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REVIEW

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Determinants of conventional and digital investment advisory decisions: a systematic literature review

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Abstract

The growing demand for digital investment advisory services and the advancing technological process led to increased attention to this topic in recent literature. In light of these developments, the question arises whether conventional and digital advisors behave differently in their investment advisory decisions. I therefore conducted a systematic literature review and evaluated 97 publications on the determinants of conventional and digital investment advisory decisions. Based on the literature, five main determinants were identified that are important for investment advisory decisions. These determinants are identical for both variants of the advice, but there are differences in the way they are addressed. This systematic literature review provides an overview of the current state of research and can therefore help identify areas where investment advice can be improved in the future.

Keywords: Investment advisory decisions, Investment advice, Robo-advice, Conventional advice, Differences

Introduction

Through the advancement of technology, digital algorithms are already able to advice clients in investment affairs. Many statistics forecast an ongoing rise of assets under management in the robo-advisory market. Statista (2022), for example, projects that approximately 3.13 trillion USDs will be managed worldwide by robo-advisor in 2026, which represents a circa 75 percent increase to the year 2022. This form of advising cannot only be cheaper in terms of lower operating costs (see e.g. Deloitte GmbH 2016, p. 4), but might also provide clients with higher returns than most of the conventional advisors due to e.g. lower provisions (see e.g. Jung et al. 2019, p. 414). Furthermore, robo-advisors may not be influenced by emotions (see Rosenberg 2019), so that such robots may also bypass behavioral biases (see e.g. Uhl and Rohner 2018, p. 48), if programmed properly.

There is now a large body of literature on digital investment advice, so that it is worth investigating whether there are fundamental differences in decision making between conventional and digital investment advice. Therefore, the objective of this paper was to systematically review the literature on the determinants of conventional and digital investment advisory decisions. In this context, it was important to find out whether the two variants of advice differ in their decision-making with respect to the determinants. Thereby, implications could be derived that are valuable not only for banks or investment advisory firms but also for investors. Thus, this paper systemizes and critically presents relevant publications. The main concepts covered in this thesis were briefly explained in the beginning. After the applied methodology of this systematic literature review was described, the obtained findings were discussed, and conclusions were drawn.

Theoretical foundation

Investment advice

According to Investopedia (2021) "investment advice is any recommendation or guidance that attempts to educate, inform, or guide an investor regarding a particular investment product or series of products". Investment Advice is in high demand all over the world. The reasons why clients seek investment advice are especially time constraints, convenience, security, and error avoidance and unfamiliarity with trading processes (see e.g. Jansen et al. 2008, p. 8; Spatt 2020, p. 218).

Advancing technology transformed the traditional business model of the advisor-client relationship in investment advisory from face-to-face encounters to more and more digital alternatives. Thus, investment advice today can be divided into conventional advice by humans, digital advice or a hybrid combination (see Metzler et al. 2022).

Conventional advice

Traditional investment advice involves a meeting between an advisor and a client. A typical practice standard for a financial planning process is that of the CFP Board (2019, p. 10f). Accordingly, the advisor asks the client about his or her personal and financial circumstances and discusses the client's investment goals. Based on these data, the advisor provides a personalized investment recommendation.

Advisors may be independent or employed by an advisory firm or bank, which often directs them to sell specific products (see Hoechle et al. 2018). It is not necessary to have completed professional training or to have been certified in order to be allowed to provide investment advice (Rubin 2015, p. 537f). A certification such as the CFP or the CFA attests that an advisor has undergone professional training and an examination.

Digital advice

Digital advice is often associated with the term "robo-advisor" (hereafter: "RA"). This is, however, not the only application of digital advice. Generally, digital advice can be categorized into direct to consumer, business to business or hybrid models (see Phoon and Koh 2018, p. 86). Accordingly, an algorithm either interacts directly with the client without any human interference or it supports conventional advisors in their decision-making. It is also common that the investment recommendation is determined by algorithms and the outcomes are then interpreted by the human advisor and presented to the client, which represents a hybrid solution (see Metzler et al. 2022).

Purely digital RAs usually follow a similar decision-making approach as conventional advisors (see Beketov et al. 2018, p. 365f; Jung et al. 2018a, p. 83f; Jung et al. 2019, p.

410f). Today, such algorithms predominantly use only variants of Markowitz's (1952) Modern Portfolio Theory (hereafter: "MPT") for portfolio allocation (see e.g. Hayes 2020, p. 573f). As technology advances, algorithms are becoming increasingly sophisticated and are attempting to apply more complex models based on machine learning (hereafter: "ML) or artificial intelligence (hereafter: "AI), which is however not yet the standard (see e.g. Beketov et al. 2018, p. 369).

Determinants of investment advisory decisions

There are a variety of factors that may be relevant to an advisor's investment decision. Most important for an advisor is to consider the personal situation of the client, which is referred to in this thesis as the "client profile". A client profile should include data about the client's demographic, psychological, and financial circumstances (see Thanki and Baser 2021, p. 59).

The European Union, for example, introduced laws such as the MiFID I in 2007, which was further developed into the MiFID II in 2018. Article 25 (2) of MiFID II stipulates that the advisor "shall obtain the necessary information regarding the client". According to the ESMA (2018) guidelines, necessary information contains the client's financial situation, its financial knowledge and its investment experience. Example include age, family situation, marital status, employment situation, need for liquidity, risk tolerance and investment objectives (see ESMA 2018, p. 8f).

While any financial advisor must follow the legislation of its country, for certified advisors, there are additional guidelines set by their respective institution. Advisors acting under e.g. the CFP Board (2019) Code of Ethics, in addition to the necessary information mentioned above, should also obtain the following client data: health, life expectancy, values, attitudes, expectations, earnings potential, goals, needs, priorities, and current course of action. Based on the client profile and market developments, the advisor must decide on a suitable investment strategy that he or she then recommends to the client (see e.g. CFP Board 2019, p. 10f).

From the advisor's point of view, the achievement of personal benefits, which might be contrary to the client's interest, can be of great importance when making recommendations. For instance, higher provisions on certain investment products might incentivize advisors and create conflicts of interest (see e.g. Chen and Richardson 2019, p. 174).

