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Automation of investment advisory services: Exploring the landscape of robo-advisors

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Abstract

In an era defined by fast-paced technological advancements and the expansion of AI-based solutions, the traditional financial advisory field is reshaping. A FinTech innovation, robo-advisory, offers customers the possibility of fully digital and cost-effective investment advice, challenging traditional solutions.

Despite robo-advisors reducing costs, providing immediate personalised solutions, and generally improving investment performance, it seems unlikely that they will completely replace traditional advisory at this stage. Challenges tied to limited interaction, surface-level customer profiling and technical integration remain, indicating that various hybrid models are the most probable options for now. Still, new research and advancements in technology have the potential to significantly change the field and answer growing demand from younger generations.

This thesis presents a review of the current robo-advisory landscape, assessing the benefits and challenges it offers from various perspectives. Furthermore, robo-advisors' potential for the future is discussed, proposing future research targets and tangible implications to practice. Current literature is reviewed, and a professional is consulted in a semi-structured interview to provide thorough research.

Keywords Robo-advisor, Robo-advisory, Financial advisory, Artificial intelligence, Investing, FinTech, Automation

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1 Introduction

In the 21st century, the world has witnessed rapid digitalisation and automation of processes across industries, challenging entities to reshape existing systems. The continuous development of artificial intelligence (AI) is now creating a second wave of digital transformation. AI has reached a point where it is no longer just a buzzword but provides tangible implementation possibilities, bringing its use closer to wider public and service industries (Huang & Rust, 2018), which presents intriguing research opportunities.

An estimate by experts suggests that approximately 50% of current work tasks could be automated by 2055 (Manyika et al., 2017). The financial sector has not fallen short of this trend, and financial technology (FinTech) solutions have emerged as key components in strategies (Jung, Dorner, Weinhardt, & Pusmaz, 2018b). AI-based systems allow financial service (FS) providers to offer increasingly effective and personalised services by leveraging their customer data, making FS providers considerable actors in the industry's digital transformation (Caron, 2019; Groot, 2017).

Today, the extensive field of FinTech encompasses a wide range of innovations to cater to diverse customer bases and needs (Königstorfer & Thalmann, 2020). To name a few, AI algorithms have been utilised in the finance industry to improve lending, asset management, payments, contracts and trading, risk management, accounting, and customer experience (Herrmann & Masawi, 2022). Among these innovations are robo-advisors, which are automating the field of financial advisory.

Challenging established FS providers to follow, smaller independent actors have led the way by introducing robo-advisors (Rasiwala & Kohl, 2021), and creating a completely automated digital alternative to traditional human financial advisors. First introduced after the 2008 financial crisis (Phoon, 2018), the robo-advisor industry has since been estimated to grow to $16 trillion in assets under management (AuM) by 2025 (Deloitte, 2016b). The most significant robo-advisor platforms today in terms of reported AuMs include actors such as Vanguard's Digital Advisor, Betterment and Wealthfront.

Passive investing being on the rise (Uhl & Rohner, 2018), robo-advisors combine its benefits with a digital and cost-effective platform that automatically optimises and rebalances a unique portfolio to match each customer's personal needs and preferences. Among other advantages, the larger target group and scalability of robo-advisors can provide significant competitive advantages to their providers (Wirtz et al., 2018).

Nevertheless, robo-advisors are still considered to be in their rather early days (Phoon, 2018), currently pointing towards hybrid models as potential solutions to make up for independent robo-advisors' missing competencies. Today, both customer wariness and technical implementation processes have posed challenges for robo-advisor providers. Since the adoption rate of robo-advisors makes up for a quite small margin of investors (Belanche, Casaló, & Flaviàn, 2019), and research is yet to be comprehensive (Jung, Dorner, Glaser, & Morana, 2018a), a lucrative opportunity is presented for new insights to enrich the existing studies.

1.1 Research objectives and research questions

This thesis concentrates on providing an overview of the present state of robo-advisory and assessing it, aiming to gain insights into its potential influence on the future of financial advisory. Furthermore, the research intends to define relevant concepts and offer practical insights for the future through carefully considered academic research.

The research questions of this thesis are:

1. *What is the present state of robo-advisory solutions?*
2. *What are the current main benefits and challenges of robo-advisory?*
3. *How could robo-advisory solutions evolve the future of the financial advisory field?*

1.2 Scope and structure of research

This thesis focuses specifically on robo-advisory solutions within the financial advisory field. Despite some overlapping findings and themes, it does not offer a comprehensive review of AI-driven solutions within the financial services sector. The research is not oriented toward any geographic region particularly. As further detailed in the methodology section, the primary method of research in this thesis is a literature review, completed by an interview with an expert in the field.

The structure of the thesis is as follows: Chapter 2 introduces a theoretical background for this thesis. It provides essential definitions to improve readability and comprehension. Additionally, it explains how robo-advisory solutions function and distinguishes sub-categories as well as potential differences among robo-advisors. Chapter 3 specifies the research methods used for the thesis and introduces all parties involved in the interview. Chapter 4, research findings and analysis, identifies and analyses both the current benefits and challenges of robo-advisory services. Furthermore, it identifies factors that might affect their adoption among customers. Chapter 5 discusses the thesis' implications to research and practice, elaborating on possible limitations and suggestions for future research as well. Chapter 6 presents the conclusions of the thesis and Chapter 7 acts as the list of references.

2 Theoretical background

This chapter will define the terms and technologies most commonly referred to in this thesis to facilitate and clarify the research. Additionally, the general mechanism of robo-advisors will be explained, and categorisations of robo-advisors will be introduced.

