Departments of Ca' Foscari University of Venice. The questionnaire was distributed via e-mail from the departments' offices. While participation was completely voluntary and anonymous, each student that participated and completed successfully the whole questionnaire obtained as a payoff a code that allowed them to participate in a lottery that awarded four University-branded sweatshirts.

Summary statistics and balance between conditions

In total we obtain *N = 249* answers, and we discarded incomplete answers, non-coherent answers, and those whose completion time was lower than the first quartile of the distribution of completion times. Doing so we obtained *n = 127* valid answers. The difference between the total answers and the valid answers is considerably high due to the relevant number of people who started and never finished the experiment. We recognize as one of the limitations of our approach: given the absence of a formal setting and location for the experiment and given the probability-linked (non-monetary) nature of the payoff, the length of the experiment (median completion time was around 13 minutes) may have acted as a disincentive to the participation. The functioning of the focal part of the experiment (portfolio choice and recommendation) is analogous to the one of the original paper, described before.

We now present some summary statistics about the pool of subjects. All the following statistics are realized on the *n = 127* answers that we considered valid. We show five pairs of tables where, in each pair, the first table shows the summary of all the subjects and the second table compares the mean values of the subjects the obtained a recommendation from the human advisor (H) and those who received the recommendation from the robotic (R) advisor.

Table 5.1. and *Table 5.2.* show information about the socio-demographic characteristics of the subjects. The variable "Age" is concentrated between the values of 22 and 25, but this is reasonable given that we distributed the survey on a pool of Master's Degree students. The variable "Gender" takes the value of 1 for females and 0 for males: we may see that around 60% of the respondents were females. A slightly high difference exists between those who obtained the robotic recommendation and those who received the human recommendation; thus, we should keep this into consideration in our conclusions. The variable "Income" ranges between 1 and 4 where 1 represents an annual income

lower than 30,000€ and 4 represents an annual income higher than 100,000€. Here we refer to the overall family income of students. As we see, most of the subjects, belong to the lower income bands ("<30,000€" and "between 30,000€ and 60,000€"). The variable "Worker" assumes the value of 0 for students that do not work, 1 for part-time workers and 2 for full-time workers. Most of the subjects are only students, with a small part of them being also part-time workers. Last but not least, participant showed an average level of financial literacy. The variable ranged between 0 and 4 and is the result of a portfolio ordering task. As we see from the quartiles, most subject either scored the maximum or the minimum, certifying our initial idea of the existence of a logical ordering of portfolios. Such a task is useful to test both the understanding of the portfolio descriptions but also to test the understanding of the mechanisms of risk and return. Realizing a t-test on the differences between the mean values of the two groups (human and robot) we can see that most of them are not significant, with the exception of the variable "Gender" that is significant at 5%.

Demographic (all)

	Mean	SD	Min	Max	Q1	Q3
Age	24.268	3.886	21	48	23	24
Female	0.606	0.491	0	1	0	1
Income	1.787	0.783	1	4	1	2
Worker	0.488	0.700	0	2	0	1
Literacy	2.370	1.812	0	4	0	4

Table 5.1.: Summary statistics of the socio-demographic characteristics of the respondents (n = 127).

Demographic (R/H)

	Mean (R)	Mean (H)	Diff.	Description
Age	23.785	24.774	-0.990	Age
Female	0.538	0.677	-0.139	Gender
Income	1.815	1.758	0.057	Income
Worker	0.477	0.500	-0.023	Student and Worker
Literacy	2.185	2.565	-0.380	Financial Literacy

Table 5.2.: Balance table for the socio-demographic characteristics of the respondents (n = 127). We show the comparison between the average for the variables between the two groups defined by the nature of the recommendation (Robotic R vs. Human H).

Table 5.3. and *Table 5.4.* show the summary statistics and balance table for the personality traits of the respondents. The variable "Overconfidence" ranges between -1 and 3 where a value of -1 indicates a light underconfidence, 0 indicates a proper calibration, and 1-2-3 indicate the different levels of overconfidence (with 3 being "highly overconfident"). As we see, most subjects show a certain level of overconfidence, on average between "slightly overconfident" and "averagely overconfident". The other five variables are computed using the TIPI (Ten Items Personality Inventory) scale and each variable is built as the mean of two items (one normal item and one reverse item). All variables range between 1 and 7 where 1 represents a minimal level of the trait and 7 a very high level of the trait.

Subjects showed on average high degrees of consciousness, agreeableness, and openness to novelty, while emotional stability and extravagance are slightly lower. On limitation of this approach is that is based on direct questions and not on a task or on an external evaluation; thus, people may, at times, give too optimistic self-evaluations. None of the differences between the two groups in the balance table is significant.

Personality (all)

	Mean	SD	Min	Max	Q1	Q3
Overconfidence	1.622	1.076	-1	3	1	2
Extravagance	3.610	1.480	1	7	2.5	5
Agreeableness	5.051	0.982	2.5	7	4.5	6
Consicousness	5.402	0.986	2.5	7	4.5	6
Emotional Stability	4.232	1.182	1	7	3.5	5
Opennes to novelty	4.665	1.050	1.5	7	4	5.5

Table 5.3.: Summary statistics of the personality traits of the respondents (n = 127), measured through a miscalibration task and the TIPI (Ten Items Personality Inventory) scale.

Personality (R/H)

	Mean (R)	Mean (H)	Diff.	Description
Overconfidence	2.185	2.565	-0.380	Overconfidence
Extravagance	3.592	3.629	-0.037	TIPI M1
Agreeableness	5.177	4.919	0.258	TIPI M2
Consicousness	5.454	5.347	0.107	TIPI M3
Emotional Stability	4.385	4.073	0.312	TIPI M4
Opennes to novelty	4.723	4.605	0.118	TIPI M5

Table 5.4.: Balance table for the personality traits of the respondents (n = 127). We show the comparison between the average for the variables between the two groups defined by the nature of the recommendation (Robotic R vs. Human H).

Table 5.5. and *Table 5.6.* investigate the level of interpersonal trust shown by participants. Specifically, given the importance of trust in the client-advisor relationship, we wanted to understand whether people had a high or low *a priori* level of interpersonal trust. We suppose that people showing low degrees of trust (in general) will be more reluctant to accept external recommendations from people that they do not know. The approach we chose employs the scale of the World Value Survey. The variable "T_Gen" measures the level of interpersonal trust in general and takes the value of 1 when the subject said that they trust (in general) other people and 0 when they said they do not. All the other variables show levels of trust in specific categories of people and range between 1 (do not trust at all) and 4 (trust completely). Looking at the results we can clearly see that people have the highest level of trust for family members and "other people that they know directly" while they showed lower levels of trust for neighbours and people met for the first time. Moreover, levels of trust towards people of other nationalities and religions have the exact same mean value; because of the similarity of these two variables, in the final questionnaire we will just keep one of them. One

other limitation of the approach is that it does not test trust towards professionals (advisors, lawyers, etc.). While some can argue that professionals must be either comprehended in T_first (if these are newly met professionals) or in T_know (when we talk about well-known professionals), these questions are not able to capture the effect given by the "professionalism" and competence of the person. Indeed, when we deal with a professional, we may feel more comfortable because we are aware of the level of experience and knowledge of the person. This is furtherly increased when we consider jobs that require external examinations and listing in public registers. Looking at the balance table we see that differences are very small and non-significant.

Trust Pers. (all)

	Mean	SD	Min	Max	Q1	Q3
T_Gen	0.402	0.492	0	1	0	1
T_fam	3.685	0.545	1	4	3	4
T_neigb	2.394	0.747	1	4	2	3
T_know	3.181	0.510	2	4	3	3
T_first	2.031	0.755	1	3	1	3
T_fore	2.661	0.681	1	4	2	3
T_rel	2.661	0.669	1	4	2	3

Table 5.5.: Summary statistics of the level of interpersonal trust of the respondents (n = 127), measured through the scale of the World Value Survey.

Trust Pers. (R/H)

	Mean (R)	Mean (H)	Diff.	Description
T_Gen	0.431	0.371	0.060	Trust in general
T_fam	3.615	3.758	-0.143	Trust in family members
T_neigb	2.415	2.371	0.044	Trsut in neighbours
T_know	3.200	3.161	0.039	Trust in people you know
T_first	2.000	2.065	-0.065	Trust in people you meet for the first time
T_fore	2.662	2.661	0.000	Trust in foreign people
T_rel	2.662	2.661	0.000	Trust in people of other religions

Table 5.6.: Balance table for the level of interpersonal trust of the respondents (n = 127). We show the comparison between the average for the variables between the two groups defined by the nature of the recommendation (Robotic R vs. Human H).

In conclusion, *Table 5.7.* and *Table 5.8.*, measure the levels of trust in automation. As we see, people have an overall high level of Familiarity with automated systems and showed average levels of trust in automation in general. The level of trust in automation might be influenced by the low values of the variable "R/C" (Reliability/Confidence), that captures the perceived reliability of the system when managing requests, and by the low value of "Propensity to Trust", that captures the general *a priori* level of trust towards machines. Scores are well balanced between the two groups.

Trust Aut. (all)

	Mean	SD	Min	Max	Q1	Q3
R/C	2.866	0.569	1.17	4.5	2.5	3.17
U/P	3.252	0.582	1.5	4.5	3	3.5
Familiarity	3.524	0.904	1	5	3	4
Developers	3.154	0.689	1	5	2.5	3.5
Propensity to trust	2.940	0.659	1.33	5	2.67	3.33
Trust in Automation	3.016	0.802	1	5	2.5	3.5

Table 5.7.: Summary statistics of the level of trust in automation of the respondents (n = 127), measured using the 19-item approach from Korber (2019).

Trust Aut. (R/H)

	Mean (R)	Mean (H)	Diff.	Description
R/C	2.853	2.879	-0.0256328	Reliability/Confidence
U/P	3.300	3.202	0.0983871	Understanding/Predictability
Familiarity	3.538	3.508	0.03039702	Familiarity
Developers	3.108	3.202	-0.0939206	Intention of Developers
Propensity to trust	2.831	3.054	-0.2224864	Propensity to trust
Trust in Automation	2.977	3.056	-0.0795285	Trust in Automation

Table 5.8.: Balance table for the level of trust in automation of the respondents (n = 127). We show the comparison between the average for the variables between the two groups defined by the nature of the recommendation (Robotic R vs. Human H).

As said, in this pilot questionnaire, we used chatbots as the subject of people's evaluation. While this parallelism allows us to measure trust in automation more concretely, we recognize that chatbots have been diffused for a long time now and often interact with people wishing to speak verbally with human assistants. Thus, we should account that the role played by previous experiences might be crucial. *Tables 5.9-5.12.* show the levels of experience and comfort with chatbots. Specifically, we tested the state of these two factors with different categories of chatbots, from more basic and less urgent services (clothes shop) to more delicate ones (banks, public services). The variables "Exp_gen" and "Comf_gen" test on the other hand the level of experience and comfort with chatbots in general, without referring to any particular category. The former takes the value of 1 for people that never interacted nor heard about the existence of chatbots; 2 for those who have heard of the existence of chatbots but never interacted with them; 3 for those who interacted only a few times with chatbots; 4 for those who interacted several times with chatbots and thus have a high level of experience. We see that most people already had experience with chatbots in general, with the most frequent categories being banks' chatbots and clothes shops' chatbots. Also, they showed higher degrees of comfort with chatbots managing requests inherent to "less delicate" services, while interaction with banks and public institutions' chatbots, made people feel less comfortable. Balance tables show an overall good balance between groups, with the only exception being the variable

"Exp_elec" that consider experience with chatbots of manufacturing firms. Anyway, because of our scope of analysis we may consider this difference to be irrelevant.

Exp. Aut. (all)

	Mean	SD	Min	Max	Q1	Q3
Exp_gen	3.409	0.705	1	4	3	4
Exp_bank	0.409	0.494	0	1	0	1
Exp_tras	0.291	0.456	0	1	0	1
Exp_elec	0.236	0.426	0	1	0	0
Exp_cloth	0.315	0.466	0	1	0	1
Exp_pub	0.276	0.449	0	1	0	1

Table 5.9.: Summary statistics of the level of experience with automated systems of the respondents (n = 127).

Exp. Aut. (R/H)

	Mean (R)	Mean (H)	Diff.	Description
Exp_gen	3.508	3.306	0.201	Experience in general
Exp_bank	0.523	0.290	0.233	Experience with banks' automated systems
Exp_tras	0.277	0.306	-0.030	Experience with tranportation companies' automated systems
Exp_elec	0.308	0.161	0.146	Experience with manufacturers' automated systems
Exp_cloth	0.308	0.323	-0.015	Experience with clothes shops' automated systems
Exp_pub	0.323	0.226	0.097	Experience with public services' automated systems

Table 5.10.: Balance table for the level of experience with automated systems of the respondents (n = 127). We show the comparison between the average for the variables between the two groups defined by the nature of the recommendation (Robotic R vs. Human H).

Comf. Aut. (all)

	Mean	SD	Min	Max	Q1	Q3
Comf_gen	2.150	0.631	1	3	2	3
Comf_bank	1.945	0.780	1	3	1	3
Comf_tras	2.244	0.742	1	3	2	3
Comf_elec	2.291	0.680	1	3	2	3
Comf_cloth	2.331	0.777	1	3	2	3
Comf_pub	1.898	0.775	1	3	1	3

Table 5.11.: Summary statistics of the level of comfort when interacting with automated systems of the respondents (n = 127).

Comf. Aut. (R/H)

	Mean (R)	Mean (H)	Diff.	Description
Comf_gen	2.123	2.177	-0.054	Comfort in general
Comf_bank	1.954	1.935	0.018	Comfort with banks' automated systems
Comf_tras	2.215	2.274	-0.059	Comfort with tranportation companies' automated systems
Comf_elec	2.262	2.323	-0.061	Comfort with manufacturers' automated systems
Comf_cloth	2.246	2.419	-0.173	Comfort with clothes shops' automated systems
Comf_pub	1.877	1.919	-0.042	Comfort with public services' automated systems

Table 5.12.: Balance table for the level of comfort when interacting with automated systems of the respondents (n = 127). We show the comparison between the average for the variables between the two groups defined by the nature of the recommendation (Robotic R vs. Human H).

In the following sub-section, we repeat the same analysis performed in the cited paper, and we try to investigate also the possible roles played by the new variables we added. In parallel, we will argue the limitations of our new sections and the margins of improvement of the original experiment.

5.3.3. Improving the questionnaire: validation and ex-post analysis of limitations

In this subsection we present the results of the ex-post analysis of the data gathered through the pilot questionnaire, further discussing eventual limitations of the approaches used.