In addition, some countries and certification agencies imposed a fiduciary duty on advisors to mitigate conflicts of interest. This means that such advisors must subordinate their own interests and give their advice in the best interest of the client (see Rubin 2015, p. 525). Advisors who are subject to such regulations must take this into account when recommending to clients.

It could also be possible, that behavioral biases or misguided beliefs affect advisors in their investment advisory decision, i.e. advisors might deviate from rational behavior because they might be unconsciously influenced by irrational factors (see e.g. Baker et al. 2017; Linnainmaa et al. 2021).

Inderst and Ottaviani (2012), one of the earliest papers focusing on factors impacting advisory decisions, discussed the role of conventional financial advice in retail financial markets and the potential conflicts of interest that can arise between advisors and consumers. Their paper addresses determinants such as limited consumer knowledge, conflicts of interest, policy interventions, disclosure, financial literacy, and the importance of empirical research in the realm of conventional financial advice. Apart from this paper there is a lack of research that gathers all potential determinants that may influence investment advisory decisions. Although some papers, such as Inderst and Ottaviani (2012), identified some determinants, no paper developed a holistic framework of all potential determinants influencing investment advisory decisions. Especially in the context of steadily increasing automation and digitalization in the investment advisory industry, the determinants can be strongly influenced by all means of new digital tools, such as computer algorithms, machine learning and artificial intelligence. Therefore, it is time to systematically condense all new research findings relating to advisory decisions covering both conventional and digital advisors. To the best of my knowledge, no systematic literature review has yet been conducted that addresses the determinants of investment advisory decisions comparing both conventional and digital advisors. For this reason, the aim of this paper is to systematically examine these determinants in the context of conventional and digital investment advice based on existing literature and to present the current state of research on this topic. The approach was to conduct an independent analysis of all determinants from the ground up, without relying too heavily on earlier literature summaries that may be outdated. For this reason, the current paper takes a holistic approach, developing a framework that encompasses all determinants, particularly in the context of comparing conventional and digital advisors. This comprehensive framework is a novel contribution, as it has not been explored by previous researchers. Especially companies who offer investment advice in either way conventional or digital can benefit from the findings. Clients who have to choose one of the alternatives may also profit.

Methodology

Literature search strategy

This systematic literature review is, as far as it was applicable, in accordance with the reporting guidance provided by the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement (see Page et al. 2021). The analysis was limited to a qualitative synthesis of the results.

The intention of this systematic review was to provide a broad overview of the state of research. Thus, the applied inclusion criteria for the literature search were deliberately not too narrowed. An overview of all inclusion and exclusion criteria is displayed in Table 1.

The review includes only English-written publications. It was essential to select only publications consistent with the objectives of this work. Thus, the research question of a study must relate to one of the following contents: determinants of investment advisory decisions, factors influencing the advisory decision or differences in the decision making of conventional and digital advisors. This thesis considered only the advisor's perspective and not the investor's. Accordingly, no consideration was given to how clients proceed with advisory recommendations or whether they accept the advisor. Country-specific regulations were not discussed, only generally applicable principles. Furthermore, it was feasible to include only peer-reviewed publications. In the case in which articles have not been reviewed but were cited frequently and used appropriate data and

Table 1 Inclusion and exclusion criteria

Criterium	Included	Excluded
Language of publication	English	All other languages than English
Research question studied	All factors that could possibly influence investment advice; determinants that are necessary to give suitable advice to the clients; comparison of conventional and digital advice giving	All publications that consider only the perspective of investors, e.g. investors who are biased; publications that consider country specific regulations and general laws
Type of publication	Articles, studies and reviews that are peer-reviewed (exception if not peer-reviewed: frequently cited, appropriate data and methodology)	Publications that have not yet been peer-reviewed; articles that lack relevant content and methodology
Data description	Only publications with a clear description of the used data	All publications that lack a clear data description
Methodology description	Only publications with a clear description of the applied methodology	All publications that lack a clear methodology description
Reported outcomes	Only publications with clearly reported outcomes	All publications that lack a clear outcome description
Publication date	All publications available	–
Study population	No limitation, but representative	Studies with not representative samples
Geographic location of the study	Studies that consider one or more of the countries of the world (no limitation to one country)	–

Table 2 Search string strategies

ID:	Nuance	Search string
1	Robo-advisor's decision	("Digital advi*" OR "Robo* advi*") AND ("decision*" OR "recommendation") AND ("investment*" OR "Financ*")
2	Conventional advisor's decision	("Financ* advi*" OR "Financ* advice" OR "Conventional advi*" OR "human advi*" OR "In* Person advi*") AND ("recommendation" OR "decision*") AND ("investment*" OR "Financ*")
3	Comparison	("Digital advi*" OR "robo* advi*" OR "human advi*" OR "conventional advi*" OR "In* person advi*") AND ("compar*" OR "difference*") AND ("investment*" OR "Financ*")
4	Uncategorized Search	Keyword search
5	Uncategorized Search	Forward and Backward search

methodology, an exception was made. For an effective synthesis of the individual publications, it was necessary that they encompass a comprehensible description of their used data and their applied empirical methodology. There was no restriction regarding the publication date since this review dealt with both the chronologically earlier conventional advisors and the more modern digital advisors. The population and the data of the studies have to be appropriately large and representative so that statistical methods can be applied meaningfully. Furthermore, no limitations regarding the geographical location of the studies were made.

Methodologically, five search string strategies regarding different nuances were defined to obtain a fully comprehensive literature review. Each search string strategy consists of a different string combination, that is listed in Table 2. The keywords were identified through a preliminary web search on Google Scholar.