2.1 Defining AI and robo-advisors

In general, artificial intelligence (AI) refers to technology that displays self-learning capabilities and mimics aspects of human intelligence, for instance, pattern recognition and decision-making (Huang & Rust, 2018; Ongsulee, 2018). The term artificial intelligence encompasses several sub-fields such as machine learning and neural networks representing more specific derivatives of the technology. AI applications can show substantial differences in levels of intelligence, starting from rule-based mechanical AI often used in service robots, moving to advanced empathetic AI describing technologies mimicking emotional abilities (Huang & Rust, 2018). A common concept regarding artificial intelligence is that it increasingly enables machines to execute specific tasks and roles traditionally belonging to humans in our society (Dwivedi et al., 2021).

The functionality of AI is based on the data it is provided with as it cannot produce intuitively any new information. As Kaplan and Haenlein (2019) discuss in their study, achieving adaptable and specific outcomes is possible through AI's capability to learn from external data. While AI functions mimic cognitive tasks such as learning, problem-solving and generating text, they have not yet achieved to effectively present the full complexity of human characteristics (Dwivedi et al., 2021). These include features such as emotional intelligence, empathy, and true creativity.

In the financial sector, more specifically within the field of financial advisory, artificial intelligence and automation algorithms have been used to develop robo-advisors. The term “robo-advisory” stands for digital platforms that utilise interactive and intelligent assistance elements to guide users through automated processes and advise them in financial decisions and investing (Sironi, 2016). By employing these elements, robo-advisors are able to provide fully individualised and digitalised financial advice, all without the need for human interaction. Although the term robo-advisory may rarely be expanded into other fields, this thesis uses it exclusively to refer to financial advisory.

Despite the “robo”-prefix, it is crucial to note that not all the literature on service robots, in general, fully applies to the current existing robo-advisors since they are rather categorised as fee-for-service platforms (Wexler & Oberlander, 2020). While some researchers agree that virtual software learning and adapting over time using AI can be seen as service robots (Wirtz et al., 2018), others mainly use this term to portray only technology with some physical interface as well (Belanche, Casaló, Flavián, & Schepers, 2020).

2.2 General technology and categorisations of robo-advisors

In terms of the technology of robo-advisors, it is first crucial to recognize that not all platforms share universal qualities and current robo-advisors can differ substantially in their levels of technological advancement (Beketov, Lehmann, & Wittke 2018; Phoon, 2018). To illustrate the differences in technology sophistication and automation, Deloitte (2016b) suggests a classification of robo-advisors into four categories.

The robo-advisors in the first two classes use online questionnaires to offer an allocation based on a handful of listed products or pre-determined portfolios. The trades are either executed in a manual or semi-automatic way by the customers themselves or by human advisors and some may offer limited rebalancing options overseen by humans. The third and fourth classes of robo-advisors are more sophisticated and further automated platforms that use algorithms and quantitative methods to create and continuously rebalance the portfolio. Accounts and platforms are integrated into the service, and investor discretion and involvement depend on the platform and personal preferences. The fourth and most advanced robo-advisor class differs from the previous classes by using artificial intelligence to self-learn about external factors and personal needs, offering continuous real-time modifications (Beketov et al., 2018; Deloitte, 2016b).

In general, the standard process of robo-advisors can be described by a five-step outline that includes (1) selecting the asset offering, (2) profiling the investor, (3) allocating assets and optimizing the portfolio, (4) rebalancing and monitoring, and (5) reviewing performance (Beketov et al., 2018).

The asset offering curated in the first stage might vary substantially between service providers. For instance, both big institutions and independent actors offer robo-advisory platforms, each of whom has different objectives and cost structures in their core business models (Deloitte, 2016a; Phoon, 2018; Shanmuganathan, 2020). However, most robo-advisors mainly base their asset selection on exchange-traded funds (ETF), accompanied by some cost-effective securities such as indexed mutual funds (Beketov et al., 2018; D'Acunto, Prabhala, & Rossi, 2019).

Robo-advisors' ability to create personalised solutions is based on the second step of the general workflow which is customer risk profiling. To generate optimal advice and solutions for each customer, an initial questionnaire is provided. By answering the set of questions, the algorithm learns about the customer's risk tolerance, investment goals, time horizon for investing, financial situation, demographical facts, and return expectations. In addition, the algorithm can be taught to learn about the customer's preferences regarding sustainability, ethics, and specific business sectors (Bhatia, Chandani, & Chhateja, 2020; Jung et al., 2018a; Rossi et al., 2021). By conducting a comprehensive risk analysis based on the answers, the robo-advisor can identify an investor profile and create an optimal personalised portfolio for each individual.

The method of allocating assets and optimizing the portfolio varies among robo-advisors. According to Beketov et al.'s (2018) study, the majority of robo-advisory platforms base their portfolio optimization on Modern Portfolio Theory (MPT) by Markowitz (1952, 1959). MPT is mentioned in several research papers as a fundamental model for robo-advisors (D'Acunto et al., 2019; Shanmuganathan, 2020). In brief, Markowitz's model forms an efficient frontier of portfolios, which maximizes expected returns, allowing investors to select an optimal portfolio based on given individual risk preferences (Elton & Gruber, 1997). In general, other common methods are sample portfolios and constant portfolio weights, which include specific various models sometimes difficult to further clarify due to undisclosed information by service providers (Beketov et al., 2018).