Results of the pilot experiment and discussion of the margins of improvement

We start by showing the distribution of choices of participants. We had four different portfolios marked with a colour instead of a number. In the experiment the “Blue” portfolio was the safest; the “Yellow” one had a medium-low riskiness; the “Red” one a medium-high riskiness; and, the “Green” portfolio was the riskiest one. *Figure 5.7.* and *Figure 5.8.* show the choices of participants, grouped for the two treatments. Specifically, the bar-chart compares the percentage of users that chose a portfolio in their initial choice (labelled “first”), the advice received (“advice”) and their final choice after receiving the recommendation (labelled “post”). *Figure 5.7.* refers to the human treatment and *Figure 5.8.* to the robotic treatment.

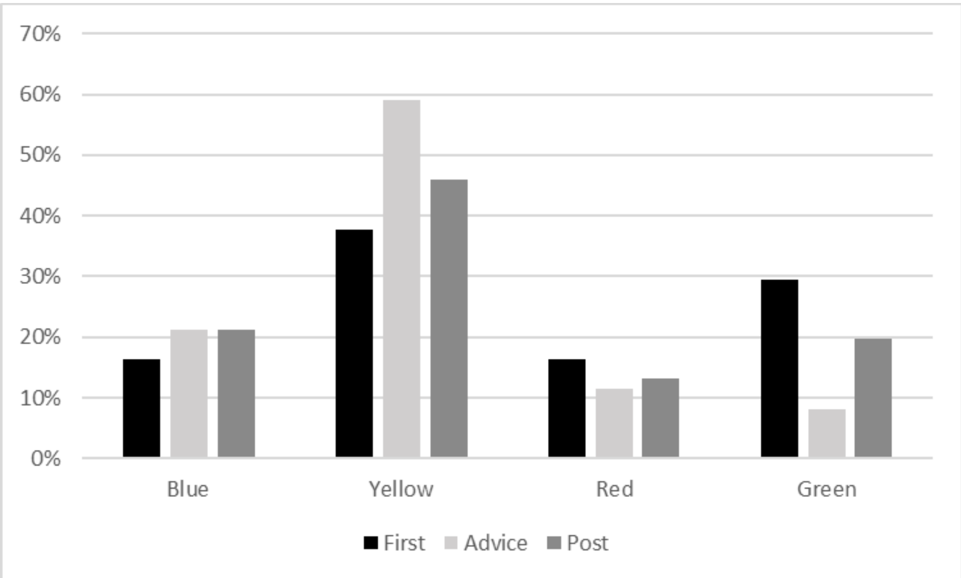

Figure 5.7.: Comparison between the initial choice, advice and final choice. Human advisor

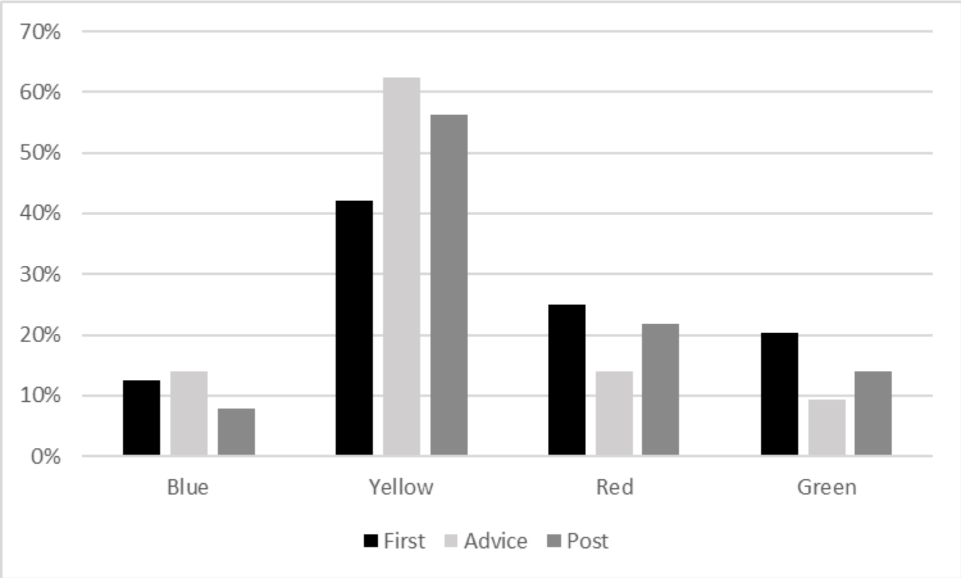

Figure 5.8.: Comparison between the initial choice, advice and final choice. Robotic Advisor

Following the original approach of the cited paper, we use a Probit regression model on the acceptance of the recommendation. The dependent variable is thus a dummy that takes the value of 1 if the recommendation is followed (thus final choice = advice) and 0 otherwise. We build three different models:

In Model 1 ($n = 127$), shown in *Figure 5.9.*, we have a quite simple regression, where the dependent variable is regressed on the type of treatment and on the correspondence of the initial choice and the recommendation. Here, the variable "human" represents the treatment used and takes the value of 1 when the recommendation was delivered through a video by the "human" advisor, and 0 when the recommendation was portrayed as generated by a robot. The variable "firstadvice" is a dummy variable that represents "confirmation bias" and thus takes the value of 1 when the advice received coincides with the initial portfolio choice of the subject. The variable "firstadvice", as we see, absorbs almost completely the variability of the acceptance of the recommendation (dependent variable) and has a positive and statistically significant (at any confidence level) coefficient, meaning that when the initial choice coincides with the advice received the probability to accept the recommendation is extremely high. While this seems to confirm one of the main conclusions of the paper by Alemanni et al. (2020), we already argued a possible limitation and way of improvement of this measure. We believe confirmation bias to play a significant role, but we want to verify whether we may obtain the same results with a different way of testing it. The coefficient of the "human" variable is negative – so we may believe that the probability to accept the recommendation becomes higher when the recommendation is portrayed as robot-generated – but the p-value is quite high and thus the coefficient can be considered as non-statistically significant.

finaladvice	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
human	-.2560132	.2222038	-1.15	0.249	-.6915246	.1794982
firstadvice	1.733671	.2784142	6.23	0.000	1.187989	2.279353

Figure 5.9.: Probit regression. Dependent variable: D(Final=Advice). Independent variables: treatment (human vs. robot), D(First=Advice). In the regression we obtain a p-value of 0.000, indicating an almost perfect fit.

In Model 2 (*n = 127*), shown in *Figure 5.10.*, we add to the regression two supplementary variables that verify the impact of the initial choice and of the advice to verify whether the acceptance of the recommendation might depend on the riskiness of the portfolio. Indeed, we can see that, again the dominating variable is "firstadvice" that explains the majority of the variability of the dependent variable. The variable "advice" that represents the riskiness of the advised portfolio (values from 1 to 4 where 1 represents the low-risk portfolio and 4 the high-risk portfolio) and the variable "first" that represents the riskiness of the portfolio chosen at the beginning of the experiment have non-statistically significant coefficients, as well as the treatment.

finaladvice	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
human	-.1357639	.2752794	-0.49	0.622	-.6753016	.4037737
advice	-.1689552	.1855537	-0.91	0.363	-.5326337	.1947234
first	.0470491	.1262868	0.37	0.709	-.2004685	.2945667
firstadvice	1.947754	.3395868	5.74	0.000	1.282176	2.613331

Figure 5.10.: Probit regression. Dependent variable: D(Final=Advice). Independent variables: treatment (human vs. robot), D(First=Advice), riskiness of the advised portfolio, riskiness of the initial portfolio. In the regression we obtain a p-value of 0.000, indicating an almost perfect fit.

In Model 3 (*n =56*), in *Figure 5.11.*, we keep only participants that failed to correctly assess the right portfolio, and thus their initial choice is different from the recommendation, and we verify the effect of the treatment, again also considering the riskiness of the initial choice. Here, while the sample size is more reduced, we can see that the three variables have again non-statistically significant coefficients, meaning a limited impact of the riskiness of the portfolios on the final choice and acceptance of the recommendation.

finaladvice	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
human	.1489462	.3470753	0.43	0.668	-.5313088	.8292013
advice	-.2563496	.1974281	-1.30	0.194	-.6433016	.1306025
first	.0378838	.1301754	0.29	0.771	-.2172553	.2930229

Figure 5.11.: Probit regression. Dependent variable: D(Final=Advice). Independent variables: treatment (human vs. robot), riskiness of the advised portfolio, riskiness of the initial portfolio. In the regression we obtain a p-value of 0.279, indicating a poor fit.

After this initial evaluation, we also test the possible role played by the new variables that we introduced, specifically, interpersonal trust and trust in automation. To measure them we chose to use the general constructs (see above). We split the dataset into two sub-groups, depending on the treatment. Considering those (n=65) who were advised by the robot, in *Figure 5.12.* we see that the recommendation is again strongly influenced by the correspondence between the initial choice and the advice.

finaladvice	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
trust_aut	-.0884875	.0898175	-0.99	0.325	-.2645265	.0875515
T_Gen	.0808972	.4233798	0.19	0.848	-.748912	.9107064
firstadvice	2.137691	.4898161	4.36	0.000	1.177669	3.097712

Figure 5.12.: Probit regression (n=65). Dependent variable: D(Final=Advice). Independent variables: trust in automation, interpersonal trust and D(First=Advice). In the regression we obtain a p-value of 0.0001, indicating an almost perfect fit.

When we rule out the variable "firstadvice" (*Figure 5.13.*) we see that for those that received the "robotic" recommendation, trust in automation plays a significant role. The regression shows a positive relationship between the two variables and testifies a positive role of trust in automation on the probability of accepting the advice. Interpersonal trust, on the other hand plays a minor (non-significant) role.

finaladvice	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
trust_aut	.1382854	.0684708	2.02	0.043	.0040852	.2724857
T_Gen	.2651026	.3268461	0.81	0.417	-.3755041	.9057092

Figure 5.13.: Probit regression (n=65). Dependent variable: D(Final=Advice). Independent variables: trust in automation, interpersonal trust. In the regression we obtain a p-value of 0.044, indicating an excellent fit.

Considering, on the other hand, only those (n=61) who received the recommendation we obtain approximately the same result with respect to the role of confirmation bias (*Figure 5.14.*). This time, when we remove the variable "firstadvice", we should expect to see a relevant role played by interpersonal trust and a minor role played by trust in automation.

finaladvice	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
trust_aut	-.0884875	.0898175	-0.99	0.325	-.2645265	.0875515
T_Gen	.0808972	.4233798	0.19	0.848	-.748912	.9107064
firstadvice	2.137691	.4898161	4.36	0.000	1.177669	3.097712

Figure 5.14.: Probit regression (n=61). Dependent variable: D(Final=Advice). Independent variables: trust in automation, interpersonal trust and D(First=Advice). In the regression we obtain a p-value of 0.000, indicating an almost perfect fit.

Contrary to our expectations, we see that trust in automation still plays an important role (*Figure 5.15.*) we see again a prominent role of trust in automation and only a minor role of interpersonal trust. This might depend on the low variability of the scale "T_Gen" that has just two different values. Anyway, more probably the high value of trust in automation might be a result of the way in which we delivered the human recommendation. While in the original experiment by Alemanni et al. (2020) used a physical human being to communicate the recommendation, giving a real impression of humanly generated advice, we could only use a series of pre-recorded videos, and this might have reduced the difference between the two treatments.

finaladvice	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
trust_aut	.2199693	.0696122	3.16	0.002	.0835319	.3564067
T_Gen	-.4150706	.3447394	-1.20	0.229	-1.090747	.2606062

Figure 5.15.: Probit regression (n=61). Dependent variable: D(Final=Advice). Independent variables: trust in automation, interpersonal trust. In the regression we obtain a p-value of 0.044, indicating an excellent fit.

Conclusions of the pilot experiment

Our pilot study allowed us to better understand the possible ways of improving the original experiment. Specifically, we evidenced how variables like trust in automation and interpersonal trust may play a role in determining and predicting the willingness of individuals to accept or refuse a recommendation, coming from a human or a robotic entity. Moreover, we showed how using such a way to assess confirmation bias may be effective but at the same time represents an "unstable" way of assessing the presence of the bias. Indeed, as we argued before, if we suppose that a hypothetical investor receives a recommendation equal to their initial choice, we are giving no valid reason to the subject to change his mind for the final choice and thus opt for a different portfolio. In the final experiment we propose, conversely, to sage the impact of confirmation bias (and of recommendations coherent with initial choices) on the overall satisfaction with the advisory service and on the willingness to utilize it again in the future. Moreover, given the importance of trust in automation that we evidenced, we will exploit the data gathered through this this experiment to carry on a further validation of the scale, aiming at simplifying it (see next paragraph). Also, we noticed that using chatbots as the subject at issue for the assessment of trust in automation exposes the results excessively to the previous experiences of subjects with chatbots, rather than generating a more objective and general measure of trust in automation. Another possible way of improving our pilot experiment is to use a different category of subjects. While using university students is quite practical and effective, this significantly limits the age span. Furthermore, most students, because of their young age, low experience and limited fund availability, have never invested nor considered the possibility of hiring a financial advisor. Students have also very similar backgrounds and levels of education (high school diploma for Bachelor's students and Bachelor's degree for Master's students) and, as argued in literature, are generally more comfortable when interacting with automated systems and technology in general. In the final experiment, we thus opt to carry the experiment on a pool of adults reached through various channels (see *Section 5.5.*). Finally, we evidenced that the actual role that interpersonal trust may play in such a matter is partially obscured by the structure of the experiment. While, because of the technical absence of material space to carry on the experiment using human advisors we decide to slightly modify the trust scale to better assess the eventual role of interpersonal trust. In the scale of the World Value Survey, we lacked a specific measure of trust in professionals delivering services to customers (e.g., financial advisors, lawyers, etc.) and thus we decide to replace the item "trust in people of other religions" that is less relevant for our purposes (and almost perfectly correlated with the item "trust in people of other nationalities"), with an item that tests "trust in professionals delivering services".

Validation of the scale "Trust in Automation"

Now we utilize the data we gathered in the pilot experiment to validate and analyse the "Trust in Automation" scale. In order to obtain a more precise validation process, we submitted the "trust in automation" section of the questionnaire to an additional pool of *N = 107* subjects, and we integrated the data. Before merging the two datasets, we compared the two samples to verify whether significant differences were observed with respect to socio-demographic aspects or other factors. Running a simple of t-test, we confirmed the homogeneity of the data and thus we can proceed with the validation.

Tables 5.13., 5.14., 5.15. show some summary statistics about the (aggregated) pool of subjects, distinguishing between those who had previous experiences with chatbots and those who never had experiences with chatbots. Because all the participants had as their first language Italian and we had no way to test their level of proficiency in English, we delivered the questionnaire in Italian. In the following tables we coded "Gender" with F=0 and M=1; "Exp_Gen" ranges again between 1 and 4 with 4 representing a high experience with chatbots, 3 represents a little experience, 2 represents those who had no previous experience with chatbots but have heard about their existence, 1 represent those who didn't knew chatbots at all (never used nor heard of); other "Exp_*" variables are either 1 for those who used that kind of chatbot and 1 for those who did not; the five categories of chatbots describe and increased relevance of the activity: bank, public service, transportation firm, retail and maintenance for home electrical appliances, clothes shop; "C_*" defines the level of comfort in the interaction with that kind of chatbot and ranges between 1 (low comfort) and 3 (high comfort); those who had no previous experiences with the respective chatbot were asked to make an estimate of their comfort with that kind of chatbot.