It was crucial to find all possible synonyms for RAs and for conventional advisors, since different publishers used various spellings and terms. According to the Oxford English Dictionary (2022) the term "adviser" has equal meaning as the now more common term "advisor". To identify relevant literature, a search for "advi*" was performed. The asterisk "*" indicates that the word or word fragment before the "*" can end in several ways. This allowed the database to show all related publications. A similar approach was applied to obtain the financial context. Thus, "Financ*" as string can mean e.g. "financial" or "Finance" and "Decision*" can stand for e.g. "decision making process" or other terms. Furthermore, authors might use either one of the expressions "financial advisor", "conventional advisor", "In-person advisor" or "human advisor" to indicate that their article concerns conventional advisors. For this reason, the enumerated terms were connected with the logical operator "OR" in the search string. A similar approach was applied for the variety of expressions for RAs. Since, "digital advisor", "robo* advisor" and "digital advice" function as synonyms for RAs, they were linked together with "OR".

First, RAs' decisions were considered. Therefore, all synonyms for RA were connected with ("decision*" OR "recommendation") and ("investment" OR "Financ*") by the logical operator "AND". Second, these keywords were linked to the synonyms of conventional advisors, so that this angle could also be taken into account. Additionally, it was searched for publications that compare the two advisory types regarding their decision-making process. In few cases the search string combinations had to be slightly adjusted to adapt to the search mask of the database (see Appendix 1).

In addition, uncategorized search in other sources was performed to ensure completeness, especially forward and backward search. This means checking whether the publication was cited by other articles (forward search) or whether the article cites other articles (backward search). Publications that were important to consider and not yet found through the aforementioned search string strategies were then included.

For an extensive literature search, the databases Scopus and IEEE Xplore were selected as these are recognized scientific databases. Besides, also a search in the Social Science Research Network SSRN was performed. The obtained records of each search strategy were noted and are presented in "Overview of studies included" section of this paper. In addition, a detailed literature search report is provided in Appendix 1.

Study selection

After performing the literature search, the records had to be selected from the databases. Titles and abstracts were screened for relevance based on the inclusion criteria. The detailed findings per database and query were reported in Appendix 2. Duplicates were removed and the remaining publications were subjected to a full-text analysis. In the full text analysis, the contents of the respective study were examined in greater depth, so that only relevant publications were selected.

All articles that did not meet the inclusion criteria were eliminated. This approach ensured that the literature search was conducted in a systematic process, so that the selection bias could be mitigated to a minimum.

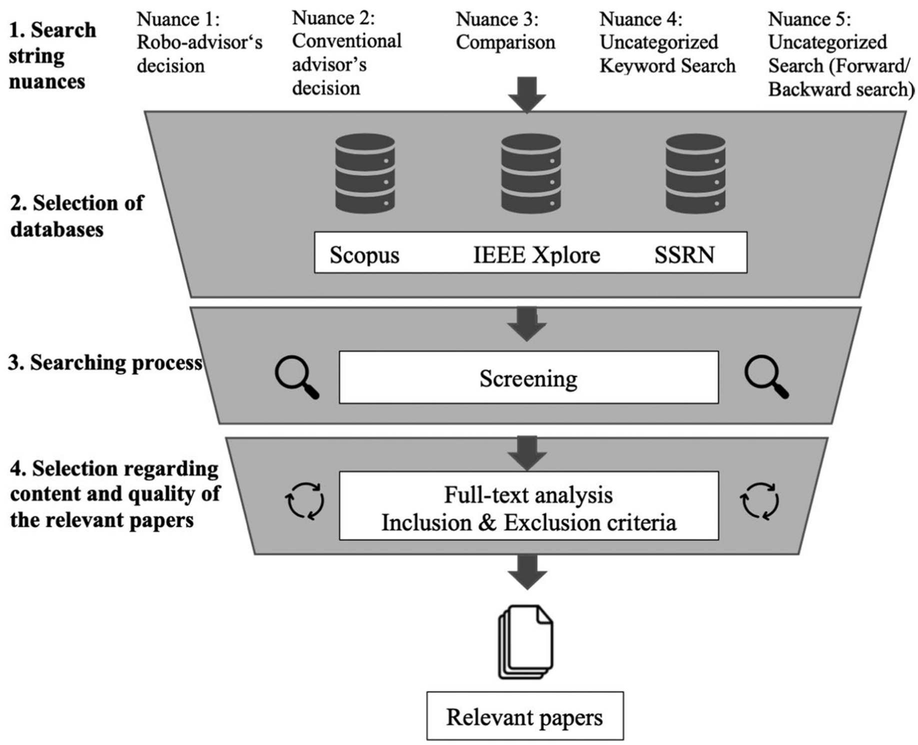

Fig. 1 Literature search and selection procedure

The overall literature search and selection procedure is summarized in Fig. 1.

Study assessment

All publications that were found through the above presented literature search strategy were evaluated regarding specific assessment criteria, that are categorized in Table 3.

In terms of content, each relevant study was analyzed in terms of the setting in which it was conducted, the data used, and its limitations. Special emphasis was placed on the results and conclusions of the individual studies.

The quality of an individual study was evaluated according to quality criteria of data, i.e. it was scrutinized whether the used data was representative. It was also examined whether some authors did various simplifying limitations, which could affect the validity of the results. The publications were each assessed regarding their statistical methods. A study with a good quality utilizes reasonable and proper empirical methodology, such as statistical regression models. It was ensured that the journals

Table 3 Assessment criteria

Assessment criterium: content	Assessment criterium: quality
Data	Quality of the used data
Limitations	Number of limitations in the study
Setting	Feasible statistical methodology
Results	Citation tracking
Conclusions	Transferability of the results

in which the publication appeared had a reasonable impact factor. Besides, citation tracking was performed as a quality measure for the study.

Through these evaluations, conclusions about the significance and transferability of the results could be drawn. The study assessment was performed during the full-text analysis and was not reported for each study.

Results and discussion

Overview of studies included

The selection process is illustrated as a PRISMA flow chart in Fig. 2. Appendix 2 provides deeper insights into the obtained records, sorted by the particular search strategy which was used in the respective database.