Since robo-advisory platforms combine MPT (or other allocation models) with the assumption of efficient markets, it is believed that the optimal portfolios for customers can be created by a varied selection of exchange-traded funds (ETFs) and index funds (D'Acunto et al., 2019; Jung et al., 2018a; Uhl & Rohner, 2018). Evidently, the lack of active fund management allows the majority of platforms to offer low fees.

Less frequently mentioned in research, robo-advisors which trade mostly individual stocks and mutual funds with a high level of specialisation exist as well (D'Acunto & Rossi, 2021). Meant for a short or medium investment horizon, these platforms calculate allocations by seeking to maximize Sharpe ratios based on data offered by the service provider, such as expected returns of the traded securities. D'Acunto and Rossi (2021) emphasize the simplicity and effectiveness as competitive advantages of these solutions, describing that the implementation of the calculated trades simply needs a single approval by the investor.

Robo-advisors can be categorised and differentiated based on the platform's level of investor involvement and discretion (D'Acunto & Rossi, 2021). Based on similar attributes, Jung et al. (2018a) have divided robo-advisors into passive vs. active platforms and dynamic vs. static platforms, respectively.

Passive robo-advisors providing low investor involvement independently rebalance the portfolio using quantitative methods, while active robo-advisors offer customers rebalancing suggestions and require trade approval, leaving the actual execution to the customers themselves. When it comes to investor discretion, robo-advisors can be classified as either static or dynamic. A dynamic platform is created in a way that allows the customer to adjust the portfolio weights and individual assets at their own discretion. In opposition, static platforms with low investor discretion determine the investment strategy and portfolio assembly method after the initial risk analysis with limited possibility of modifying allocations (D'Acunto & Rossi, 2021; Jung et al., 2018a).

As previously mentioned, robo-advisory platforms have further been developed to serve different purposes and meet a wide range of objectives. For instance, Shanmuganathan (2020) categorises robo-advisory platforms based on the purpose and counterparties involved as follows:

1. Stand-alone robo-advisory services
2. Registered investment advisor (RIA) partnerships
3. Full-service wealth managers with E-advisory capabilities

Stand-alone robo-advisory services are independent actors offering portfolio management through online platforms directly targeted at end customers (B2C). Although service providers may vary in specific features and supplementary services, the core concept and mechanism remain relatively similar (Shanmuganathan, 2020). This thesis will mainly focus on stand-alone robo-advisory.

In contrast, registered investment advisor partnerships are primarily created for B2B purposes. RIAs offer digital wealth management platforms to institutions such as banks or insurance companies. These platforms are customisable to cater for the needs of the financial institution and the algorithm learns to reflect the specific institution's operations and objectives (Shanmuganathan, 2020).

Full-service wealth managers with E-advisory capabilities are B2B2C models that resemble RIAs but hold a difference regarding customer data. These are systems in which robo-advisory actors offer the platforms which then gain access to the institution's customers and their data. This enables further development of the learning algorithm and therefore the accuracy of the solutions offered (Shanmuganathan, 2020).

3 Methodology

The primary research method used in this thesis is a comprehensive literature review of previous studies around the research topic and questions. Additionally, an interview with an investment professional with experience and knowledge in robo-advisors is conducted. The interview adds significant value to the thesis by providing insights from the practical application of robo-advisors and a new perspective on the topic.

3.1 Literature review: approach and scope

The research included in this thesis was extracted mainly from the Scopus database. The careful curation and functionality of the Scopus database allowed a search that was specific yet broad enough search to cover the topic of the thesis. In some instances, Google Scholar was used as an additional source to find all the full versions of cited literature.

To form a comprehensive understanding of the research conducted in the field, the literature review was carried out using a funnel approach. Since robo-advisory is still rather new and lacks extensive research, this method enabled gathering an initial picture of the broader literature before narrowing it down to the specifics. Furthermore, the approach was crucial in the beginning to confirm that the amount and quality of literature is sufficient to conduct a literature review on this topic at all. In addition, the backwards searching method was utilized.

The search from titles, keywords and abstracts from Scopus was conducted at a rather general level at first. The search words included "FinTech", "investment", "business", "AI", and "finance". The search words were then narrowed down to more specific ones such as "robo-advisory". Due to the nature of Scopus, synonyms of the search words were used as well to not rule out any results. Moreover, the literature was arranged from cited by highest to cited by lowest and more recent literature was preferred. Still, lower cited articles were considered as well due to the constantly changing nature of the subject. The relevance of the content specifically for the thesis was reviewed by skim-reading articles along with the abstracts and titles and evaluating whether the research brings new knowledge and perspective.

Most of the literature chosen are academic research articles, including a few conference papers. The academic quality of the literature was determined by researching the journals' impact factors (preferably IF over 1) and using the Finnish site "Julkaisufoorumi.fi" to identify the academic ratings of the journals.

To highlight, the objective of the literature review was to collect relevant research to cover the topic from various perspectives and find opposing and supporting views. It does not cover the full literature on the subject, nor does it mean to do so.

3.2 Interview: structure and participants

A semi-structured interview was conducted with a professional in the field to gain further insights into robo-advisory services in practice and point out both advantages and disadvantages that may have not been covered in the literature. As Barriball (1994) observes, semi-structured interviews allow in-depth exploration of even complex topics while providing the possibility to further clarify and explain one's answers. Open-ended questions were used to avoid short and shallow answers, keeping the nature of the interview more conversational. The 45-minute interview was held through Zoom. The meeting was recorded and transcribed. The interviewee as well as the company wished to stay anonymous.