All subjects

	n	Mean	SD	Min	Max	Q1	Q3
Age	234	23.17	3.42	19	48	21	24
Gender	234	0.39	0.49	0	1	0	1
Exp_Gen	234	3.29	0.74	1	4	3	4
Exp_Bank	234	0.37	0.48	0	1	0	1
Exp_Pub	234	0.25	0.44	0	1	0	1
Exp_Trans	234	0.29	0.46	0	1	0	1
Exp_Elec	234	0.26	0.44	0	1	0	1
Exp_Vest	234	0.31	0.46	0	1	0	1
C_Gen	234	2.06	0.66	1	3	2	2.25
C_Bank	234	1.93	0.78	1	3	1	3
C_Pub	234	1.93	0.80	1	3	1	3
C_Trans	234	2.20	0.74	1	3	2	3
C_Elec	234	2.15	0.74	1	3	2	3
C_Vest	234	2.12	0.81	1	3	1	3

Table 5.13.: summary statistics of the sample (all subjects).

Considering all the subjects who answered our questionnaire we can see that most of them were females (61%) and most of them under 24 years old, with an average age of 23.17 years, which is reasonable given the objective of the analysis. We can also see that most people had already previously interacted with chatbots (3.29 on a maximum of 4) and that for each category of chatbot approximately 1 in 3 subjects had previously interacted with it. The average level of comfort is not particularly high, and we see that the mean value is lower for banks and public services chatbots and quite higher for the other chatbot categories. This information is interesting because it tells us that people might feel less comfortable with chatbots that should help them with services that can be considered more "important" and "delicate". We use a simple T-test with equal variances (previously checked) to verify the statistical significance of this difference and we found the difference to be statistically significant at the 95% confidence level; we can thus conclude that young people, on average, feel more comfortable with chatbots when they are dealing with less “delicate” services. *Figure 5.16.* contains the results of the hypothesis test of the comparison between C_Bank and C_Trans. Similar results are obtained by comparing C_Bank and C_Pub with all other categories.

Variable	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
C_Bank	234	1.931624	.0511964	.7831541	1.830757	2.032491
C_Trans	234	2.196581	.0486337	.7439521	2.100763	2.292399
diff	234	-.2649573	.0595849	.9114735	-.3823513	-.1475633

```
     mean(diff) = mean(C_Bank - C_Trans)                          t =  -4.4467
 H0: mean(diff) = 0                              Degrees of freedom =      233

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Figure 5.16.: T-test for the difference between C_Bank and C_Pub. The difference is statistically significant at 95% confidence level.

The comparison between *Table 5.14.* and *Table 5.15.* (below) shows that there is no significant difference in the levels of comfort in the various categories between those who had previously interacted with chatbots and those who didn’t. In analysing this we should keep in mind the difference in the dimension of the two samples that may alter the data. Anyway, most people in the age band 20-35, in general, know and have interacted with chatbots thus this kind of distribution can be considered reasonable.

Experienced

	n	Mean	SD	Min	Max	Q1	Q3
Age	203	23.31	3.43	19	48	21	24
Gender	203	0.40	0.49	0	1	0	1
Education	203	2.47	0.74	1	4	2	3
Exp_Gen	203	3.51	0.50	3	4	3	4
Exp_Bank	203	0.42	0.50	0	1	0	1
Exp_Pub	203	0.29	0.46	0	1	0	1
Exp_Trans	203	0.33	0.47	0	1	0	1
Exp_Elec	203	0.30	0.46	0	1	0	1
Exp_Vest	203	0.36	0.48	0	1	0	1
C_Gen	203	2.06	0.67	1	3	2	3
C_Bank	203	1.93	0.79	1	3	1	3
C_Pub	203	1.96	0.81	1	3	1	3
C_Trans	203	2.22	0.74	1	3	2	3
C_Elec	203	2.15	0.74	1	3	2	3
C_Vest	203	2.13	0.80	1	3	1	3

Table 5.14.: summary statistics of the sample (only subjects that had previously interacted with chatbots)

Non-Experienced

	n	Mean	SD	Min	Max	Q1	Q3
Age	31	22.26	3.22	19	35	20	23
Gender	31	0.29	0.46	0	1	0	1
Exp_Gen*	31	0.87	0.34	0	1	1	1
C_Gen	31	2.03	0.60	1	3	2	2
C_Bank	31	1.94	0.77	1	3	1	3
C_Pub	31	1.74	0.73	1	3	1	2
C_Trans	31	2.06	0.77	1	3	1	3
C_Elec	31	2.19	0.75	1	3	2	3
C_Vest	31	2.10	0.87	1	3	1	3

*Table 5.15.: summary statistics of the sample (only subjects that had no previous interactions with chatbots). * Standardized*

Accounting for the reduced dimension of the sample for a complete and formal factor analysis, we decide anyway to start by exploring the factors analysed by our items. The idea is to verify whether in our context one or two items to measure trust in automation may be enough, to obtain a simple measure. We will conduct the analysis only on the 17 items that the paper argues to be determinant of Trust in Automation, measured through the other 2 items. We begin by showing the correlations between the items in our questionnaire and by testing whether are data is adequate to perform an Exploratory Factor Analysis. As we may see from *Table 5.16.*, items are correlated, in general, but no item has extremely high correlation.

	RC1	UP1	F1	D1	PT1	RC2	UP2	D2	RC3	UP3	PT2	RC4	RC5	UP4	F2	PT3	RC6
RC1	1.0000																
UP1	0.5248	1.0000															
F1	0.0244	0.2211	1.0000														
D1	0.4321	0.4286	0.3213	1.0000													
PT1	-0.0904	-0.1087	-0.1484	-0.0159	1.0000												
RC2	0.4870	0.4235	0.0882	0.5365	0.0488	1.0000											
UP2	0.2935	0.2143	-0.0162	0.1041	0.1383	0.3422	1.0000										
D2	0.3616	0.2882	0.1433	0.3497	0.0707	0.3295	0.0331	1.0000									
RC3	-0.0804	-0.0427	-0.1436	-0.0256	0.3127	0.0582	0.2691	-0.1209	1.0000								
UP3	0.1456	0.2268	0.2776	0.2040	-0.0540	0.2418	-0.0345	0.0835	-0.0567	1.0000							
PT2	0.4237	0.3098	0.0801	0.4291	0.1684	0.4001	0.2659	0.2497	0.0043	0.1808	1.0000						
RC4	0.3733	0.2522	-0.0055	0.3552	0.0164	0.3070	0.1393	0.2975	0.0042	0.1509	0.2627	1.0000					
RC5	0.0753	0.0156	-0.2633	0.0685	0.2289	0.1157	0.1650	0.0635	0.3676	-0.1088	0.0900	0.1695	1.0000				
UP4	0.0732	0.1456	-0.0407	0.0254	0.1779	0.0291	0.4346	-0.0049	0.3022	0.0359	0.0426	0.0687	0.2398	1.0000			
F2	0.0540	0.1595	0.4815	0.1347	-0.0670	0.1044	0.0057	-0.0090	0.0314	0.3064	0.1316	-0.0671	-0.1630	-0.0196	1.0000		
PT3	0.6183	0.4418	0.1447	0.4865	0.0286	0.5906	0.3613	0.2925	0.0775	0.1317	0.4547	0.4577	0.1131	0.0822	0.2042	1.0000	
RC6	0.4339	0.2970	0.0985	0.3716	0.1179	0.4556	0.3616	0.2949	0.0089	0.0931	0.4571	0.4133	0.0076	0.0927	0.1083	0.6703	1.0000

Table 5.16.: correlation matrix of the 19 items to measure trust in automation.

To test whether those correlations are adequate for a factor analysis, we use the Barlett Sphericity Test and the Kaiser-Meyer-Olkin Measure of Sampling Adequacy. Specifically, The Barlett Test (Barlett-Test: $\chi^2(136) = 1225.91$, p-value < 0.001) is used to test whether the variables are sufficiently correlated to perform a factor analysis. We want this result to be significant. The KMO Measure (KMO = .795), on the other hand, provides us with an overall measure of the shared variance between each pair of variables. We want this value to be high, possibly higher than 0.65. The outputs are shown in *Figure 5.17.* shows the results of the two tests. Both results are satisfying and thus we can proceed with our EFA.

```
Bartlett test of sphericity

Chi-square          =          1225.914
Degrees of freedom =               136
p-value             =             0.000
H0: variables are not intercorrelated