The database search resulted in a total of 4138 identified records. In addition, 25 records were found through other sources. Of the total 4163 records, 44 were excluded due to language. The remaining 4119 records were screened using the selection procedures described in "Study selection" section. Thereby, 3897 articles could be excluded because they were recognizably not relevant to the topic. Among the remaining articles were 52 duplicates. The eligibility of the remaining 170 publications was further assessed in a full text analysis. After this analysis, a total of 52 articles were excluded mainly for content reasons. 21 publications were excluded because they were of limited relevance or methodologically inadequate, or a more recent

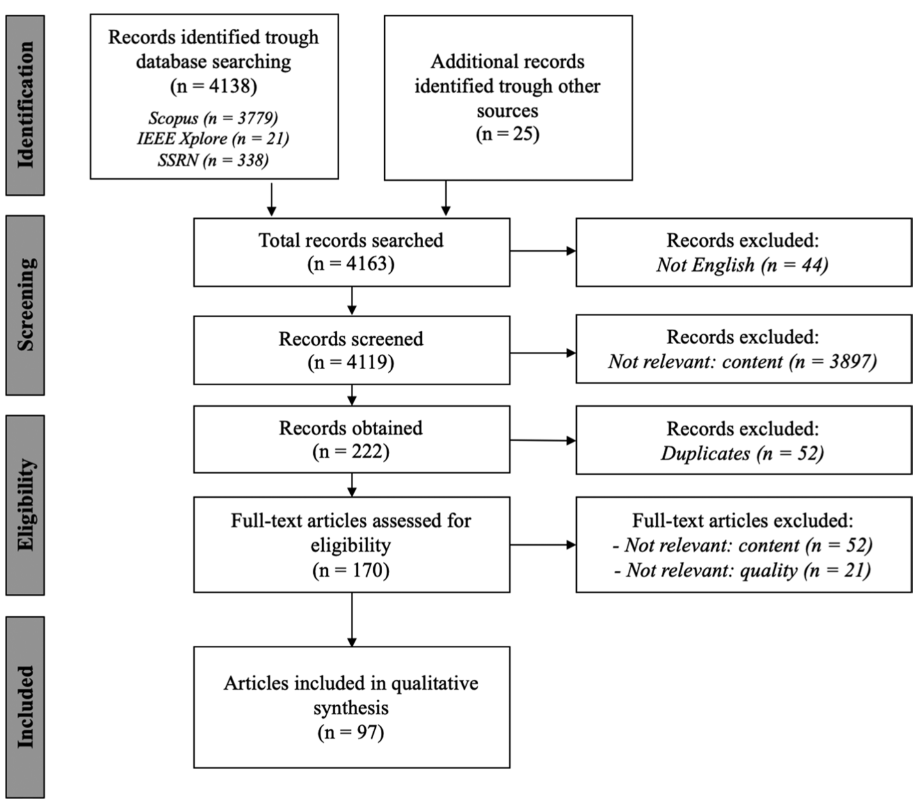

Fig. 2 PRISMA flow chart

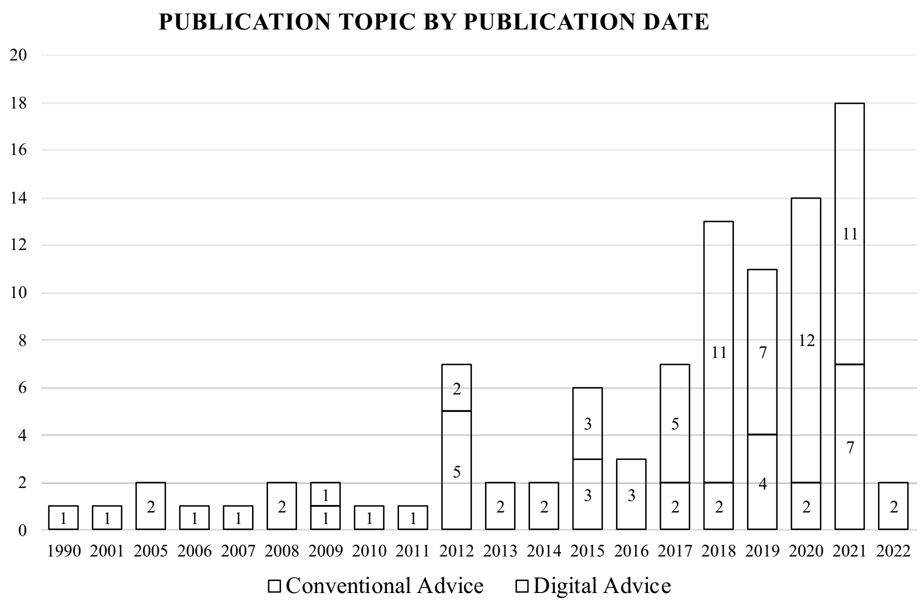

Fig. 3 Publication topic by publication date

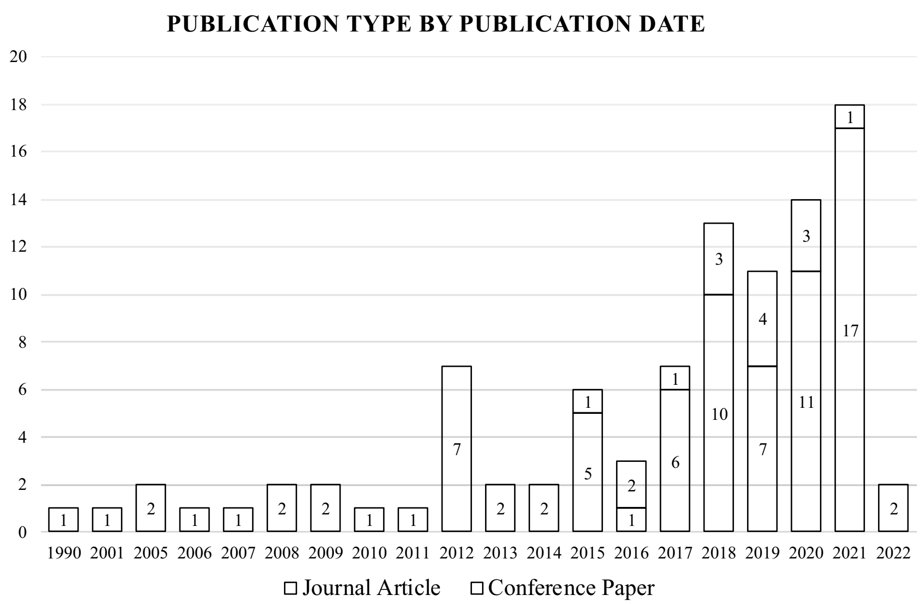

Fig. 4 Publication type by publication date

version of the publication was used. The 97 articles that survived the selection process were included in this systematic literature review.