The interview questions were carefully chosen by considering the current developments in the field of robo-advisory and by investigating the company in question. In order to gain a comprehensive understanding, the interview covered aspects related to both the technical side and robo-advisory on a more general level.

3.2.1 Interviewee Y

Interviewee Y is an investment professional who has been consulting the launch of a robo-advisory company (Company X) in Finland. Their consulting experience extends across diverse business sectors, and they possess great knowledge of investment advisory services and their digitalisation processes. As company X was about to introduce their digital advisory services in Finland, the interviewee provided insights about the Finnish market and investors, thus offering valuable information to the company as it hadn't operated in Finland previously.

Among other key responsibilities, Interviewee Y worked towards improving the risk profiling process and aligning the investment options and asset allocations to be accurately in line with customer profiles. In addition, they played a vital role in sharing information and promoting the platform to the Finnish audience.

3.2.2 Company X

Company X is a Nordic robo-advisory company founded in 2015 offering investment advisory through a completely digital platform, currently managing more than 2 billion euros for over 100 000 active customers. Company X is an independent actor and classifies as a stand-alone robo-advisory service. The company operates purely on a B2C basis. As most of the stand-alone robo-advisory services do, the platform focuses on creating well-diversified and customised low-cost investment options for their customers.

4 Research findings and analysis

This chapter will present the findings of the literature review regarding both the advantages and disadvantages of robo-advisory, adding insights from the interview to enrich the contents of existing literature. Additionally, factors influencing robo-advisors' adoption among customers will be introduced to shed light on the effect of individual differences and provide depth to the findings.

4.1 Benefits of robo-advisory

The first actors offering robo-advisory services were able to recognize an opportunity in the existing financial advisory market. Customers lacking the financial means to have a financial advisor were brought a digital platform enabling them to have access to personalised portfolio optimization and low-cost opportunities to invest in (D'Acunto et al., 2019; D'Hondt, De Winne Ghysels, & Raymond, 2020; Tao, Su, Xiao, Dai, & Khalid, 2021). Robo-advisory has since continued establishing a position as an option for traditional financial advisory by offering various benefits discussed in the following chapter.

4.1.1 General advantages: customers and service providers

As mentioned, above all, robo-advisors have managed to gain their position in the market through their ability to offer the significant advantages of financial advising while maintaining lower costs (D'Hondt et al., 2020). The cost efficiency of the services combined with increased flexibility and customisability of the allocation options compared to traditional banks (Uhl & Rohner, 2018) indicates that robo-advisors offer strong competition to traditional human advisors (Beketov et al., 2018).

“The possibility to receive personalised asset allocations and portfolio optimization without high costs is a significant benefit that has not been widely offered before robo-advisors“ (Interviewee Y).

Uhl and Rohner (2018) illustrate robo-advsiors’ competitive cost advantages by comparing active fund management to passive investment vehicles – typically used by robo-advisor platforms. High management fees, underperformance against benchmark indexes, and the challenge of locating the outperforming funds all point to the fact that, on average, actively managed funds are not worth the price, especially after the impact of taxes (Brunel, 1998).

Moreover, customers perceive it as a competitive advantage that digital advisory platforms do not hold personal agendas or opinions (D’Acunto et al., 2019; Scopino, 2015). As the advisory mechanism of robo-advisors relies on quantitative analysis, it is easier for customers to discuss financial issues without the fear of judgment (Lui & Lamb, 2018) and the feeling of being sold products that might not be in their best interests (D’Acunto et al., 2019). Likewise, Brenner and Meyll (2020) discovered that robo-advisory customers were close to 16% less likely to turn to traditional financial advisors and this effect was even stronger among customers fearing investment fraud.

One of the well-known and rather evident perks of robo-advisory services is the accessibility of digital and automated platforms, which are usually efficient, yet easy and convenient to use (Belanche et al., 2019; Lui & Lamb, 2018). As research establishes, it is increasingly valuable to customers in today’s fast-paced digital society that services are immediately available and allow time-efficient usage (Fisch, Laboure, & Turner, 2019; Uhl & Rohner, 2018).

While complex cognitive functions combined with emotional and social aspects are still out of service robots’ reach, Wirtz et al. (2018) point out that robots may even be better than humans in steadily performing in routine service encounters. As robots are not prone to behavioural fluctuations, it enables them to deliver consistent and reliable service (Belanche et al., 2020). Consequently, service robots can enhance service employee satisfaction and productivity by taking over routine tasks (Lacity & Willcocks, 2016). Although current robo-advisors are digital platforms and do not completely compare to conversational service robots, it is crucial to consider the cognitive aspects of service encounters.

Furthermore, Wirtz et al. (2018) note that robo-delivered services offer substantial advantages in scale and scope, enabling cost savings for the service providers since most likely a majority of the costs of digital services come from back-office functions and development. The efficiency and affordability of robo-delivered services, such as robo-advisory, open up an opportunity to increase the availability and accessibility of the services to a larger audience (Belanche et al., 2019; Wirtz et al., 2018).

4.1.2 Improved investment performance

Tao et al.'s (2021) research reports improved investment performance, demonstrating that robo-advisors outperform conventional mutual funds by comparing their risk-adjusted returns in the US from 2016 to 2019. The key reasons contributing to the improvement are automatic rebalancing, mean-variance optimality, and better screening of investment options (Tao et al., 2021). Moreover, Rossi et al. (2021) analyse the effect of a robo-advisor on the portfolios of previously autonomous investors, similarly discovering a positive impact that stems from a reduction in both idiosyncratic and portfolio risk among other factors.