Kaiser-Meyer-Olkin Measure of Sampling Adequacy
KMO                 =      0.795
```

Figure 5.17.: Barlett Test and KMO Measure for our data.

Using the Principal Component – Factor method we then isolate our factors. As retention criteria we decide to retain only factors with an Eigenvalue greater than 1, but we also considered uniqueness values. Recall that the Eigenvalue represents the portion of the total variance of our correlation matrix that is explained by the items in the factor. In this way we retain 4 different factors. Results are shown in *Table 5.17.* (below). As we may see, one initial factor captures several items and several constructs of the original paper by Korber (2019). Namely, Reliability/Competence (4 of 6 items), Intention of Developers and Propensity to Trust (2 of 3 items) are comprised in this factor. Moreover, we have a distinct factor for Familiarity (that comprises also one of the items of Understanding/Predictability and one separate item for Understanding/Predictability itself. While we may assume some imprecision depending on the reduced size of the sample (we should have used a sample with at least 500 elements), we can see that Reliability/Competence, Intention of Developers and Propensity to Trust may share some common attributes when relating them to chatbots. We thus may consider the results acceptable (while not excellent) and redefine a simplified model. The reason behind the compression of many items into the first factor might depend either on the reduced sample size or, more likely, on the fact that often the intention of developers is associated with the performances and with how much I trust the chatbot (automated system) owner company *a priori*: if a developers has the intention to create a more satisfying and fast customer service they should develop a competent and effective chatbot, otherwise I may interpret that as an intention to just filter and reduce the amount of calls and complaints received directly via e-mail or telephone. The last factor, on the other hand captures the following three items: “A system malfunction is likely”, “The system might make sporadic errors”, and “One should be careful with unfamiliar automated systems”, all of them relating, in some ways, to the possibility for the system to generate wrong outputs. All factor loadings retained are greater than .40, thus we may consider this satisfying enough.

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
PT3	0.7799				0.3047
RC1	0.7593				0.3353
RC2	0.7187				0.4393
RC6	0.6960				0.4764
D1	0.6948				0.4393
RC4	0.6556				0.5741
PT2	0.6290				0.5415
D2	0.6213				0.5684
UP1	0.5571				0.4911
F2		0.8204			0.3347
F1		0.7665			0.3594
UP3		0.5770			0.6117
UP2			0.7565		0.3087
UP4			0.7401		0.4222
PT1				0.8084	0.3530
RC3				0.5836	0.3917
RC5				0.5195	0.5269

Table 5.17.: Rotated factor loadings. Oblique (oblimin) rotation and sorting.

Measuring the overall reliability of the scale through the Cronbach’s Alpha we obtain 0.76 which is slightly below the satisfying level (0.8), but we still can consider it as acceptable. On the other hand, Alphas of the single factors were not extremely satisfactory (F1 = 0.85, F2 = 0.72, F3 = 0.61, F4 = 0.56) but, again, we may consider them to be sufficient given the limitations of the validation. Given the differences of our factors with respect to the ones highlighted by Korber (2019) we have no sufficient ground to conduct a Confirmatory Factor Analysis. In conclusion, if we measure each factor we find a positive relationship with the construct that defines "Trust in Automation": the subjects with higher values on the construct, show an overall higher score in the four factors. We can thus argue that two items may, for our purposes, be enough to measure trust in automation. Anyway, we also may want to include in this section of the experiment some additional items among the ones that constituted the original questionnaire to have, in any case, a measurement of the four factors. Moreover, in our experiment we already tested the level of trust in the financial system and in other people (that measures the overall propensity to trust), whether subjects had any previous experience with Robo-Advisors, and their level of understanding of how Robo-Advisors designed the portfolios and worked, thus we may suppose to have all the necessary information to verify the willingness to rely on Robo-Advisors.

The following section presents the structure of the improved experiment and discusses our final choices of questions and tasks and questions to measure specific factors.

5.4. Structure of the improved experiment

In this section, we present the structure of the final experiment. Given the margins of improvement that we found in the original questionnaire by Alemanni et al. (2020) and the limitations and results of the new sections that we proposed, we modify the overall structure of the experiment. This time, we extended the scope of the experiment, to also include adults and older people, and not only students. This decision is mainly motivated by the fact that the majority of university students have never invested their money, and those who did, hardly interacted with a financial advisor. Indeed, they typically have very limited availability of funds and are not willing to spend this money to hire financial advisors to obtain meagre returns. Moreover, most students are young and come from newer and more tech-savvy generations; thus, they tend to show an overall higher level of trust towards machines and automated systems. On the other hand, adults and elder people have a higher chance of having interacted through the course of their life with financial advisors. Descriptive statistics and other information about our pool of respondents can be found in *Section 5. 5.*. On average, we estimated the experiment to last between 10 and 13 minutes.

The experiment begins with a brief introduction that explains the rules and functioning of the questionnaire. Given the high discrepancy between total answers and valid answers, this time we decided to give no payoff to participants, to prevent people from giving random or fast answers just to obtain a compensation. Moreover, given the length of the experiment, we decided to allow participants to interrupt the questionnaire at any moment and to continue with it in a second moment.

Then, in a first section, participants were asked to respond to some socio-demographic questions, indicating their age, gender, income, and study title. With respect to the variable "income", in light of the evidence shown by the pilot questionnaire, we modified the bands: this time we used four bands each one comprehending 20,000€, with the last one being "over 60,000€". This section is key because it allows us to measure the socio-demographic traits of participants and to verify whether results may be influenced by such aspects. Successively, we collect data about investment and financial knowledge and experience of participants, by asking them whether they have ever invested money independently or through a financial advisor. This section allows us also to understand whether subjects are aware of the existence and functioning of Robo-Advisors. Those who never heard or just were not sure about the functioning of Robo-Advisors were then asked to read the following text (originally in Italian) describing Robo-Advisors: "*Robo-Advisors (automated financial advisory services) are platforms, often owned by banks or investment firms, through which savers can invest their money. To construct investment portfolios, the Robo-Advisor asks the client a series of questions in the form of a questionnaire to gather information about their goals and risk preferences. Subsequently, using sophisticated mathematical and learning models, the Robo-Advisor builds the investment portfolio for the client based on the answers provided in the questionnaire. Robo-Advisors have several characteristics, including the advantage of generally lower costs compared to "human" financial advisors, as well as greater ease of use and computational power in portfolio analysis*". Last but not least, here we asked participants to rate their investment knowledge on a five-levels scale from "insufficient" to "excellent". Given our purposes, we opt for this self-assessment of financial knowledge to preserve simplicity in our questionnaire. Moreover, we argue that traditional approaches with questions about diversification and risk-return patterns are nowadays well-known among people and especially among those that have previous experiences with financial advisory. On the other hand, while more elaborate tasks to assess the level of financial and investment knowledge represent a powerful instrument and give more objective and realistic evaluations, they also increase the overall length and complexity of the questionnaire.

In the second part of the experiment, participants were asked to make an investment choice, in the exact same way as in the original questionnaire by Alemanni et al. (2020). This time we use only four portfolios instead of six. Moreover, because of the way in which portfolios are described here, we add a question that verifies whether subjects correctly understood the risk-return profile of their portfolio. As argued before, understanding this is fundamental for the interpretation of the results. Anyway, respondents were not informed on the correctness of their answer to this question. After this initial choice, risk tolerance of individuals was tested through two different procedures: first, we asked participant to communicate a self-assessed level of risk tolerance through a single simple question. Then, using the 13 questions of the well-known Grabble and Lytton's risk tolerance quiz approach we obtained an objective measure of risk aversion.

In a third part of the experiment, subject needed to answer some questions and complete a simple task to measure some of their personality traits. Specifically, we employ the TIPI (Ten Items Personality Inventory) scale to measure the different aspects of the personality of subjects and the miscalibration task described before to measure the level of overconfidence. Given the overall high degree of overconfidence shown by subjects in the pilot questionnaire we decided to partially reduce the difficulty of the questions, substituting just one of them with a slightly easier one.

After this, people were randomly assigned to one condition, Robot or Human, and were presented with a recommendation. Before this, we decided to remind all subjects their initial choice, to avoid non-coherent answers in the acceptance/refute of the recommendation. Those assigned to the Robot condition visualized this message (in Italian): "Based on your previous answers, now an Artificial Intelligence software will generate an investment recommendation that is suitable for your risk profile. You will be advised on one of the 4 portfolios for which you had to make the initial choice". Then, the recommendation was communicated on the screen, with a plain text recommending one portfolio. Those assigned to the Human condition, after a couple of seconds, read this message "Based on the previous responses, a specialized financial advisor has generated an investment recommendation for you that they believe is suitable for your risk profile. You will be advised on one of the 4 portfolios for which you had to make the initial choice. If you don't see the video message immediately, please wait a few seconds". After this they saw a videoclip where a person (identified as a "financial advisor") recommended them a portfolio. The choice of the portfolio was performed in the exact same way, independently from the condition (Robot or Human). After receiving the recommendation, subjects that obtained a different recommendation from the initial one, needed to decide whether they wanted to accept the new advised portfolio, or they wanted to keep the initial one, or, again, if they wanted to switch to a different portfolio that was neither the initial one nor the recommended one. After making their choice, people were asked to rate how satisfied they were with the brief advisory experience they had and whether they would be intentioned to consider using similar platforms in the future. Those who said that they would not were also asked to motivate it. These two questions are the key innovation of our approach and use the overall satisfaction to measure the confirmation bias.

In the last part of the experiment, subjects had to answer some questions to verify their levels of trust in automation and interpersonal trust. The section regarding interpersonal trust is very similar to the one of the pilot questionnaires (taken from the World Value Survey) but the last category (people of other religions) was removed due to its similarity with the previous one (people of other nationalities) and replaced with a new one, addressing the level of trust towards professionals. On the other hand, considering the results of the validation, we modified the section addressing trust in automation in two ways. First, we changed the reference object: this time, instead of pointing to chatbots, we refer to a generic automated system, to avoid specific negative/positive experiences to alter the data. Moreover, we reduced the number of questions, leaving only six items and considering the relevant factors extracted in the Exploratory Factor Analysis.

5.5. Summary statistics of respondents and results

5.5.1. Pool of subjects and summary statistics

This time, for our improved version of the experiment, we decided to distribute the questionnaire to a pool of adults that have a higher chance of being investor themselves and have more funds available. Specifically, participants were recruited through various channels and on a voluntary basis. No payoff was given in exchange for the participation to the experiment. In total, $N = 158$ individuals answered the questionnaire. After eliminating incomplete and incoherent answers and those which were completed too fast (the average completion time was 693 seconds) we ended up with $n = 146$ valid answers.

Sociodemographic characteristics