The following figures provide insights into the composition and the structure of the relevant literature used. Figure 3 illustrates the number of publications included in this systematic literature review, sorted by the form of advice over time. It can be seen that the volume of publications has risen in recent years, and that authors are increasingly focusing on the digital variant of advice. Figure 4, which lists the publication types by publication date, displays that a large proportion of the new ideas are still published as conference papers. The conference papers used here dealt predominantly with proposals related to digital advice, suggesting that these ideas were not yet ready for journal articles.

Framework: determinants of investment advisory decisions

Investment advisory decisions are influenced by a variety of different factors. In this thesis, an attempt was made to systematize the identified determinants in an organized framework (see Fig. 5). Accordingly, not only the client profile, the investment strategy and laws, but also conflicts of interests and biases determine an advisor's investment decision.

Figure 6 presents the literature dealing with each identified determinant. It can be seen that most publications addressed the client profile. For investment strategy, only publications dealing with digital or digitally supported investment advice were found. In the context of conflicts of interest, the majority of publications dealt with conventional advisors, whereas almost the same number of publications were found on biases for each type of advice. In the synthesis, each determinant is reviewed based on the literature.

Synthesis

Client profile

Client profile: general In order to provide an investment recommendation that is optimally tailored to the needs of the client, an advisor needs a detailed profile of its client. Thus, data about the client's personal circumstances (see "Determinants of investment advisory decisions" section) have to be collected by the advisor. Without these data a recommendation in the client's interest is hardly possible.

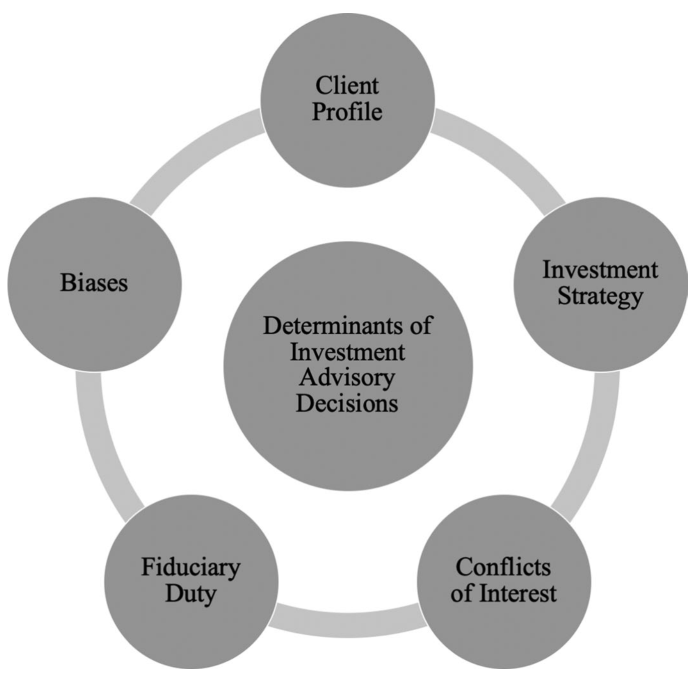

Fig. 5 Determinants of investment advisory decisions

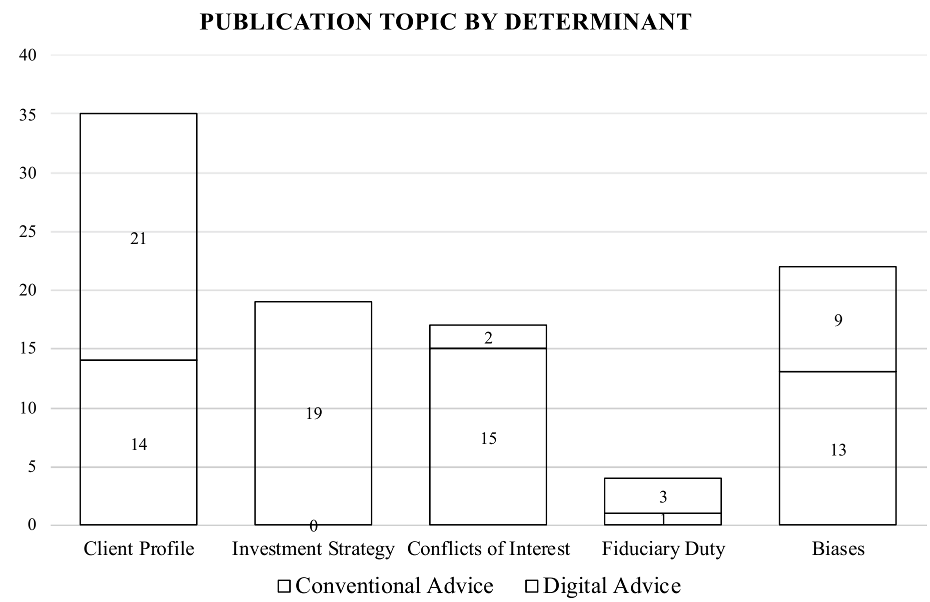

Fig. 6 Publication topic by determinant

In general, conventional advisors collect data from their clients either through a questionnaire or in a personal meeting to create a fully comprehensive client profile (see Cooper et al. 2014, p. 273). The legislators, however, do not provide standardized questionnaires, so that advisors rely on their own judgment when interpreting the obtained data (see Baeckström et al. 2021, p. 716; Hubble and Grable 2019, p. 73).

Without trust the client may not provide its advisor with the necessary data, so that an advisor must ensure that the relationship between advisor and client is characterized by mutual trust. Client's trust in the advisor is connected to the client's financial literacy, its age and its willingness to take investment risk (see e.g. Lachance and Tang 2012, p. 222f.).