Robo-advisors have been shown to both mitigate behavioural biases and mistakes of investors as well as improve diversification in some cases (D'Acunto et al., 2019; Rossi et al., 2021). Behavioural biases refer to the various thought processes behind irrational investment decisions made by investors (Kumar

& Goyal, 2015). As demonstrated by D'Acunto et al.'s (2019) study, using robo-advisory to invest decreases the susceptibility to widely recognized and well-documented behavioural biases such as trend-chasing, the disposition effect, and the rank effect.

Furthermore, Uhl and Rohner (2018) describe the effect of behavioural biases by quantifying investors' behavioural gaps which measure the difference between the performance of security indexes compared to the realized performance of average security investors. Their net behavioural gap estimate computed with rough averages, shows a nearly 3% difference between robo-advice investors and average fund investors. The percentage considers estimated fees and is therefore called a net behavioural gap. To illustrate, Figure 1 by Uhl and Rohner (2018) depicts a hypothetical price development of three investor scenarios across a 20-year period. The model assumes costs of 1,5% for both the "average rational investor" and "average behavioural investor", and costs of 0,5% for the "robo-advisor". The effect of the behavioural gap sets apart the lowest performing investor compared to the top two investors without one.

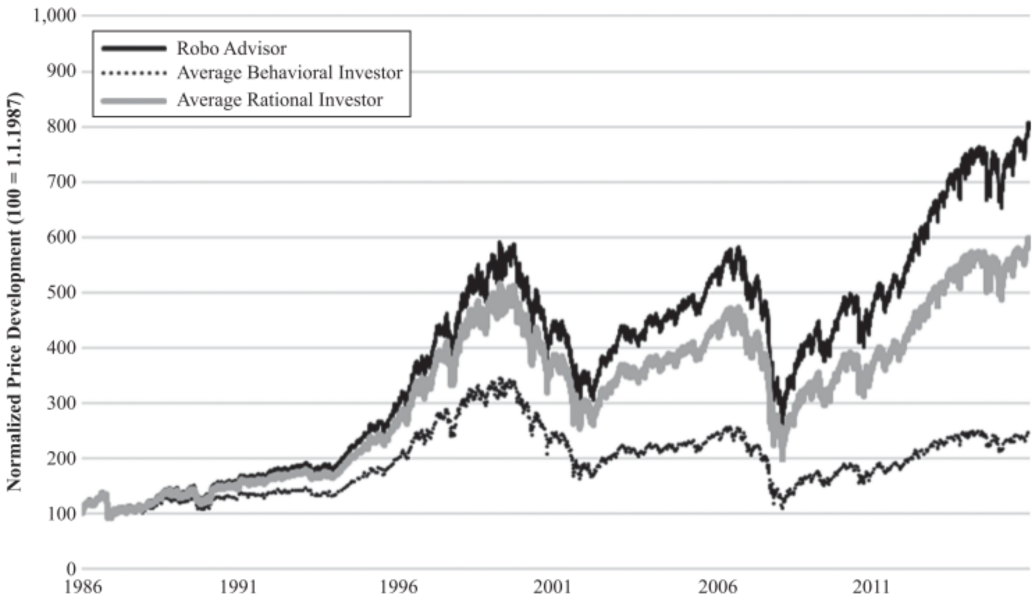

Figure 1: "Historical Price Development of the Various Solutions, 1987-2016" (Uhl & Rohner, 2018, p.48)

Interviewee Y pointed out that robo-advisors that automatically rebalance allocations to match the strategic weights and the risk profile can increase the profit of the portfolio by acting oppositely to most investors vulnerable to biases. For instance, while investors participating in trend chasing may buy securities already high in value, the algorithm operates in the opposite way and avoids participation in a bubble. Studies incorporating the effect of regular rebalancing on portfolio performance concur with the observations of the interviewee (Rossi et al., 2021; Uhl & Rohner, 2018).

4.2 Challenges and disadvantages of robo-advisory

Despite the numerous advantages, robo-advisory is still a relatively new development in the field of financial advisory and therefore the level of adoption remains rather low (Bhatia et al., 2020). To make digital advisory platforms widely available, improvements to certain challenges need to be further researched and addressed. Difficulties present themselves both in the form of concerns from customers adapting to the use of the technology (Jung et al., 2018a) and challenges in the implementation processes of service providers (Ashta & Herrmann, 2021; Kruse, Wunderlich, & Beck, 2019).

4.2.1 Disadvantages from a customer perspective

From a customer's perspective, one of the biggest concerns regarding robo-advisors remains their inability to consult in situations requiring high emotional and social skills (Hildebrand & Bergner, 2021). Research indicates that for the foreseeable future, emotions that robots can display will be simulated rather than genuine emotions (Huang & Rust, 2018). Conversation management skills in AI-powered solutions are far from being comparable to human interaction (Lui & Lamb, 2018) and the ability to understand and consult a customer's individual financial situation on a more complex level is not yet attainable (Hohenberger, Lee, & Coughlin, 2019). Interviewee Y agreed that robo-advisors can be disregarded due to their purely qualitative method of advisory, lacking empathy and a human touch.

Furthermore, the interviewee emphasized that an issue with robo-advisors is the lack of a calming presence in times of uncertainty or downturns in the market. They mentioned that the level of commitment and patience may be lower when a human advisor is not involved and therefore the risk of anxious investors giving up and potentially selling investments may be higher in difficult times. Similarly, Bhatia et al. (2020) note that difficult times in the markets may amplify investors' insecurities and biases, especially not having the possibility to voice emotional concerns.