Table 5.18. shows summary statistics for sociodemographic variables in our pool of subjects. Specifically, we see that the average age is around 41 years, and that the distribution of ages is pretty symmetrical. The youngest respondent is 20 while the oldest is 76 years old and the standard deviation of our pool is approximately 13.24, certifying a good degree of variability. From the point of view of gender, we have an almost perfect equality between men (49%) and women (51%). The variable "Income" represents the total annual income of the subject, including the other members of the household. As said before, in light of what we observed in the pilot experiment, we slightly modified the bands. This time, the value ranges between 1 and 4, where 1 means a total annual income lower than 20,000€ and 4 represents an income greater than 60,000€. With respect to the results of the pilot experiment, more subjects concentrate in the central bands, but this seems reasonable given that respondents of this experiment are adults that probably work full- or part-time. The variable "Education" ranges between 1 and 4, where 1 represents the lowest degree of education (middle school or lower), 2 represents an (earned) high school diploma, 3 includes a Bachelor's degree, and 4 is for those who completed also their Master's degree or obtained higher level degrees (e.g., PhD).

	Mean	SD	Q1	Q2	Q3	Min	Max
Age	41,41	13,24	31	40,5	50	20,00	76,00
Female	0,51	0,50	0	1	1	0,00	1,00
Income	2,53	0,98	2	2	3	1,00	4,00
Education	2,57	1,12	2	2	4	1,00	4,00

Table 5.18.: Descriptive statistics for sociodemographic variables of our sample (n=146).

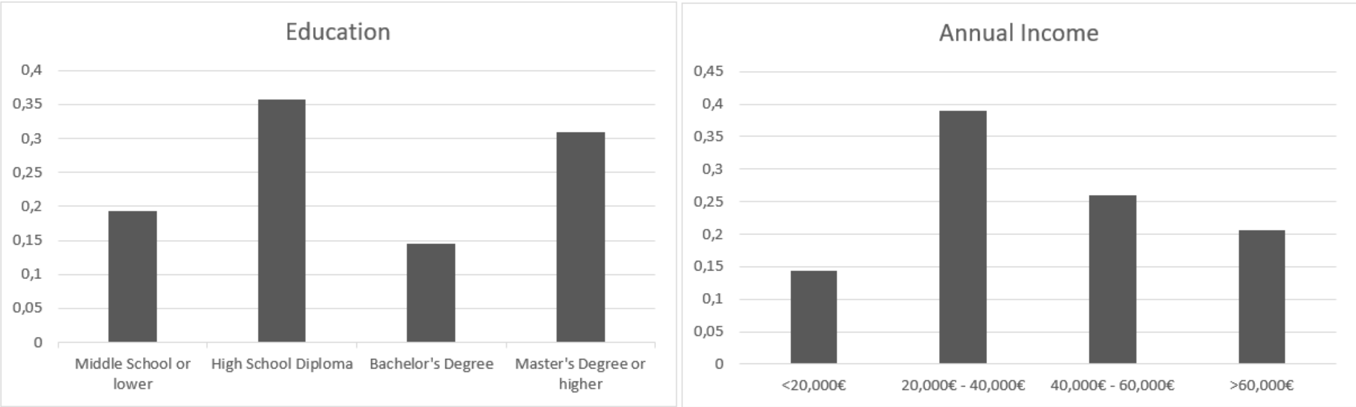

Figure 5.18.: Histograms for education (left) and income (right).

We also verify the existence of eventual correlation between the sociodemographic variables, shown in *Table 5.19.*, seeing that significant correlations exists between age and income (older people tend to have higher income) and the degree of education and gender (females of our sample are, on average, slightly more educated). All the other correlations are not significant at 5% level and thus can be ignored.

	Age	Female	Income	Educat~n
Age	**1.0000**			
Female	**-0.0632**	**1.0000**		
Income	**0.3974***	**-0.1486**	**1.0000**	
Education	**-0.1410**	**0.2132***	**0.0834**	**1.0000**

Table 5.19.: Correlation matrix of sociodemographic variables. "" means that the correlation is significant at 5% tolerance level.*

Investment habits and usage of financial advisory services

With respect to financial habits and choices of the adults that participated in our experiment, we observed that, at the time of the experiment, 50% (73 out of 146) of participants were investing their money in some kind of financial instrument; 17.8% (26 out of 146) of participants invested their money in the past but not at the moment; the remaining 32.2% (47 out of 146) of participants never invested their money before. Regarding specifically the use of financial advisory among our subjects, the majority (49.3%) never used any kind of financial advisory service while 21.9% used advisory services in the past; the remaining 28.8% (32 out of 146) of respondents utilizes advisory services at the moment. Among those 32, just 6 people interacted in the past with Robo-Advisors, while none of the subjects uses Robo-Advisory services at the moment. Also, we asked subjects to rate their investment and financial knowledge on a qualitative scale from 1 (very low) to 5 (excellent). *Figure 5.19.* shows the results of the self-evaluation. We can see how most people rated their investment knowledges as either average or sufficient, while only a minority rated their knowledge as excellent. Anyway, values are quite high with respect to the typical scale that one would have expected. A possible explanation for this might be related to the fact that we have a high number of people that invest (or invested in the past) their money and thus respondents might be (even unconsciously) reluctant to judge their knowledge as "poor" but at the same time saying that they are currently investing their money (maybe even without the help of an advisor). On the other hand, we should also consider that those who invest should, at least in theory, gain some knowledge from their practical experience.

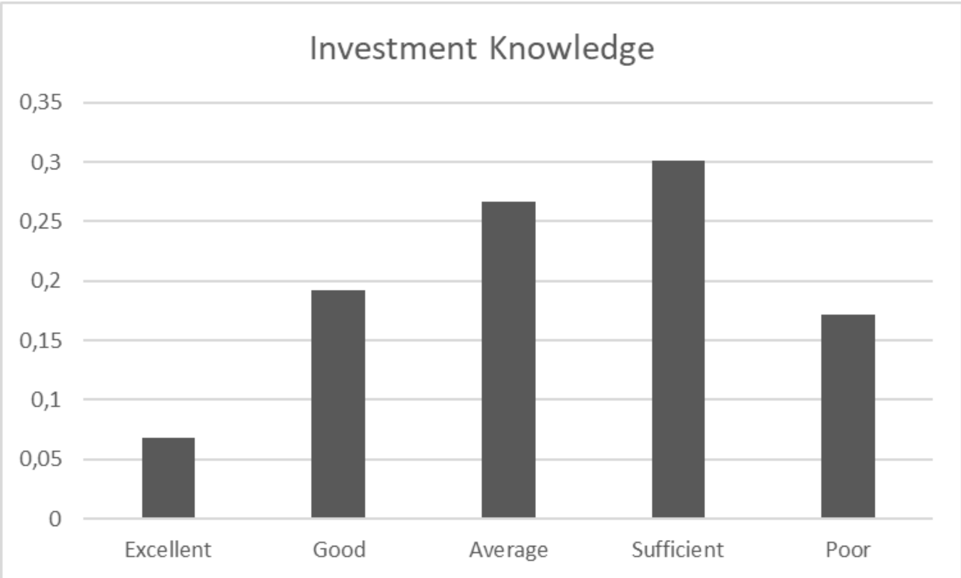

Figure 5.19.: Histogram of self-assessed investment knowledge of participants to the experiment.

Moreover, we test the relationship between demographic traits and investment behaviour or advisory usage. Using a series of repeated Kruskal-Wallis equality-of-populations rank tests we indeed verify whether those who never invested and never used any kind of financial advisory service showed differences in the age, gender, levels of education and income. The test compares the medians of the two groups and determines whether they might be extracted from the same origin population, at least with respect to the variable at issue. Results of the tests reveal that those who never invested are different from those who did with respect to age (χ^2 = 10.321, p-value: 0.0013), level of education (χ^2 = 3.132, p-value: 0.0768), and income (χ^2 = 13.432, p-value: 0.0002). On the other hand, those who used financial advisory services at least once in their life showed differences from those who did not with respect to age (χ^2 = 39.370, p-value: 0.0001) and income (χ^2 = 18.337, p-value: 0.0001). Gender seems to be less relevant, and the level of education is relevant only when distinguishing between investors and non-investors. We further investigate the nature of such discrepancies in *Table 5.20.* and *Table 5.21.*, showing the comparison between the medians of the variables between the two groups in the two cases. We can see that, on average, investors and advisory users are typically older, with higher incomes and with higher levels of education (relevant only for investors vs. non-investors). This is aligned with the main findings of existing studies on the demand of financial advisory, highlighted in *Chapter 1*. Additionally, we see that, as we discussed before, investors rate their investment knowledge, on average, better than those who never invested their money (χ^2 = 25.147, p-value: 0.0001). This difference reduces while still remaining significant (χ^2 = 4.111, p-value: 0.0426) when we consider the usage of financial advisory services. Indeed, people who use advisory services might be intentioned to exploit the experience and expertise of the advisor to invest their money, given their poor investment knowledge.

Ever invested?	Yes	No
Age	43,79	36,40
Income	2,74	2,09
Education	2,69	2,32
Investment Knowledge	3,02	1,98

Ever used Advisory?	Yes	No
Age	47,93	34,71
Income	2,88	2,17
Education	2,57	2,57
Investment Knowledge	2,89	2,47

Tables 5.20.-5.21.: Comparison of sociodemographic traits between those who never invested and those who did (left) and between those who used financial advisory services and those who did not (right).

Last but not least, considering Robo-Advisory services, as we said, only 6 subjects had already interacted with this kind of services. We also asked participants whether they were aware of their existence and whether they knew how Robo-Advisory services worked. In total we find that 66 people were aware of their existence while the remaining 80 never heard of them. Given the still scarce diffusion of Robo-Advisory services in Italy, we can consider the result (45.3%) as interesting and satisfactory to create variability in our pool of subjects. Anyway, we should also consider the fact that this information is gathered through self-evaluations of participants that might be biased or reluctant to admit a complete ignorance of the existence of an innovative service (especially if they rated their financial knowledge as high) and thus the data might be biased. Given such limitation, this time we prefer to adopt a less formal approach to test the dependence between characteristics and knowledge of Robo-Advisors. *Table 5.22.* shows that, on average, people who are aware of the existence of Robo-Advisory services are younger, more educated and rate their investment knowledge as higher. Most importantly we see a significant difference in the two groups if we look at the proportion of people who use (or used) financial advisory services. The reason might depend both on an irrational reluctance to admit ignorance towards this topic or on the fact that people who needed to hire a financial advisor might have explored various options and might have heard about Robo-Advisory through advertisement or introduced to them by their advisor/bank. Regarding gender and income, we see only a small difference in the two categories and thus we might hypothesize a more limited role of these variables.

Know Robo-Advisors?	Yes	No
Age	38,38	43,91
Female	0,48	0,54
Income	2,67	2,41
Education	2,83	2,35
Investment Knowledge	3,20	2,26
Ever Used Advisory	0,59	0,44

Table 5.22.: Personal traits of individuals and knowledge of Robo-Advisory

Level of interpersonal trust and trust in automation

Finally, given the importance of the levels of interpersonal trust and trust in automation in our experiment, we analyse the overall data of our pool. With respect to the results of the pilot experiment, we should expect adults to have higher levels of interpersonal trust, especially towards specific categories of subjects but, conversely, lower levels of trust in automation. *Table 5.23.* shows results for the level of interpersonal trust. The factor is measured in three different ways: “General Trust” is a binary variable that takes the value of 1 for people that said that they “in general, trust other people”, and 0 for those who said that “one should be careful when trusting other people”. “Trust Index” is built as the average of the level of trust towards various categories of subjects (neighbours, people you know, people you just met, and people from other countries), rated on a scale from 1 (do not trust at all) and 4 (trust completely). We also asked participants their level of trust towards their family members but, as we could imagine, almost all participants rated this category with the maximum score, so we did not consider this value. “Professional Trust”, in the third row, contains what we believe to be one of the most important variables: trust towards professionals delivering services (e.g., advisors, lawyers, etc.), rated again on the same scale from 1 to 4. This value was not included in the computation of the Trust Index. In general, we observe pretty high levels of trust towards other people (trust index) and towards professionals. On the other hand, subjects are equally divided with respect to the general level of interpersonal trust.

	Mean	SD	Q1	Q2	Q3	Min	Max
General Trust	0,54	0,50	0	1	1	0,00	1,00
Trust Index	2,58	0,53	2,25	2,5	3	1,00	3,75
Professional Trust	2,97	0,75	3	3	3	1,00	4,00

Table 5.23.: Interpersonal trust levels in our pool (n=146).

We then test also the eventual correlation between sociodemographic traits of individuals and the levels of interpersonal trust. *Table 5.24.* contains the correlation matrix of the variables. Apart from some, predictable, positive significant correlation between the three interpersonal trust scores, we see no significant correlation with sociodemographic traits, seeing thus an adequate variability between the various groups.

	Age	Female	Income	Educat~n	T_gen	T_index	T_prof
Age	1.0000						
Female	-0.0632	1.0000					
Income	0.3974*	-0.1486	1.0000				
Education	-0.1410	0.2132*	0.0834	1.0000			
T_gen	-0.0192	-0.1260	0.1036	0.0134	1.0000		
T_index	-0.1190	0.0642	-0.0258	0.0769	0.4410*	1.0000	
T_prof	0.1460	0.0010	0.0480	0.0104	0.3701*	0.4304*	1.0000

Table 5.24.: Correlation matrix between levels of interpersonal trust and sociodemographic traits.

The levels of trust in automation of participants have been explored through the simplified scale, as explained during the discussion of the results of the validation process. Specifically, the various items have been grouped into three factors. "Trust in automation" represents the general level of trust in automation, as the average of two items, that asked to rate on a scale from 1 (do not trust at all) to 5 (trust completely) how much the individual trusted automated systems. "Fear of errors" represents the possibility of being worried about the precision of the outcomes of an automated system, fearing the presence of mistakes or the risk of incurring in system errors (malfunctioning). Again, subjects had to give their evaluation on a scale from 1 to 5. The variable is coded in a slightly unintuitive way, so that high values represent an overall low level of worry towards the possibility of errors; the goal of such coding is to preserve the link between positive correlation and positive influence. The last factor, named "Competence", captures the level of perceived competence of automated systems on a scale from 1 to 5, together with their capability of managing complex tasks. Also, given the importance of previous experiences that we highlighted during the validation process and in the pilot experiment, we asked participants about their experience and comfort with automated systems. Regarding experience level, participants had to say whether they interacted several times with automated systems (score of 4), only a few times (score of 3), never interacted but heard of (score of 2), never interacted and never heard of (score of 1). The level of comfort is, instead, rated on a scale from 1 (low comfort) to 3 (high comfort). *Table 5.25.* shows summary statistics for the five factors. We can observe that, on average, most people had previous experiences and feel comfortable when interacting with automated systems, which is reasonable given the diffusion of those, for example, in our smartphones and PCs. Participants showed an average level of trust in automation and perceived competence, but the factor regarding the fear of incurring in errors shows a lower value, symbolizing an increased worry towards this occurrence.

	Mean	SD	Q1	Q2	Q3	Min	Max
Experience	3,40	0,65	3	3	4	1,00	4,00
Comfort	2,29	0,67	2	2	3	1,00	3,00
Trust in automation	3,73	0,94	3	4	4,5	1,50	5,00
Fear of errors	2,89	0,73	2,5	3	3,5	1,50	5,00
Competence	3,34	0,81	3	3,5	4	1,50	5,00

Table 5.25.: Summary statistics for the levels of experience, comfort and trust in automation of participants (n=146).

Figure 5.20. below shows the distribution of levels of experience and comfort when using automated systems.

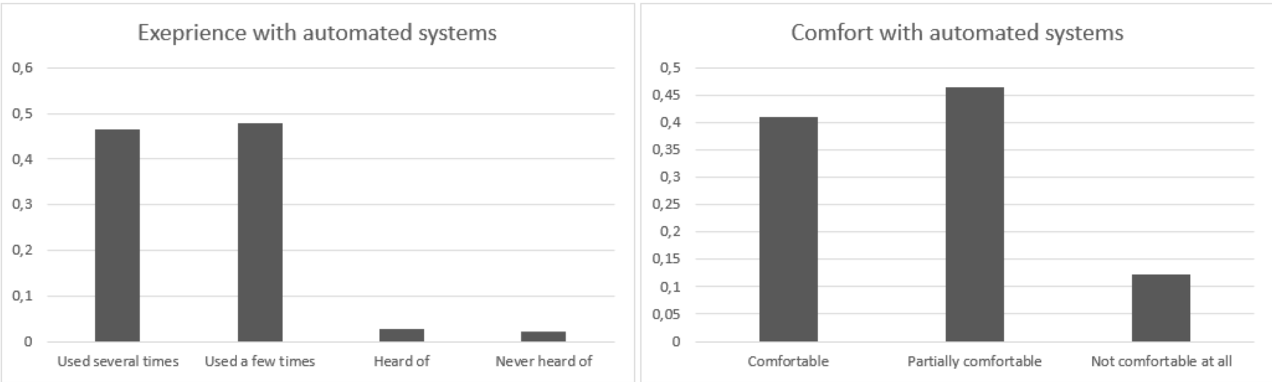

Figure 5.20.: Histograms for level of experience (left) and level of comfort (right) with automated systems.

5.5.2. Results