Advisors who can detect their clients' emotional attachment to money strengthen the financial advisory relationship (see Lozza et al. 2022, p. 623). For example, clients may associate money as a symbol of security or power, while others may perceive it as freedom, which can affect the client's risk tolerance (see Lippi et al. 2021, p. 215). Logically, the emotional intelligence of an advisor seems of crucial importance not only for building a bond of trust, but also for identifying the clients' objectives.

Digital advisors might struggle to achieve such an emotional relationship as the interaction is limited to the IT-application. Thus, it can be easier for human advisors to collect data than for RAs, as the algorithm cannot interact personally with the client and relies solely on the data provided by the client (see Puhle 2019, p. 349). The algorithm could have difficulties in properly understanding the client's objectives, especially if they are very emotional, which may lead to an inadequate evaluation of the client (see Phoon and Koh 2018, p. 91; Jung et al. 2019, p. 412). For this reason, human advisors may give more personalized advice as they are not constrained by standardized elicitation questionnaires like the RAs (see Fisch et al. 2019, p. 24). Furthermore, RAs usually ask fewer questions because it is difficult to motivate the client to invest a lot of time in an online questionnaire (see Tertilt and Scholz 2018, p. 74f).

Several authors recently studied the effects of various designs of RAs that try to influence clients' robo-advice adoption by e.g. imitating human traits through anthropomorphism, trying to mitigate client's biases or building trust (see e.g. Adam et al. 2020; Deo and Sontakke 2021; Jung et al. 2018b; Litterscheidt and Streich 2020; Morana et al. 2020; Rühr 2020). The way in which the client profile is elicited has a significant impact on the client's decision to seek advice, so the method must be designed in such a way that the client feels that he or she has been correctly assessed (see Streich 2021, p. 13). Complex RA algorithms based on AI may be opaque and non-transparent. For this reason, Bianchi and Brière (2021, p. 19) suggested that XAI (explainable AI) may mitigate the issue. This means that the algorithm is designed in such a form that it can be understood by humans by describing its processes, whereas usual ML models are often associated with a black box.

Client profile: elicitation of risk tolerance One of the most important determinants of the client profile is risk tolerance. Risk tolerance can be seen as a multidimensional entity consisting of propensity, attitude, capacity and knowledge (see Cordell 2001). Cooper et al. (2014, p. 278f) found that these four elements show low correlation between each other, so that it is necessary to query them separately.

Other authors such as Nguyen et al. (2016, p. 16) as well as Lippi et al. (2021, p. 214) observed that the client's risk tolerance is influenced by the client's financial knowledge, its trust in the advisor, and the duration of the advisory relationship. When these factors are strong, the client is willing to take more risks in the investment decision (see Nguyen et al. 2016, p. 17; Lippi et al. 2021, p. 214).

Similarly, Thanki and Baser (2021) analyzed factors that determine financial risk tolerance of clients by examining demographic, psychological, and financial literacy factors. Accordingly, "personality type, financial literacy, gender, income, marital status, occupation, and number of dependents" were significant, whereas educational background and age not (Thanki and Baser 2021, p. 59). Cooper et al. (2014, p. 275) obtained similar results by reviewing literature, with the exception that marital status showed an inconclusive correlation with risk tolerance. It is crucial to consider that financial risk tolerance is not static but alters over time. Therefore, advisors must periodically adjust their investment strategy as the client's attitude changes (see Thanki and Baser 2021, p. 59).

So (2021) evaluated 20 real questionnaires used by banks through content analysis to see which questions were asked most frequently and which were asked least frequently in order to list important risk factors. Thereby, he identified the following determinants: the setting of realistic investment goals (factual information); the risk appetite of an investor (perceptual information); the understanding of investment risk according to own practical experience and knowledge; investor behavior when suffering investment loss (behavioral information); ability to take risk (factual information), i.e. the employment status or the financial situation (see So 2021, p. 8f). Although this study was especially aimed for RAs, the findings can also be used by conventional advisors.

So (2021, p. 10) additionally made important suggestions for RAs on how to profile clients. Accordingly, RAs should ask only a limited number of questions that are straightforward and comprehensible to understand. This is essential because clients cannot ask for an explanation of a question. Furthermore, the RA should directly evaluate whether the given answers are consistent. If not, the client should be asked further questions or be asked to enter its data again.

The above-mentioned findings help advisors build a more accurate profile of their clients and better understand clients' goals.

Client profile: difficulties in evaluation Snelbecker et al. (1990, p. 378) was one of the first who described the problem that advisors often have quite decent knowledge about their products, but lack a clear understanding of their client's objectives, as this requires some sort of intuitive emotional judgement, that is not objective. Asking the clients e.g. what their risk affinity is, does not solve the problem as clients may state deficient data because they cannot evaluate themselves correctly (see Snelbecker et al. 1990, p. 379). The problem of the right interpretation of the client's data by the advisor remains. They furthermore demonstrated that advisors' interpretations varied for the same client profile and clients showed inconsistencies in their self-evaluations (see Snelbecker 1990, p. 391). This puzzle was confirmed by Jansen et al. (2008, p. 21f), who asked advisors to assess their clients regarding three risk proxies (protection seeking, risk taking and loss tolerance) and compared the answers to the self-evaluation of the respective client. Thereby, they empirically observed that advisors' and clients' assessment differed (see Jansen et al. 2008, p. 22).

Hens and Mayer (2018) showed that different investment recommendations can occur if the client is assessed incorrectly and therefore modeled with an incorrect decision theory. They came to the conclusion that the risk assessment by existing questionnaires is not sufficient (see Hens and Mayer 2018, p. 213). Bhatia et al. (2020, p. 7) stated consistently that measuring client's objectives accurately is difficult, since preferences are changing over time and may not resemble future objectives. Furthermore, the people who create questionnaires either for in-person encounters or for digital advice may be biased. A potential solution could be to hire professional experts who are educated how to design questionnaires and have financial knowledge (see Bhatia et al. 2020, p. 7).