Hildebrand and Bergner (2021) researched the difference between conversational and non-conversational robo-advisors regarding investor behaviour, firm evaluation, and perception of trust. Consistent with the previous observations, conversational robots were perceived as more trustworthy than non-conversational advisors, consequently improving the evaluation of the firm. In addition, customers advised by conversational robo-advisors were willing to invest larger sums compared to their non-conversational counterparts. The effect of the perception of trust extended to a point where the probability of investors accepting portfolios that did not even align with their preferences was higher among dialogue-based advisors.

On a related note, Interviewee Y described that risk profiling is a widely used technique in financial advisory for personalising optimal portfolios for each customer, creating commitment to the advisory service. However, they added that creating an accurate series of questions that precisely answer all consumers' needs can be a challenge. Agreeing with Salo and Haapio (2017), Interviewee Y acknowledged that in some of today's robo-advisory solutions, there is still a risk of superficial profiling, potentially leading to suboptimal solutions for customers. Robo-advisors are not generally perceived as serving clients with complex financial needs, the lack of exhaustive personalisation being one of the factors (Phoon, 2018).

Given that investors do not have constant objectives, but they vary over time, it is unrealistic that a single initial risk profiling would remain valid over a long time (Bhatia et al., 2020). Based on this, to maintain accurate optimization, a rebalancing feature from the robo-advisor would be required for the portfolio to remain optimal for an individual user.

4.2.2 Implementation challenges and potential biases

In general, traditional service providers in the financial services industry have access to large amounts of data from customers and thus theoretically have great potential to implement AI-driven solutions (Groot, 2017), such as advanced robo-advisors. Yet, current AI solutions in established and regulated FS providers bring out the fact that challenges in the implementation process are not unfamiliar (Kruse et al., 2019; Rasiwala & Kohl, 2021). Interviewee Y emphasized that the disruption to traditional services must begin with small and more agile independent actors, challenging big institutions to adapt to the constantly changing digital landscape.

To implement AI-driven solutions, organizations' IT architectures must be constantly renewed and agile. Kruse et al. (2019) describe that digital innovation may be slow and require large resources due to the lack of continuous renewal in existing IT infrastructures. Gradually broadened systems without constant improvement are difficult to restructure and thus digitalization can be challenged (Rasiwala et al., 2021). Although implied in some research, Kruse et al. (2019) critique that the absence of AI engine providers can no longer be described as a challenge since the offering has increased significantly.

In addition to IT infrastructures, Kruse et al. (2019) point out that service providers may encounter friction in both employee willingness and skills when transitioning from well-established systems to new technologies. Using India as an example, Rasiwala et al. (2021) concur that a knowledge gap in digital skills and slow adaptability of employees combined with regulations may challenge traditional service providers to implement digital changes.

For an advanced robo-advisory platform to function objectively and correctly, sufficient high-quality data and systematic training of the learning algorithm are required. Structured training data sets to enable reliable algorithms may have limited availability (Ashta & Herrmann, 2021). Interviewees in Kruse et al.'s (2019) research agree, adding that many traditional FS providers either do not have all their data digitally available or the usage is prohibited by privacy laws or regulations. Losing crucial customer data consistently raises concerns in this industry (Tobback & Martens, 2019).

As developing robo-advisor platforms requires multiple stages, the system becomes vulnerable to potential biases. A robo-advisor's biased decision-making can originate from various places, for instance, biased original data, biased experts constructing questionnaires or indirectly from the learning algorithms themselves (Bhatia et al., 2020; Königstorfer & Thalmann, 2020; Lui & Lamb, 2018). Biases can lead to unwanted suboptimal outcomes, the root causes of which might be hard to point out later due to a lack of transparency in the system, also known as the "black box" of AI (Adadi & Berrada, 2018). In the long term, a lack of system transparency can create distrust in customers and thus weaken the perceived reliability of robo-advisory services overall (Shanmuganathan, 2020).

As Salo and Haapio (2017) identify, the heavy regulatory frameworks surrounding the financial sector, more specifically financial advisory, are to be taken into consideration when implementing robo-advisors. For instance, the widely appointed MiFID II- regulation requires financial advisory clients to receive only fair and transparent information presented in an understandable manner without misleading the client. Concerns have been raised about whether this regulation is realised in robo-advisory since the information and its disclaimers are often provided solely as a text attachment, leaving the responsibility for comprehension of the contents to the customer (Salo & Haapio, 2017).

Closely related to regulations, the ethical and moral aspects of robo-advisory have faced critical questioning (Kruse et al., 2019). In addition to the concerns about the accessibility of disclaimers and crucial information, Shanmuganathan, (2020) points out that the ethical questions around robo-advisors challenge the appropriateness of providing advisory merely based on digital risk profiling. These factors are particularly emphasized among customers with limited knowledge and understanding of investing.

4.3 Factors influencing robo-advisors' adoption

Considering both positive and negative aspects of robo-advisory, the adoption to use robo-advisors is affected by various factors (Jung et al., 2018b). For instance, the customer's individual characteristics and beliefs, the service's distinct features and social influences play a role in the process. Therefore, they should be taken into consideration when implementing the services (Belanche et al., 2019, 2020; Brenner & Meyll, 2020).