After describing the main characteristics of the subjects in our pool, in this sub-section, we will analyse more specifically the results of the experiment, discussing initial portfolio choices of participants, comparing recommendations of human and robotic advisors and trying to predict some of the determinants of the choices of individuals.

First, we need to briefly describe the various distinctive elements of the experiment that divided subjects in sub-groups. As said, initially each individual was randomly assigned to one of the two treatments, with equal probability, so that we end up with 73 participants with the robotic treatment (R) and 73 participants with the (pseudo-)human treatment (H). Among the 73 that received the human treatment, 29 participants (39.7%) visualized the video recommendation with a female advisor (reader); the other visualized a male advisor (reader). All the participants were not aware of the existence of the other treatment nor of the presence of the advisor of the other gender and each participant was assigned to the conditions randomly.

Statistics on portfolio choices, advice, and acceptance of the recommendation

In our simplified 4 portfolio scenario, people were initially asked to choose one portfolio, visualizing the distribution of returns and obtaining information about the average return of the portfolio. To be sure about the full comprehension of the riskiness of portfolios, after their choice we asked subjects to rate the riskiness of the portfolio they chose, with respect to the other three. In total, 122 out of 146 subjects evaluated correctly the riskiness of their portfolio, while 24 did not. *Figure 5.21.* shows the distribution of portfolio choices of the subjects in our experiment. We see that most people preferred the medium-low risk portfolio while only less than 10% chose the portfolio with the highest riskiness. Similarly, most people obtained as a recommendation the two central portfolios. Anyway, the histogram seems to suggest a positive effect of the intervention of the advisors. While this needs to be analysed more formally, we can see that for each of the four portfolios, we can observe that the final choice bar sits in between the other two.

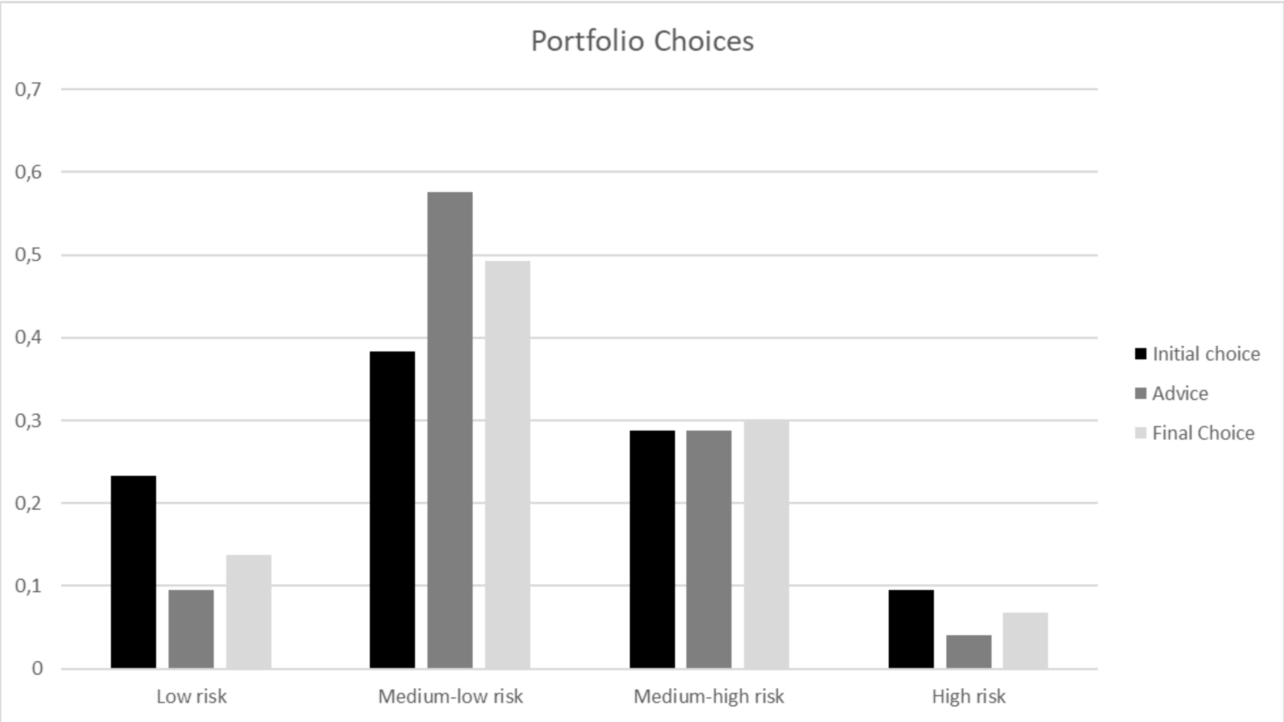

Figure 5.21.: Histogram of portfolio choices of individuals (n=146).

Successively, we verify the presence of eventual inner differences between the two groups (grouped with respect to the treatment). Looking at *Figure 5.22.* we revise some small difference in the proportion of subjects that chose the high-risk portfolio between the two treatments. While, given that recommendations are generated in the same way regardless of the type of treatment, we can observe an overall coherence of the proportions in the recommendations, we should take into account this difference between the two groups and thus consider the eventual effect of portfolio riskiness in the successive analysis. Running a Kruskal-Wallis equality-of-populations rank test we confirm the difference between the initial choices (χ^2 = 5.415, p-value: 0.0200). With respect to the advice (χ^2 = 0.104, p-value: 0.7471) and final choice (χ^2 = 0.678, p-value: 0.4101) the test confirms the equality of the populations.

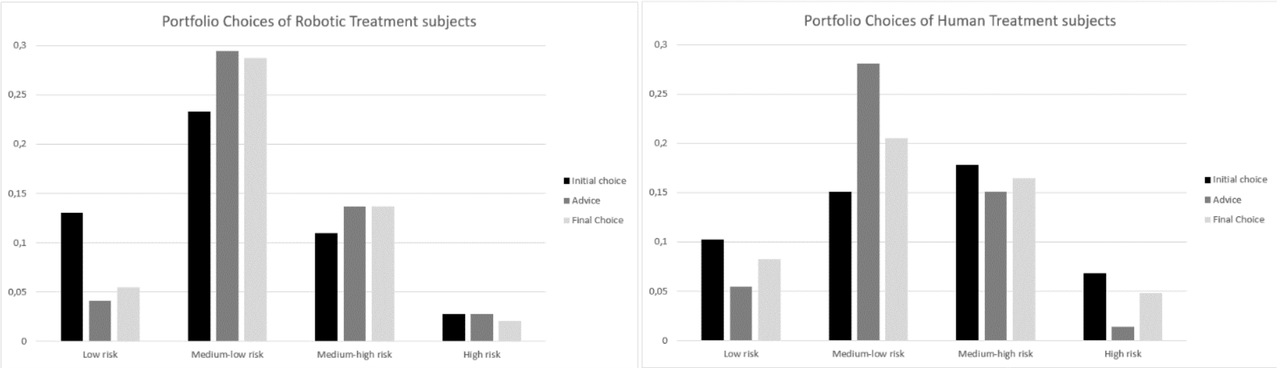

Figure 5.22.: Comparison of portfolio choices of those assigned to the robotic treatment (left) and human treatment (right).

To complete the analysis of portfolio choices, we verify the eventual differences between the two groups with respect to sociodemographic traits, investment and advisory experience/knowledge, and trust towards humans and automated systems. As we can observe from *Table 5.26.* below, differences between the two groups are minimal for all the variables. This is a positive occurrence because it reduces the eventual influence of excessive heterogeneity between the two groups and allows us to compare the conclusions more easily. Also, we run a series of simple t-tests to verify the eventual significance of the difference between the two groups but, at 5% tolerance level, none of the differences have been found to be significant.

	Robot	Human	Difference	Significant?
Age	40,53	42,29	-1,75	N
Female	0,56	0,47	0,10	N
Income	2,53	2,52	0,01	N
Education	2,62	2,52	0,10	N
Investment Knowledge	2,59	2,78	-0,19	N
Ever Invested	0,66	0,70	-0,04	N
Ever used advisory	0,52	0,49	-0,03	N
Know Robo-Advisors	0,44	0,47	-0,03	N
General Trust	0,53	0,55	-0,01	N
Trust Index	2,57	2,59	-0,02	N
Professional Trust	2,88	3,07	-0,19	N
Experience with Automation	3,38	3,42	-0,03	N
Comfort with automation	2,29	2,29	0,00	N
Trust in automation	3,69	3,76	-0,07	N
Fear of errors	2,90	2,88	0,01	N
Competence	3,32	3,36	-0,05	N

Table 5.26.: Comparison of mean values of sociodemographic factors (1-4), Investment and Advisory attitude (5-8), level of interpersonal trust (9-11), and level of comfort, experience and trust in automation (12-17), between the two groups defined by the treatment received.

Predictive analysis, confirmation bias, acceptance of the recommendation

To verify the influence of confirmation bias, the type of treatment, and other factors, on the degree of reliance on recommendations from Robo-Advisors, we asked participant to rate the quality of the service (on a five-item scale from “terrible” to “excellent”) and say whether they would consider the possibility of using similar services in the future (on a five-item scale from “surely not” to “surely yes”). Before going through these data, we also describe statistics on the eventual acceptance of the recommendation received. As shown in *Figure 5.23.*, in total, among our n = 146 participants, 66 (45.2%) chose a portfolio aligned with their risk profile and thus received a recommendation equal to their initial choice. Of the remaining 80 who received a recommendation different from their initial choice – note that our recommendation must always be considered as more suitable, at least in light of the results of the Grabble & Lytton’s risk assessment questionnaire – 36 did not accept the recommendation and kept their initial portfolio while 44 (22 robot and 22 human) accepted the recommendation of the advisor and changed portfolio. These results allow us to conclude that, at least from the point of view of the acceptance of the recommendation, there is no preference for human or robotic advisors. The slightly lower proportion of refusals for robotic advisors with respect to human advisors might depend on the lower number of users that chose a portfolio coherent with their initial risk profile. Again, we should take into account the fact that in some ways, our “human” advisor may still have been perceived as robotic by participants.

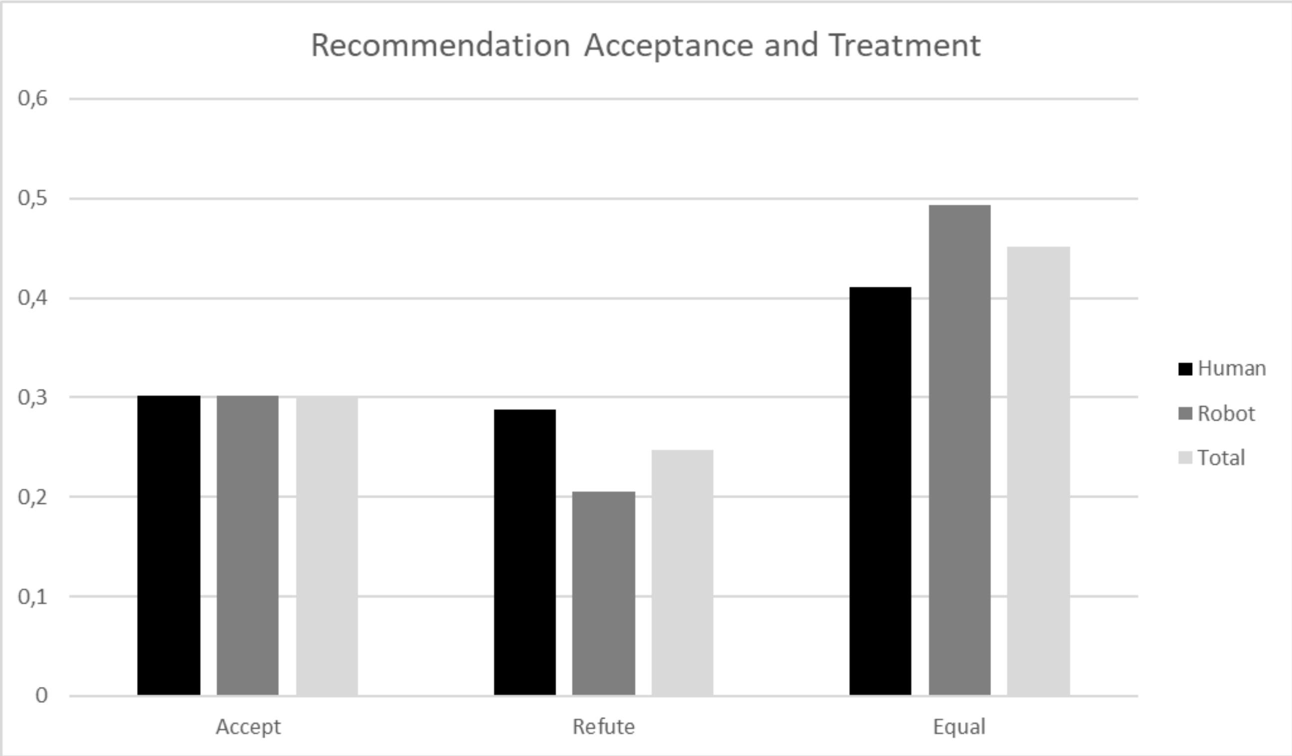

Figure 5.23.: Recommendation acceptance based on the type of treatment.

Before analysing the model through some regression analysis, we show also the data regarding the overall quality and intention to use again the service. *Figure 5.24.* shows that the quality for the two services is almost equal but seems to show a little preference for the human treatment. While we see that more people judged the robotic advice as “excellent”, on average it received also a greater number of and “terrible” evaluations. Overall, subjects rated the quality of the service as mediocre (mean value 3.34 out of 5). Given the simplicity of our risk assessment and of the setting of the experiment we can interpret this result as plausible and adequate as an evaluation of the quality of the advice.

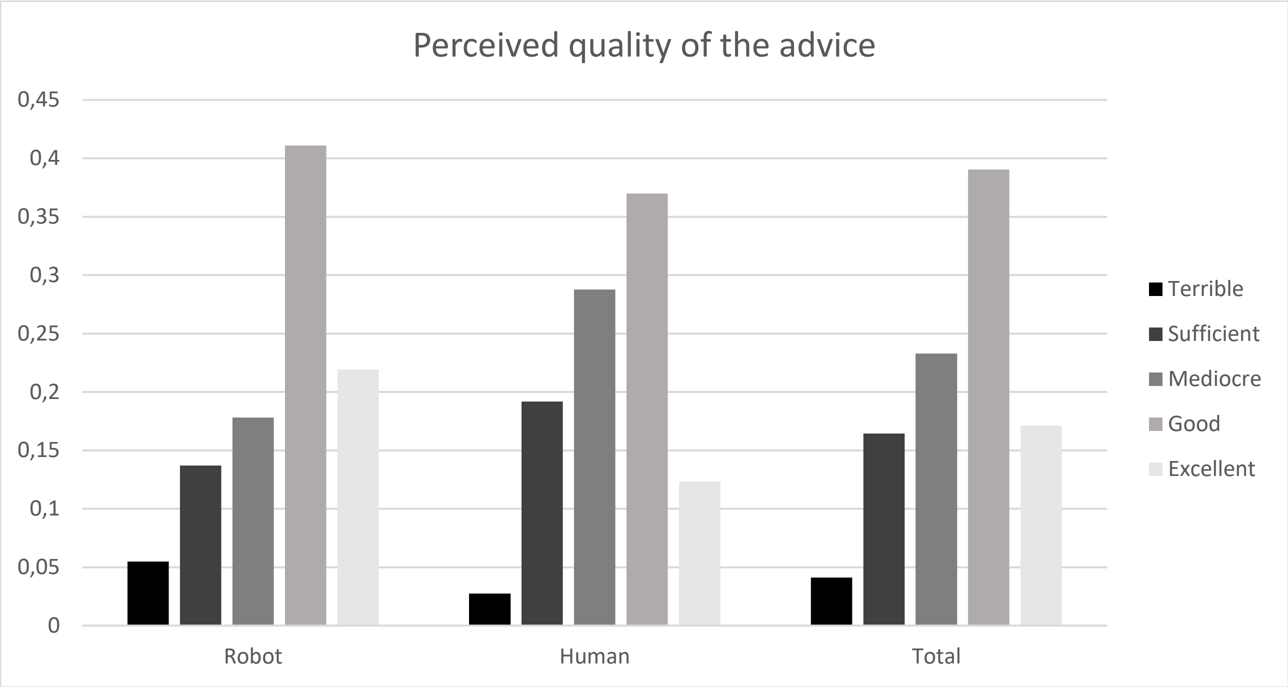

Figure 5.2416.: Perceived quality of the advisory service received.

A similar pattern can be observed when we look (*Figure 5.25.*) at the intention to utilize similar services in the future. Anyway, if we measure the correlation between the two variables, we find a correlation coefficient of 0.57, indicating a positive and significant link between the two variables. It appears reasonable to say that when people perceive the service and the recommendation as of good quality, they are at the same time more willing to utilize it.

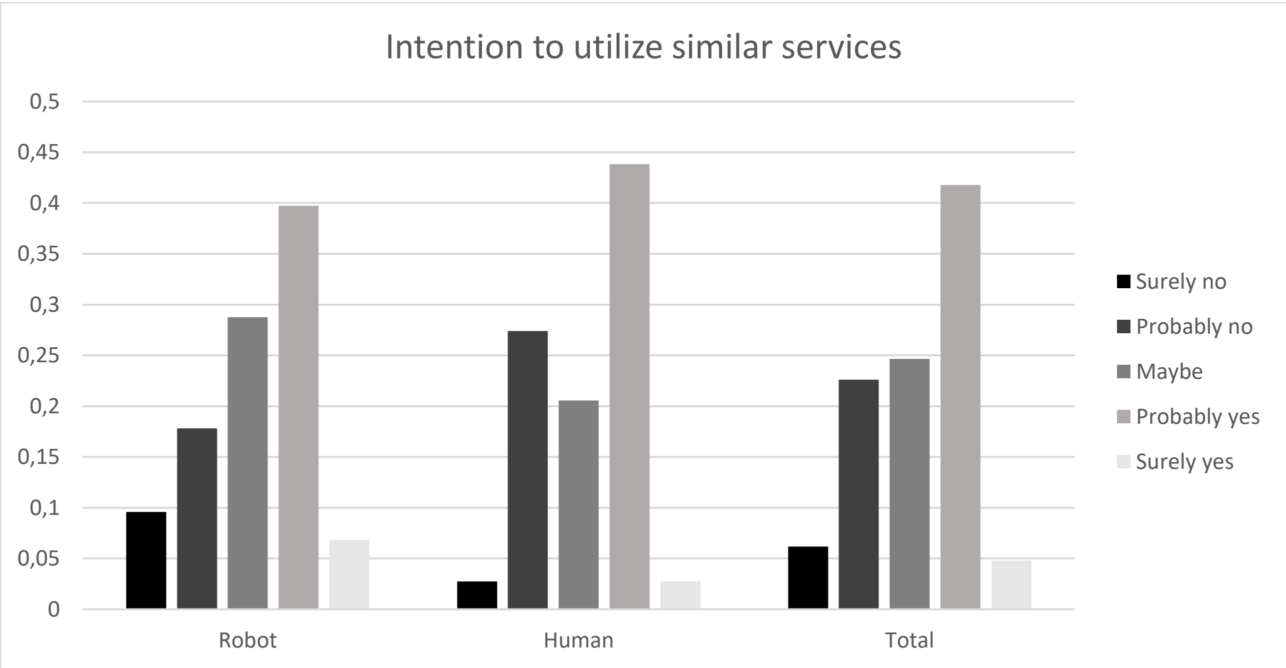

Figure 5.25.: Intention to utilize similar advisory services. in the future.

Regression Analysis

Finally, as said, to assess the effect of our variables and factors on the probability to accept the recommendation and on the overall level of perceived quality of the service, we utilize regression analysis. We build two different models to test our initial hypothesis. In a first set of analysis, we use as dependent variable the perceived quality of the service, measured as explained before. Given the high correlation between this variable and the variable measuring the intention of individuals to utilize similar services in the future, we present results obtained only with the former. The first model we build is used to assess the role of confirmation bias on the quality of the advice obtained. In light of what we discussed above and considering the descriptive statistics presented, we believe confirmation bias to be relevant, together with the levels of trust in automation and interpersonal trust (specifically towards professionals). In the model we also consider eventual preliminary knowledge of Robo-Advisors and investment knowledge in general, to keep into consideration eventual experience/knowledge effects. Before showing the results of the regression, to avoid the risk of ignoring a possible collinearity between the variables or particular cases of high correlations, we show the correlation matrix of the various regressors of the model. Looking at *Table 5.27.* we observe some correlation between the variables but none of the values seems to be excessively high to suggest collinearity. The only high correlation can be found between the perceived quality and the dummy variable that verifies the correspondence of the initial choice and the advice, furtherly supporting the thesis of the existence of confirmation bias. Regarding the other variables, we only see some correlation between investment knowledge, knowledge of Robo-Advisors and trust in automation. We thus will run the regression twice to verify whether something gets altered removing the first two variables.

	Quality	Inv_Know	R_Know	Human_~r	Choice..	T_prof	T_aut
Quality	1.0000						
Inv_Know	-0.0198	1.0000					
R_Know	-0.0012	0.3999*	1.0000				
Human_advi~r	-0.1078	0.0824	0.0275	1.0000			
Choice1_eq~e	0.5082*	-0.1326	0.0598	-0.0826	1.0000		
T_prof	0.1773*	0.0373	-0.0035	0.1280	-0.0035	1.0000	
T_aut	0.2975*	0.2446*	0.1849*	0.0366	0.0600	0.0332	1.0000

Table 5.27.: Correlation matrix between regressors in our model.

The model used for the first regression is thus the following:

$$Quality = \beta_0 + \beta_1 InvKnow + \beta_2 D(RoboKnow) + \beta_3 D(Human) + \beta_4 D(Choice1 = Advice) + \beta_5 TrustProfessionals + \beta_6 TrustAutomation + \epsilon$$

The results of the regression are shown in *Figure 5.27.*, below. As we see the investment knowledge and awareness of the existence of Robo-Advisors have non-significant coefficients and thus can be considered as having a minor influence on the perceived quality of the service. Also, the type of treatment has a non-significant coefficient, but this result might depend on the fact that people may have perceived both treatments as robotic. Anyway, such data seem to be in contrast with our initial hypothesis that people would have a slight preference for human (human-like) recommendations. More interestingly, both kinds of trust seem to influence importantly and positively the perceived quality. Indeed, results of the regression show that the higher the level of trust in automation of subjects and the higher the level of trust towards professionals, the higher the perceived quality of the advice. This kind on influence seems to be rational: we are indeed delivering a professional service (or at least simulating it) and through an automated algorithm. This is a key result that confirms one of our initial hypotheses. Also, the correspondence between initial choice and advice has a positive and highly significant coefficient, showing that subjects who received a recommendation coincident with their initial portfolio choice felt more satisfied with the advisory service. This confirms also the other hypothesis we made. Overall, the R-squared of the regression is of 0.3748 that, considering that we are analysing human behaviour and considering the reduced size of our sample, is quite satisfactory.

Source	SS	df	MS		
				Number of obs =	146
				F(6, 139) =	13.89
Model	63.9007835	6	10.6501306	Prob > F =	0.0000
Residual	106.571819	139	.766703735	R-squared =	0.3748
				Adj R-squared =	0.3479
Total	170.472603	145	1.17567312	Root MSE =	.87562

Quality	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
Inv_Know	.0111536	.0705842	0.16	0.875	-.1284039	.150711
R_Know	-.1811482	.160751	-1.13	0.262	-.4989814	.1366851
Human_advisor	-.2147844	.1470159	-1.46	0.146	-.5054611	.0758923
Choice1_eq_Advice	1.065052	.1490053	7.15	0.000	.7704418	1.359662
T_prof	.2622141	.0976541	2.69	0.008	.0691346	.4552935
T_aut	.3209443	.0805298	3.99	0.000	.1617225	.4801661
_cons	1.188869	.4239769	2.80	0.006	.3505908	2.027146

Figure 5.27.: Linear regression results for our model (n=146) with all the six regressors and a constant.

Figure 5.28. shows results of the regression by removing the first three variables, but neither the coefficients nor the R-squared are significantly impacted by this modification.

Source	SS	df	MS			
				Number of obs	=	146
				F(3, 142)	=	26.49
Model	61.1657262	3	20.3885754	Prob > F	=	0.0000
Residual	109.306877	142	.769766736	R-squared	=	0.3588
				Adj R-squared	=	0.3453
Total	170.472603	145	1.17567312	Root MSE	=	.87736

Quality	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
Choice1_eq_Advice	1.070555	.14616	7.32	0.000	.781624	1.359485
T_prof	.2456994	.0970085	2.53	0.012	.053932	.4374669
T_aut	.3026017	.0777198	3.89	0.000	.1489643	.4562391
_cons	1.144483	.4110545	2.78	0.006	.3319058	1.95706

Figure 5.28.: Linear regression results for our model (n=146) with only three regressors and a constant.

In conclusion, following what we observed previously regarding the possible impact of the riskiness of the initial choice, we try to run the regression also including this factor. Results are shown in *Figure 5.29.* below. As we see riskiness of the portfolio seems to be less relevant, at least if we consider the whole sample.

Source	SS	df	MS			
				Number of obs	=	146
				F(4, 141)	=	19.76
Model	61.239274	4	15.3098185	Prob > F	=	0.0000
Residual	109.233329	141	.774704459	R-squared	=	0.3592
				Adj R-squared	=	0.3411
Total	170.472603	145	1.17567312	Root MSE	=	.88017