Tertilt and Scholz (2018, p. 82) criticized that RAs often use only a simple standardized risk elicitation approach and found that in their sample only slightly more than half of the asked questions impacted the client's risk assessment. Thus, RAs may not be able to determine all relevant information about their clients through questionnaires and consequently may not give their advice based on the true client profile (see Fein 2015, p. 30).

According to Bianchi and Brière (2021, p. 13), RAs suffer from fuzzy legislation that does not clearly regulate how questionnaires should be structured so that clients' characteristics are difficult to assess. Thus, comparisons between client profiles are often not accurately possible because the questions and rating scales vary in different questionnaires.

D'Acunto and Rossi (2021, p. 741) explained that RAs divide their clients into categories based on their answers in the questionnaire. Clients belonging to the same category receive the same advice, although clients in a category also differ in some characteristics, which would mean that they do not receive tailored advice (see D'Acunto and Rossi 2021, p. 741). This is consistent with Fein (2015, p. 8f). Such general approaches of RAs only provide suitable advice for an average client and not individualized advice, as they only obtain limited data about an individual client through simple questionnaires (see Faloon and Scherer 2017, p. 33f). These findings are in line with Torno and Schildmann (2020, p. 103) and Scherer and Lehner (2021, p. 17f).

Albeit advisors should, conventional advisors oftentimes do not take client characteristics into account, when making a recommendation. Mullainathan et al. (2012, p. 3) showed in an audit study that in only 75% of the advisor-client encounters, the clients were even asked to provide personal information. More severely the data when obtained was often not used by the advisor, which questions the reliability of an advisor's recommendation (see Mullainathan et al. 2012, p. 3; Uhl and Rohner 2018, p. 45). RAs also do not use all obtained information of the client profile for their decision (see Tertilt and Scholz 2018, p. 82; Harrison and Samaddar 2020, p. 78).

Client profile: methods for conventional advice proposed by literature In literature there exist several methods that try to guide the advisor through the client profiling, which are methodologically very similar and intend to make the client profiling and the information gathering more effective.

For instance, Kinder and Galvan (2005) developed a theoretical model in which an advisor follows sequential steps, and this model has been empirically validated through a survey conducted by them. Accordingly, an advisor has to explore the client's needs and identify the client's vision and obstacles. In the subsequent step the advisor applies its financial knowledge to give an investment recommendation which leads then to the execution (see Kinder and Galvan 2005, p. 46).

Belkora (2015) transferred a similar model which was earlier described in medical literature to the financial context. This model can be explained by making use of the widely known iceberg model (see Belkora 2015, p. 10). Clients usually provide their advisor only some personal data and objectives (the part of the iceberg that is visible), while omitting their underlying values (the part of the iceberg that is under the water). For an advisor to completely understand the client's investment motives it is, however, essential to gather a fully comprehensive profile of its client. Through such structured model approaches, an advisor obtains more information from the client than from an unstructured interview (see e.g. Snelbecker et al. 1990, p. 380).

There are besides authors, such as Stendardi and Graham (2006), who suggested that advisors should customize client profiling to the gender of the client. They reviewed several gender studies with the result that men and women decide differently in general and in their investment affairs. They further analyzed whether advisors should behave differently when advising a woman or a man. Women are more risk averse than men and should thus be more enlightened about risks (see Stendardi and Graham 2006, p. 236). Furthermore, women are more comfortable discussing and planning their investment strategy in face-to-face encounters to build trust, whereas men are fine using the Internet or the phone for their financial affairs (see Stendardi and Graham 2006, p. 227).

Client profile: methods for digital advice proposed by literature Modern technology supported collection systems enable conventional advisors to benefit greatly from increasing digitalization. This can be seen especially in the client profiling phase.

Kilic et al. (2017, p. 4696) noted that some clients hesitate to give personal information to an advisor due to privacy concerns which led them explore digital approaches to client profiling. They considered a "joint profiling" and "task aware joint profiling" concept (see Kilic et al. 2017, p. 4697). Their first approach encompasses a separated two-step process to identify suitable investment opportunities, i.e. first the advisor and its client collect the data together on a tablet and afterwards on a subsequent page on the screen the recommended solution is displayed (see Kilic et al. 2017, p. 4698). Their latter approach directly displays the solution while entering the data (see Kilic et al. 2017, p. 4700). They found such a "task aware joint profiling" makes clients more open to provide their personal data. This is because clients can directly see the impact of the data and thus perceive the data gathering as necessary. Kilic et al. (2015, p. 1328) observed furthermore that in an advisory session guided by an IT visualized structure clients and advisors are subject to a perceived compulsion for completeness in determining the client profile.

In purely digital advising, there is no possibility of human support in the interaction with the client. Current RAs determine the client profile using questionnaires that the client fills out digitally. Several methods have been proposed in the literature on how the use of ML or AI can improve digital client profiling.

For example, Alsabah et al. (2021) integrated reinforcement learning into a RA model so that the algorithm learns the client's risk preference over time by observing portfolio decisions under different market circumstances. Dong et al. (2021) developed the model of Alsabah (2021) further by changing the underlying framework from single level mean-risk to a bi-level framework. Whereas Alsabah et al. (2021) updated the client's risk preferences through an equally weighted averaging, Dong et al. (2021, p. 2) used a dynamic weighting method, i.e. the client's most recently made decision carries the most weight, which makes the RA more accurate. Wang and Yu (2021) proposed a similar algorithm that determines the client's risk preference by analyzing its historical portfolio allocation using another ML approach.

Investment strategy

Conventional Advice: The client profile serves as the basis for the development of an individual investment strategy and for the recommendation of specific investment products. In the past, there were also a lot of scientific recommendations for conventional advisors on how to structure an optimal portfolio, such as Markowitz's (1952) Modern Portfolio Theory or other methods. However, a presentation of asset allocation theories is not within the scope of this paper.

Digital Advice: According to Jung et al. (2018a, p. 83f), digital investment advice can be structured into the following three phases: Configuration (initiation, profiling and assessment), Matching and Customization, and Maintenance (e.g. data storage). In the following, only the methods for the matching and customization phase will be discussed, as the configuration phase has implicitly already been described in the client profiling section. Maintenance is often performed as standardized background processes, without much impact on the investment recommendation, why it is not explicitly reviewed. In the recent literature, there are a number of works that addressed how RAs can independently make advisory decisions or how they can assist advisors in choosing an investment strategy. Some of these models are presented in the following.