In terms of the impact of customer characteristics, Belanche et al. (2019) find attitude as the main factor driving the intention to use robo-advisors. Moreover, agreeing with Flavián, Pérez-Rueda, Belanche, and Casaló (2022), they observe that customers' awareness and familiarity with technology have a positive influence towards using a digital platform and a negative correlation with being susceptible to subjective norms. Interestingly, technology discomfort appears to increase the intention to use automated robo-advisors since they do not require actual complex technology skills and are considered user-friendly (Flavián et al., 2022). To specify, *technology discomfort* implies a "lack of control and overwhelming complexity of technologies" differing from *insecurity towards technology* which, in contrast, reduces the intention to use AI-driven solutions (Flavián et al., 2022, p.18).

There seem to be some conflicts in research over demographic factors' influence. Belanche et al.'s (2019) study implies that age and gender are not influencing factors in robo-advisor adoption within a wide population, while Brenner and Meyll (2020) suggest that women are more likely to use traditional financial advisory services than men. It is important to acknowledge that despite multiple studies indicating older consumers are more reluctant towards new technology in general (Hudson, Orviska, & Hunady 2017; Onorato, 2018), which is intuitively logical as well, (financial) robo-advisors are rarely specified in studies and could differ from other technology.

It is rather obvious that technical features such as the available investing options, rebalancing possibilities and degree of automation affect the process of selecting a provider and adapting to use a robo-advisor. However, the information and service design plays a significant role in the process as well (Jung et al., 2018b). Conducted specifically from a user-centric perspective, Jung et al.'s (2018b) study consolidated four central service design principles for low-budget and risk-averse robo-advisory customers. The principles – "ease of interaction", "work efficiency", "information processing and cognitive load", and "advisory transparency" (Jung et al., 2018b, p.370) – were found to be key factors in terms of developing an optimal robo-advisor for such customers.

Moreover, Salo and Haapio (2017) identify the significance of information design, emphasizing that an ideal design focuses on providing information in a user-centered way. They highlight that well-portrayed information often leads to a better understanding and usability of a service, while poorly portrayed information can create misunderstandings and consequently distrust in robo-advisors. Addressing challenges with information gaps is crucial not only to improve user experience but also to comply with regulations.

As previously stated, conversational robo-advisors increase perceptions of trust and affect investing behaviour. Similarly, it seems that the humanlikeness of a service robot, to an extent, increases emotional attachment and positive feelings (Belanche et al., 2020). Nonetheless, as Lu et al. (2020) emphasize, the service context likely determines which service design is best suited. As robo-advisors are still mainly digital platforms, further research is needed to indicate optimal options specific to robo-advisors and investigate whether increasing anthropomorphism would improve the service's adoption. In fact, making robo-advisors more human-like creates a paradox since one of their commonly reported benefits is the lack of personal agendas and judgement (Lui & Lamb, 2018).

5 Discussion

In this thesis, a wide range of literature was reviewed and an interview with a professional in the field was conducted to assess the current state of robo-advisors, discuss their advantages and disadvantages, and finally draw conclusions about their role in the future of financial advisory. In addition, some factors that influence the adoption of robo-advisory were identified to gain a broader understanding of the landscape. The following section discusses this thesis' findings and implications to research and practice, identifies potential future research topics and finally concludes and summarises the research.

5.1 Implications to research

As current research regarding robo-advisors remains somewhat limited and the field is rapidly and continuously evolving, updated perspectives and findings from practice are called for (Jung et al., 2018a). This thesis contributes to research and enriches existing literature by combining varied and relevant papers in the field with current practical insights, offering an applicable overview. The interviewee broadly concurred with the findings from the research, affirming the applicability of the theoretical discoveries in existing studies.

Less than a decade ago, the availability of advanced AI-driven versions of robo-advisors was reported to be very limited, yet projections anticipated growth in their offering following advancing technologies (Deloitte, 2016a). Considering this, identifying traditional FS providers' possible challenges in implementing advanced robo-advisors remains relevant despite the seemingly scarce research particularly focused on this area. Therefore, in brief, the findings of this thesis showcase that traditional FS providers may have challenges with employees' willingness and knowledge, biases of robo-advisors due to low availability or low quality of data, and rigid or outdated infrastructures among else. Regulatory and ethical concerns are raised as well, although not only limited to advanced versions.

In addition, this thesis contributes to existing research in particular by answering the call to compare the investment performance of robo-advisors to traditional options, for instance expressed by Shanmuganathan (2020). By gathering and combining relevant and diverse findings from various previous studies, this thesis was able to demonstrate multiple factors indicating robo-advisors' ability to improve investment performance and profits.

5.2 Implications to practice

In terms of the role of robo-advisors in the foreseeable future, it appears unlikely that they would completely replace human advisors, at least in their current state. Since robo-advisors are not yet able to execute highly complex cognitive tasks and cannot portray genuine emotions, it is clear that human participation remains crucial to some financial advisory customers. Therefore, to maximise the current solutions' potential, hybrid models have been suggested in research to be generally the most functional alternatives.

Indeed, Wirtz et al. (2018) note that an effective way to benefit from robots' dominance in analytical power is to combine the strengths of AI-powered systems with humans' social and emotional skills. A solution of this kind allows the human advisor to concentrate fully on the interaction with the client, while the robo-advisor increases the effectiveness of the technical and manual aspects of the process. Brüggen, Hogreve, Holmlund, Kabadayi, and Löfgren (2017) illustrate that hybrid models enable human advisors to focus on, for instance, advising customers during important turning points in their lives as well as handling "interventions" referring to counselling and financial education.