Quality	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
Choice1	-.0246798	.0800986	-0.31	0.758	-.1830293	.1336696
Choice1_eq_Advice	1.066524	.1472104	7.24	0.000	.7754995	1.357549
T_prof	.244575	.0973875	2.51	0.013	.0520465	.4371035
T_aut	.3003244	.0783182	3.83	0.000	.1454945	.4551542
_cons	1.213578	.4694008	2.59	0.011	.2856047	2.141551

Figure 5.29.: Linear regression results including also riskiness of initial choice (n=146).

To further refine the assessment of the role of the different variables, we run three additional sets of analysis. In the first set, we will split the sample in two sub-groups, dividing them depending on the treatment they received. Through this method we want to verify whether those who decided to accept a recommendation coming from, say, robotic advisor, show a greater level of trust in automation with respect to those who refuted the recommendation. Later, in a second set of analysis we will repeat everything, this time considering only the 80 subjects that failed to correctly determine their most suitable portfolio (at least with respect to the results of our assessment process). In this way we will rule out the role of confirmation bias and thus obtain more precise results on the probability to accept the recommendation, rather than on the perceived quality or on the willingness to utilize the service in the future.

To start with the first set of analysis, as said, we split the group depending on the type of treatment received. Specifically, as reported before, 73 subjects (exactly 50% of the total participants) received the human treatment and 73 received the robotic treatment. We already presented summary statistics of the two pools and compared them before, finding no significant differences in traits and levels of trust. We thus proceed with the linear regression, keeping in mind the reduced size of the sample.

Starting from those who received the robotic treatment we can see from *Figure 5.30.* that the only relevant factor, apart for confirmation bias, is the level of trust in automation. Other regressors that were found to be significant before (including also the constant) have now non-significant coefficients. This results furtherly highlights not only the importance but also the positive role played by the level of trust in automation of individuals, when it comes to interacting with Robo-Advisors.

Source	SS	df	MS			
				Number of obs	=	73
				F(5, 67)	=	6.41
Model	30.2629385	5	6.0525877	Prob > F	=	0.0001
Residual	63.2165136	67	.943530053	R-squared	=	0.3237
				Adj R-squared	=	0.2733
Total	93.4794521	72	1.29832572	Root MSE	=	.97135

Quality	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
Inv_Know	.0643514	.109905	0.59	0.560	-.1550199	.2837227
R_Know	-.2005043	.2502401	-0.80	0.426	-.6999856	.2989771
Choice1_eq_Advice	1.041548	.2413853	4.31	0.000	.5597409	1.523355
T_prof	.2257571	.1729929	1.31	0.196	-.1195382	.5710524
T_aut	.3893054	.1171248	3.32	0.001	.1555234	.6230874
_cons	.9237151	.6915286	1.34	0.186	-.4565818	2.304012

Figure 5.30.: Linear regression results for subjects that received the robotic recommendation (n=73).

Then, with respect to the group who received the human treatment, we can observe the results of the linear regression in *Figure 5.31.* below. As we see, the most relevant predictor is again the equality of the initial choice and the recommendation obtained, furtherly supporting the presence of confirmation bias. Moreover, we see through this regression that, among those who received the human recommendation, a positive link exists between the level of trust towards professionals and the quality of the recommendation. This is aligned with our initial hypothesis. While less significant (but still significant), also the level of trust in automation seem to play a positive role in predicting the quality judgement of the recommendation from subjects. This is interesting and, as we said before, probably depends on the fact that people might have (correctly) perceived our human recommendation as robotic and algorithmically generated. The R-squared of the regression is pretty high but this might be based on the reduced variability of the dependent variable, that is mostly captured by confirmation bias.

Source	SS	df	MS			
				Number of obs	=	73
				F(5, 67)	=	10.68
Model	33.2666347	5	6.65332695	Prob > F	=	0.0000
Residual	41.7470639	67	.623090506	R-squared	=	0.4435
				Adj R-squared	=	0.4019
Total	75.0136986	72	1.04185693	Root MSE	=	.78936

Quality	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
Inv_Know	-.0421599	.0941899	-0.45	0.656	-.2301637	.1458438
R_Know	-.1275324	.2093091	-0.61	0.544	-.5453151	.2902503
Choice1_eq_Advice	1.160602	.1910973	6.07	0.000	.7791704	1.542034
T_prof	.2748411	.1133025	2.43	0.018	.0486885	.5009938
T_aut	.2341093	.1149068	2.04	0.046	.0047543	.4634642
_cons	1.345878	.5479602	2.46	0.017	.2521449	2.439611

Figure 5.31.: Linear regression results for subjects that received the human treatment (n=73).

The comparison of the two models fitted to the data of the sub-groups gives us a fundamental information regarding the nature of the quality rate of individuals. When individuals obtain the recommendation from the human(-like) advisor, the level of interpersonal trust played an important role while the level of trust in automation played only a marginal (but still considerable) role, probably because of the setting of the experiment. On the other hand, for those who received the robotic recommendation, just the level of trust in automation plays a role, while interpersonal trust might be ignored. Before drawing any kind of conclusion, we want to expand the analysis, testing again this dependence, repeating the analysis on the variable that defines the acceptance of the recommendation, possibly ruling out the effect of confirmation bias (see below).

To complete the analysis, now we consider only the 80 subjects that received a recommendation that was not coincident with their initial choice. Our aim is to obtain some information with respect to the other variables influencing the probability of accepting the recommendation. To this purpose, now we will use a probit model for the regression analysis, choosing as the dependent variable the acceptance (1) or refusal of the recommendation (0). Anyway, first we show again some statistics regarding the mean values of the different variables for the two groups (those who accepted and those who refuted). Looking at *Table 5.28.* we observe some interesting differences. While variables like age, income, education, overconfidence and knowledge show no important differences, we obtain some key information regarding the influence of gender, usage of advisory and knowledge of financial advisory. The difference regarding gender might either depend on the fact that women are, on average, more incline to refute the recommendation rather than to accept it but might also just depend on how gender is distributed in the two sub-groups. Looking more in depth, anyway, we find that among those 80, 17 out of 35 (48.57%) women accepted the recommendation, while the remaining 18 (51.43%) did not. Looking at men, we find that 27 out of 45 (60%) men accepted the recommendation while the remaining did not. This tells us that women are slightly less willing to accept the recommendation obtained. Moreover, looking at the results we also see that previous experiences with financial advisory increase significantly the probability to accept the recommendation. This might depend on the fact that people that have hired previously a financial advisor in their life might feel more comfortable in following external recommendations. Alternatively, we can argue that people that are *a priori* more inclined to follow recommendations of other people (in general) might have decided to hire a financial advisor in their past. Independently from the explanation given, the result remains interesting. Also, knowledge of the functioning of Robo-Advisors seems to have a negative influence on the probability to follow the recommendation. This could depend on various reasons. Maybe, subjects that know how Robo-Advisors work and form recommendations might retain that procedure as non-sufficiently accurate and thus be less interested in recommendations coming from robotic entities. Conversely, another explanation could lie in the fact that individuals that know how Robo-Advisors work in reality, might have perceived our procedure as too simplified and thus refuted our recommendation. Last but not least, we find the levels of trust to be quite different between those who accept the recommendation and those who do not. This is encouraging and seems to support our initial idea, confirming the positive role played by the levels of trust. We should thus expect from the probit analysis some positive coefficients for the two variables. Last but not least, also the high difference in the overall perceived quality is key to understand. Data show that clearly, people who refuted the recommendation perceived the quality of our recommendation as lower than those who accepted the recommendation. While this seems natural and obvious at some extent, this represents also a key information because it tells us that people are at least partially influenced in their choice by the low perceived quality of the service. Anyway, we should note that in our experiment we first asked subjects to accept or refute the recommendation and only successively to rate the quality of the service. In this sense, participants that accepted the recommendation might have been pushed to give higher evaluations, to avoid the mental inconsistency of "having accepted a low-quality recommendation".

	Accepted	Refuted	Difference
n	44	36	8
Age	41,00	40,17	0,83
Female	0,39	0,50	-0,11
Income	2,50	2,61	-0,11
Education	2,57	2,58	-0,02
Investment Knowledge	2,80	2,78	0,02
Ever Invested	0,70	0,75	-0,05
Ever used Advisory	0,57	0,42	0,15
Robo-Know	0,39	0,50	-0,11
Overconfidence	2,57	2,64	-0,07
Quality	3,50	2,33	1,17
Professional Trust	3,18	2,69	0,49
Trust in Automation	4,05	3,22	0,82

Table 5.2814.: Mean values of sociodemographic traits, knowledge, overconfidence, quality and levels of trust. Comparison between subjects that accepted the recommendation and subjects that refuted the recommendation.

Before going through the actual numbers, we present the model utilized to predict the acceptance or refusal of the recommendation. In light of the data that we visualized before through descriptive analysis we believe the following to be an adequate model:

$$Acceptance = \beta_0 + \beta_1 D(Female) + \beta_2 D(RoboKnow) + \beta_3 D(EverAdvisory) \\ + \beta_4 TrustProfessionals + \beta_5 TrustAutomation + \epsilon$$

Table 5.29. shows the correlation matrix between the variables that we will use in our model, again, to avoid the risk of including variables that are too highly correlated, incurring in collinearity problems. As we see none of the regressors is significantly correlated with the others, while the dependent variable seems to be significantly correlated with the levels of trust. The other three variables that we theorized as relevant are not significantly correlated but signs of the correlation coefficients confirm our supposition.

	Accepted	Female	Ever_A~y	R_Know	T_prof	T_aut
Accepted	**1.0000**					
Female	**-0.1140**	**1.0000**				
Ever_Advis~y	**0.1508**	**-0.1260**	**1.0000**			
R_Know	**-0.1140**	**-0.0667**	**0.1764**	**1.0000**		
T_prof	**0.3167***	**-0.0555**	**0.0163**	**-0.1214**	**1.0000**	
T_aut	**0.4316***	**0.0100**	**-0.0263**	**0.1427**	**-0.0082**	**1.0000**

Table 5.29.: Correlation matrix of the variables for the probit regression model (n=80).

Results of the probit regression model are shown in *Figure 5.32.* below. We can observe that gender has a non-significant coefficient, as well as the previous experiences with advisory services. On the other hand, we can see that awareness of the existence of Robo-Advisory services has a (barely) significant negative coefficient, confirming the negative effect of this factor. More interestingly, the regression confirmed the predictive role of the levels of trust in automation and trust towards professionals, both showing positive and significant coefficients, with the former one being higher and slightly more significative. While probit models cannot compute proper R-squared, the value for the Pseudo R-squared is approximately 0.2993 which, while not extremely high, can be still considered acceptable given the very small sample size.

Probit regression	Number of obs = 80
	LR chi2(5) = 32.95
	Prob > chi2 = 0.0000
Log likelihood = -38.576395	Pseudo R2 = 0.2993

Accepted	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Female	-.3755712	.340069	-1.10	0.269	-1.042094	.2909519
Ever_Advisory	.5516879	.3394549	1.63	0.104	-.1136315	1.217007
R_Know	-.6928031	.3535991	-1.96	0.050	-1.385845	.0002384
T_prof	.6510112	.2321365	2.80	0.005	.1960319	1.10599
T_aut	.8017521	.1903673	4.21	0.000	.4286391	1.174865
_cons	-4.501458	1.05097	-4.28	0.000	-6.561322	-2.441594

Figure 5.32.: Results of the probit regression (n=80).

Last but not least, to consolidate the conclusions we made before about the role of the levels of trust on the quality of the service, we also complement the analysis by repeating it on the reduced sample, that considers only those who received a recommendation different from their initial choice. Specifically, this time we split the sub-sample of 80 subjects in two sub-groups, depending on the treatment and we will try to fit the probit model to the data, even if the sizes of the samples are very limited. Of these 80 subjects, 37 received the robotic treatment while the remaining 43 received the recommendation from the human advisor.

Figure 5.33. shows the results of the probit regression for those who received the robotic treatment. Results show that when we eliminate the effect of confirmation bias, the probability to accept the recommendation is adequately predicted by the level of trust in automation. Indeed, Data show that those who accepted the recommendation showed, on average, an higher level of trust in automation. This furtherly confirms the idea that trust in automation plays a key role in determining the attitude towards Robo-Advisors and also the tendency to follow recommendations provided by robotic entities. Other variables, including the level of interpersonal trust, have coefficients that are non-statistically significant and thus seem not to influence the acceptance of the recommendations.