Moreover, reflecting the research of Wexler and Oberlander (2020), hybrid models offer traditional service providers the possibility to expand their clientele without disrupting the trust of existing often long-term relationships between clients and advisors. Offering the digital solution as a voluntary option along with traditional financial advising can promote robo-advsiors' positive reputation among customers and employees as well as the wider audience. Jung et al. (2018b) note that hybrid models may help low-budget and cautious customers to adjust to robo-advisory, which would otherwise be perceived as an overwhelming obstacle. In addition, hybrid models can allow an opportunity for traditional providers to not let independent actors gain all control in the competitive field (Wexler & Oberlander, 2020).

When advocating for a wider usage of robo-advisory, it is beneficial to recognise that the solutions are not yet necessarily suitable for all customer categories. In light of existing research and this thesis' findings, cost-conscious investors favouring passive strategies without specifically complex financial needs seem to be the ideal customers to use robo-advisory services. By identifying such target groups service providers can tailor the advisory solutions correctly and market towards customers that benefit from them the most. The target groups are to be re-assessed in case of technical advancements, such as the ones proposed in the following chapter of this discussion.

Similarly, to further make robo-advisors widely recognized and accessible, effort is needed to continuously improve service design and seek optimal solutions. In addition to clear information design, the perception of trustworthiness can be improved by implementing user-centric service design principles.

5.3 Future research

In case of broader adoption of robo-advisors in the future, empirical studies would be instrumental in gaining extensive data on usage patterns. Larger data sets would enable more comprehensive user behaviour analysis, allowing further innovation and modification of the current systems based on factual findings.

Current portfolio-building algorithms and customer profiling systems remain on a rather general level, presenting an opportunity for future research to develop more specific alternative approaches. For instance, Interviewee Y discussed the possibility of creating various investor categories and integrating alternative investment strategies such as small/big cap, momentum, or value investing. D'Acunto et al. (2019) similarly point out that robo-advisors' further customisation for different investor categories' needs could enhance overall usability.

One of the challenges for established FS providers being the implementation of AI-based systems into existing IT infrastructure, extensive research and systems are required to solve the issues. Research into data security, transparency and accurate unbiased training data in this regard could enable financial institutions to narrow the gap with independent actors.

To avoid issues regarding ethical and moral aspects in the future, a framework for service providers should be researched. Since robo-advisory is such a new field, regulators might tighten the regulations in the future as its use becomes more significant. Developing a framework in advance would prevent possible conflicts with regulatory authorities and build credibility around robo-advisory.

5.4 Limitations

This thesis is not an exhaustive review of all literature concerning robo-advisors, and the findings come with limitations. As previously mentioned, AI-based systems in financial services in general remain relatively new and research specific to robo-advisors is limited in some areas. Particularly the research regarding the quantitative methods and technologies behind robo-advisors seems to be rather scarce, resulting in limited variation in referenced literature on this specific topic. While this thesis provides an outlook of the key themes and elements currently researched in the robo-advisory field, certainly, some aspects are yet to be researched. The landscape of these systems is constantly evolving, and innovations arise regularly, thus a certain finding may already be outdated despite the cited research being recent.

Regarding the selection of literature, unintentional selection bias might have influenced the choices despite careful consideration of research articles and an objective outlook on the subject in general. Furthermore, Interviewee Y might have a positive bias towards robo-advisors since he has actively participated in developing and marketing Company X's services. Finally, it cannot be ruled out that due to the concise nature of this thesis, some important research findings may have been left out.

6 Conclusion

The second wave of digital transformation combined with the increasing popularity of passive investing and cost-consciousness among investors have provided an optimal opportunity for the field of financial advisory to develop and robo-advisory providers to locate a market gap. While robo-advisory widens the availability of investment advisory and modernizes it, it is likely that in its current state robo-advisory will continue as an effective option rather than a comprehensive standalone solution for all financial advisory customers.

The advantages of robo-advisory present themselves to both customers and service providers. Customers appreciate the lower costs and the user-friendly platforms to create personalised portfolios, ultimately improving investment performance. Fear of financial fraud and traditional advisors' agendas seem to drive customers towards digital robo-advisors, meanwhile, scalability offers cost-saving opportunities for service providers.

Nonetheless, certain challenges have slowed down the progress of robo-advisors. For instance, the absence of human touch and genuine conversation as well as doubts concerning superficial risk profiling have posed concerns for some customers. The integration of AI-based technology into existing systems may cause friction and ineffectiveness related to several elements such as the accuracy and availability of training data. Although service providers can promote the systems' adoption by improving aspects like information and service design, certain factors remain beyond their control.

Overall, robo-advisory presents a considerable direction for the future development of traditional financial advisory. Through conducting continuous research and applying improving technologies, as suggested, a majority of current challenges could be overcome, making robo-advisory increasingly approachable for both customers and service providers. Especially considering the ongoing fast-paced shift to automated services in our society, particularly among the younger generation, robo-advisory holds significant promise for wide adoption, at least as a hybrid model combined with self-standing solutions.

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Appendix

Tentative list of questions for the semi-structured interview:

1. What is your role at Company X? Do you have previous experience working with AI solutions and/or investment advisory services?

2. What was the original purpose of founding Company X?

3. Could you explain in more detail how company X operates?

4. What were the most significant challenges faced during Company X's development?

5. How was data management handled? Which obstacles did you have to overcome while implementing AI?

6. Which regulations did Company X need to comply with?

7. In your opinion, what are the main benefits and strengths of using AI solutions in investment services?

8. What potential opportunities and changes can service like Company X bring to consumers? What about the financial sector in general?

9. How would you improve the service? What areas of research should be pursued further in this field?