```
Probit regression                                       Number of obs =     37
                                                        LR chi2(5)    =  20.41
                                                        Prob > chi2   = 0.0010
Log likelihood = -14.773228                             Pseudo R2     = 0.4086
```

Accepted	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Female	-.8083503	.5916672	-1.37	0.172	-1.967997	.3512961
Ever_Advisory	.2118855	.5390702	0.39	0.694	-.8446728	1.268444
R_Know	-.9580689	.5700613	-1.68	0.093	-2.075369	.1592308
T_prof	.3462351	.3919026	0.88	0.377	-.4218799	1.11435
T_aut	1.119816	.3180041	3.52	0.000	.4965394	1.743093
_cons	-4.109869	1.567813	-2.62	0.009	-7.182725	-1.037012

Figure 5.33.: Probit regression results for the subjects that received the robotic treatment (only those who received a recommendation different from their initial choice).

In *Figure 5.34.* we observe on the other hand the results for subjects that received the human treatment. Again, these results seem to confirm also for the probability to accept the recommendation the results that we found before, with respect to the perceived quality of the service. Indeed, we see that the level of interpersonal trust plays a significant role, together with the level of trust in automation.

```
Probit regression                                       Number of obs =     43
                                                        LR chi2(5)    =  19.02
                                                        Prob > chi2   = 0.0019
Log likelihood = -20.283975                             Pseudo R2     = 0.3192
```

Accepted	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Female	-.07928	.4959376	-0.16	0.873	-1.0513	.8927399
Ever_Advisory	.9857669	.4881147	2.02	0.043	.0290796	1.942454
R_Know	-.316494	.4821584	-0.66	0.512	-1.261507	.6285191
T_prof	.8824088	.3122698	2.83	0.005	.2703712	1.494446
T_aut	.5604865	.2839548	1.97	0.048	.0039454	1.117028
_cons	-4.966221	1.654331	-3.00	0.003	-8.20865	-1.723793

Figure 5.34.: Probit regression results for the subjects that received the robotic treatment (only those who received a recommendation different from their initial choice).

Gender Bias

Regarding the fourth and last hypothesis, we have too few data to obtain any kind of significant result using regression analysis and thus we only verify the role of gender from the descriptive point of view and through a more basic hypothesis testing. Of course, we can only exploit data obtained from those assigned to the human treatment, namely 73 participants. Before going through the analysis, we show some comparison statistics between the two groups to ascertain whether results might be spurious and influenced by other variables. Specifically, we will present the comparison only between sociodemographic traits and between the variables that the previous model suggested to be relevant in determining the perceived quality of the service. We will try to test gender bias along two different directories: first, we will compare the results of those who visualized the video with the male advisor and those who visualized the video with the female advisor, to see whether there is an absolute preference for one of the two genders, independently by the gender of the respondent. Later we will compare data dividing subjects depending on whether they obtained the recommendation from an advisor of the same/opposite gender.

With respect to the first set of analysis inherent to gender bias (absolute preference for male vs. female advisor) we see that among our 73 subjects that received the "human" recommendation, 44 were assigned to the male advisor and the remaining 29 to the female advisor. *Table 5.30.* reports the comparison between some of the main variables that we believe to have a possible influence on the perceived quality. Overall, no important differences between the two groups can be observed in none of the important variables and neither in the riskiness of the portfolio chosen initially, thus, while accounting for the reduced sample size, we are safe to proceed.

	Male Advisor	Female Advisor	Difference
Age	40,84	44,48	-3,64
Female	0,45	0,48	-0,03
Income	2,43	2,66	-0,22
Education	2,50	2,55	-0,05
Investmetn Knowledge	2,64	3,00	-0,36
Correspondence of Choice and advice	0,39	0,45	-0,06
Professional Trust	3,11	3,00	0,11
Trust in Automation	3,76	3,76	0,00
Initial Choice	2,39	2,48	-0,10

Table 5.30.: Comparison between subjects' traits, divided by the gender of the advisor (only human treatment, n=73).

To verify our hypothesis of an absolute preference we utilize a simple Kruskal-Wallis equality-of-populations test and compare the median values of the two sub-groups. We run the test twice, using as the outcome variable first the perceived quality of the service (χ^2 = 0.170, p-value: 0.6803) and then the intention to utilize it in the future (χ^2 = 0.026, p-value: 0.8716). As we could expect, looking at the results reported in brackets, the difference between the two groups seems to be very small and non-statistically significant. This may either depend on a real absence of absolute preference or on the fact that our sample dimension is reduced.

We repeat the same procedure, this time dividing subjects depending on whether they received a recommendation from an advisor with the same gender as them or not. Specifically, we observe that, among the 73 that received the human recommendation, 35 visualized a video of the advisor of the opposite gender, while 38 received the recommendation from an advisor of the same gender. Again, in *Table 5.31.*, we compare all the key variables to assess the presence of eventual external influences. The results evidence no significant differences in all variables but the gender. Indeed, there is a majority of males that received a recommendation from other male, while most females received a recommendation from a male. This might depend slightly on the fact that, due to chance, there is a majority of recommendations (44 vs. 29) coming from the male advisor.

	Equal Gender	Different Gender	Difference
Age	39,11	45,74	-6,64
Female	0,37	0,57	-0,20
Income	2,39	2,66	-0,26
Education	2,53	2,51	0,01
Investmetn Knowledge	2,74	2,83	-0,09
Correspondence of Choice and advice	0,42	0,40	0,02
Professional Trust	2,92	3,23	-0,31
Trust in Automation	3,74	3,79	-0,05
Initial Choice	2,42	2,43	-0,01

Table 5.31.: Comparison between subjects' traits, divided by the correspondence/difference with the gender of the advisor (only human treatment, n=73).

We run again the Kruskal-Wallis equality-of-populations test and verify that, both when we use as the outcome variable the perceived quality (χ^2 = 0.881, p-value: 0.3270) and the intention to utilize the service in the future (χ^2 = 0.365, p-value: 0.5459), the discrepancies are not relevant and thus there is no preference for recommendations obtained from advisors of the same/different gender.

To finally conclude on our fourth hypothesis, because of the little difference that we observed in the gender in the two groups, we want to run another test, this time dividing subjects into four different sub-groups, namely one for each combination of gender of the subject and gender of the advisor. Each sub-group was marked by two letters, the first one representing the gender of the subject (M=Male, F=female) and the second one representing the gender of the advisor. To test whether any differences can be revised between those four groups we utilize again the Kruskal-Wallis test. Again, results confirm the absence of any kind of difference (χ^2 = 1.225, p-value: 0.7470), leading us to conclude that, accounted for the reduced sample size, no significant differences depending on the gender of the advisor can be revised.

CONCLUSIONS, LIMITATIONS, AND IDEAS FOR FURTHER WORK

In the present work we have explored in depth the matter of financial advisory. Specifically, we focused our attention on one of the most recent innovations in the Fintech domain: Robo-Advisors. This new kind of systems aim at revolutionizing the financial advisory market, providing customers with a low-cost but highly efficient and effective service. The absence of direct and continuous involvement of a human being allows, indeed, Robo-Advisors to minimize expenses for customers, allowing them to access a system with a very high computational power. In this way, access to financial advisory services will be made easier both for those with limited availability of funds, like young people and students, and for those with physical limitations, reduced time availability or material issues that prevent them from reaching continuously their advisor and interact with them face to face. Moreover, Robo-Advisors promise people to represent a valid solution to the problems related with human behaviour, from errors depending on irrational biases to voluntary frauds arising from conflicts of interests. In this sense, we began our work presenting the main feature of traditional advisory services, opposed with those of innovative Robo-Advisors. We discussed in depth all the procedures, roles and regulations that surround advisory services, and we defined precisely the environment in which they operate. Also, we presented the current state of the demand of each kind of advisory service, focussing specifically on the Italian panorama. Robo-Advisors seem indeed to be a valid choice for a country in which there is a diffused sentiment of mistrust towards classical banking institutions and where most people struggle to save high amounts of money to invest. Nonetheless, the demand of Robo-Advisory services in Italy seems to be still scarce. Young people indeed do not seem to be interested neither in these innovative types of advisory, while adults still prefer to give their money to human advisors, with which they can interact and confront. Utilization of Robo-Advisors and, most importantly, reliance on their recommendations represents a key factor for their survival. In the present work, we focused our attention exactly on this phenomenon, and we tried to study the factors that may determine the intention to rely on recommendation provided by Robo-Advisors and the intention to utilize them for personal investments. Before starting our experimental analysis, we carefully reviewed the literature inherent to the possible elements that scholars individuated as possible incentives to the utilization and reliance on robots' suggestions. The attention of researchers has focused particularly on the role of anthropomorphisation of Robo-Advisors and on the importance of people's trust towards automated systems. If human-human advisory relationships are mainly governed by interpersonal trustworthiness, machine-human relationships are driven by trust in automation.

Starting from a recent paper by Alemanni et al. (2020) that studies reliance on recommendations generated by Robo-Advisors and utilizing a scale to measure levels of trust in automation, we conducted in total three experiment to gain precious information about our research idea.

What we find is that, coherently with what was found in the paper from which we took inspiration, one of the main factors that influences reliance on the recommendation of Robo-Advisors and the perception of the quality of such advisors, is what we call "confirmation bias". When people have initial opinion that are confirmed by the recommendations of the Robo-Advisors, they immediately become more satisfied with the service and increase the probability to rely on its suggestions. This is a natural human tendency and has been shown to significantly influence perception of external stimulus and information selection. This first finding has some important implications, rather than for the initial diffusion and growth in popularity of Robo-Advisors but rather for customer retention. Indeed, Robo-Advisors that generate recommendation from scratch without the possibility to consider the initial beliefs and investment intentions of customers might incur in the risk of generating negative feelings as a consequence of the violation of confirmation bias-related implicit mental rules. While hybrid models of advisory are able to start from the ideas of clients and develop investment strategies consequently, pure robotic advisory may struggle in this sense. In light of this first results, we thus believe that the development and utilization of systems and procedures that may allow people to include their beliefs, ideas, and choices prior to the generation of investment recommendation and portfolio might become a powerful way to raise the popularity and utilization of Robo-Advisors. Moreover, another key finding of our study, that expands the results of the original study, concerns the role of trust in automation (and consequently algorithm aversion). Our results show how trust in automation represents a fundamental factor that pushes people towards or away from the utilization of such services. People that do not trust automated services, indeed, do not utilize Robo-Advisors and/or do not follow their recommendations. Unless we want to consider trust in automation as an *a priori* defined component of the personality, and thus fixed at an immutable level, our finding contains an important message for regulators, developers, and banks offering Robo-Advisory services. From the point of view of regulators, the introduction of norms that favour transparency and ensure high quality standards in the methods utilised by robots, may increase the level of trust in automation of people that will feel more safe and more assured about the adequacy of the performances and therefore will possibly trust more the system. Banks offering these services, on the other hand, may want to promote interventions and campaigns to raise awareness about the functioning and reliability of automated services, to increase levels of trust towards specific kinds of automation, especially those used for investments. A more gradual kind of transition that, starting from pure in-person model, slowly dematerializes and automizes single parts of the process, to progressively reach, if not a complete, at least a very high degree of automation of the service, is suggested. In this sense, the recently diffused digital banks, the ones that do not have physical locations in which customers can obtain services, might be in an advantaged position, having already built some kind of trust towards their digital and automated systems.

Also, through our experiments we do not revise any kind of preference for recommendations delivered through videos of human advisors. While this might constitute a spurious result if we consider it as a comparison between human recommendation and robotic recommendations, this might at the same time have some implications with respect to the degree of anthropomorphisation of Robo-Advisors and automated systems in general. While we do not have a certain interpretation of the reason underlying the lower reliance on recommendations delivered through the video, we might suppose the reason to be related to a sort of complexity effect. Possibly, the observation of the video may have generated in people an impression of simplicity and low complexity of the algorithm, resulting then in a judgement of inappropriateness of the methods used. Another possible explanation, might be that people who wanted to use an automated system similar to a Robo-Advisors, visualizing the video might have considered the involvement of a human being and thus became less interested in the recommendation, that was intended as purely generated by a robotic entity. We are aware of the fact that our setting constitutes a limitation to the validity of this last conclusion, but the results remain still interesting and interpretable. Last but not least, even though in our simplified setting, we find no influence of the gender of the human advisor: people seemed not to be interested indeed in the gender of the reader of the recommendation, neither from an absolute point of view (male vs. female, in general) nor from the own relative point of view (same gender vs. opposite gender).

Looking at the limitations of our approach we need to consider the very reduced size of our sample. While many values, both in simple hypothesis testing and in regression analysis, showed good significance levels and seemed to be reasonably correlated with our outcome variables, an analysis using a bigger sample of subjects might have for sure a better predictive validity. Moreover, we account that the way in which we assessed some factors, especially overconfidence and personality traits, might not be adequate for our purposes. Indeed, most people resulted as overconfident in our sample, but this is hardly plausible in reality. The simple task we used to measure overconfidence presents some drawbacks related to the fact that people often will not weight the precision they are given to build the confidence interval (that is, people will presumably build the same interval in a similar task if we asked for 90% precision or 75% precision, despite the two values being different), but they will just make a point estimate (or guess) of the measure and define an interval revising coarsely their estimate upwards and downwards. On the other hand, we measured personality traits through the Ten Items Personality Inventory (TIPI) scale, but we found no specific relevance of such variables. This might either depend on the reduced size of our sample or on the fact that, while being a well consolidated and popular scale to use, it might not be suitable for our purposes. Arguably, traits measured by this scale might be considered as less important with respect to investment and advisory choices. Another limitation might be related to the poor geographical diversification of our sample. Most of the subjects which participated were recruited between Venetian region and Friuli-Venezia Giulia, with no subjects living in other regions of Italy. As we know, Italy is a rather heterogeneous country, at least from the financial and investment point of view, with some non-negligible social and economic gaps between the various regions. Larger scale experiments, both from the point of view of the number of participants and the geographical area of interest, may have a better predictive validity and produce more precise and interesting results.

On the ground given by this work, many possible further developments are possible. First of all, as said, larger scale studies focusing on the same topic will surely yield new and more important conclusions. Moreover, a lot of work needs to be done with respect to the importance of the design of the interfaces and platforms of Robo-Advisors. Anthropomorphisation of machines is a tendency that is gradually diffusing, impacting in various ways the perception of algorithms. While this might contribute for sure to make robotic advisors to appear as more friendly and trustworthy, some studies have proven how this reduces the perceived complexity of the mechanisms used whit this possibly resulting in a loss of interest towards Robo-Advisors. Finally, on the role of regulators, and on the importance of public interventions, campaigns and advertisement of Robo-Advisors with respect to trust in automation and utilization of advisory services, there seems to be a wide space for research, that becomes a necessity for the prosperous development of Robo-Advisors.

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