García-Crespo et al. (2012) and Gonzalez-Carrasco et al. (2012) developed similar investment recommendation systems that attempted to provide tailored advice. The principle of these models is based on predefined social and psychological character traits that are classified into different risk tolerance categories. The investment products offered are allocated to one of these categories by financial experts. After the client has been profiled and categorized with regard to these criteria, the algorithm maps the client in a matrix and additionally projects the investment products into the matrix (see García-Crespo et al. 2012, p. 105; Gonzalez-Carrasco et al. 2012, p. 65). In this way, the advisor can give his client a personalized investment recommendation.

Zibriczky (2016) created a literature review of different recommender system concepts and their application in different financial contexts. Accordingly, these systems rely either on collaborative filtering, content-based filtering, knowledge-based recommendation, case-based recommendation or a mixture of those.

In practice, collaborative filtering systems recommend products on the basis of what similar users prefer, whereas content-based filtering systems recommend products that are similar to already held products by a user. The knowledge-based and the case-based recommendation system are very similar as both advice on the grounds of past experiences (see Leonardi et al. 2016, p. 33). Each of the algorithms requires a lot of data to perform analyzes.

Xue et al. (2018b, p. 54528) proposed to integrate a financial social relationship factor into a collaborative filtering algorithm to calculate the similarity of users more precisely. Their analysis showed that their extended approach outperformed pure collaborative filtering systems. (see Xue et al. 2018b, p. 54534).

The most sensible approach to aid advisors in their decision making is according to Musto et al. (2015) an IT-supported case-based recommendation system. Such systems usually consist of five steps: retrieve, reuse, revise, review, and retain (see Musto et al. 2015, p. 103f). Thus, various advice cases that were stored in a memory can be retrieved on demand regarding the similarity to a new issue. The system revises the cases and clusters similar portfolio choices together to provide the advisor different options to choose from. The ranking process sorts those in order to optimize the balance between similarity and diversity and evaluates the performance of each case portfolio based on historical yields. Their results showed that such case-based recommendation system approaches can outperform human advice (see Musto et al. 2015, p. 109). According to Leonardi et al. (2016), such a case-based recommendation system is not restricted to an initial investment recommendation but provides also a deeper understanding of an existing client's portfolio. By that, an advisor and its client can see whether comparable clients opted for similar investment strategies and thereby derive necessary actions (see Leonardi et al. 2016, p. 38).

A multitude of authors developed RA algorithms which are based on various ML techniques aiming at creating more accurate portfolio allocation recommendations. In principle, the proposed models are similar in structure, though the authors used different assumptions and methodologies. For example, Day et al. (2018) were among the first who developed a RA model for scientific purposes. Therefore, they combined a big data deep-learning algorithm with the Black and Litterman (1990) model to find optimal allocation weights. Wang and Yu (2021) presented a reinforced learning algorithm that attempts to create an allocation strategy through iterative learning and optimization of a historical price dataset without relying on estimates. In addition, similar proposals for ML application in the Robo-advisory segment were presented, such as the models of Ahn et al. (2020), Chen et al. (2018), Damrongsakmethee and Neagoe (2020), Day and Lin (2019), Gu et al. (2019), Xue et al. (2018a) and Wang et al. (2019).

Another approach is to let an algorithm analyze past financial news announcements compared to stock prices to predict market prices from future news (see, e.g., Schumaker and Chen 2009; Geva and Zahavi 2014; Leow et al. 2021). In addition, Leow et al. (2021) integrated Twitter sentiment analysis into such a RA model.

These ML systems are continuously evolving, so that it is expected that more conventional advisors will rely on such systems in their decision-making process to keep up with purely digital advisors (see e.g. Beketov et al. 2018, p. 369; Coombs and Redman 2018, p. 20f).

Fang et al. (2022) conducted a review and analysis of cryptocurrency trading strategies, identifying various methods such as basic regression methods, linear classifiers and clustering, time series analysis (e.g., GARCH), decision trees, and probabilistic classifiers or modern portfolio theory that can be applied in developing such an investment strategy. Additionally, Sebastião and Godinho (2021) explored various ML techniques for forecasting cryptocurrency returns, finding that while they can predict returns, the precision power heavily relies on the chosen ML model technique. These papers show that digital aided advice is not limited to standard investment products, but is also transferable to more complex portfolio securities such as cryptocurrencies.

Conflicts of interest

Currently, there is still relatively little literature on conflicts of interest dealing with RAs, which makes a valid comparison of RAs and traditional investment advisors impossible. For this reason, the following paragraph deals almost exclusively with conflicts of interest in traditional investment advice. However, many of these conflicts can also be transferred to the context of RAs. "Contrary to the general assumption that RAs" section deals exclusively with conflicts of interest of digital advisors.

Conflicts of interest: compensation style Determinants that are not in the client's best interest may affect investment advisory decisions. Advisor's compensation is a serious problem in investment decisions because advisors could be influenced by the commissions received for individual investment products (see Rubin 2015, p. 538f). The problem is exacerbated when sales commissions are a critical part of the advisor's compensation, making advisors more sales-focused (see Rubin 2015, p. 539). This could lead advisors to recommend funds, not for their chances of growth, but for the potential commissions these funds pay to the advisors (see e.g. Spatt 2020, p. 222f.;

Chen and Richardson 2019, p. 174; Gottschalk 2020, p. 23), so that the client's utility of the investments is often not the first priority in the advisory decision (see e.g. Sah 2019, p. 62).

Angelova and Regner (2013) analyzed several different payment styles in regard to conflicts of interest in an experimental setting. They compared inter alia the effectiveness of a voluntary prepayment, an obligatory prepayment, a voluntary bonus afterwards, and a combination of a voluntary prepayment and a bonus afterwards in fostering advisors to give truthful advice and in reducing conflicts of interest. By performing the sender-receiver model of Crawford and Sobel (1982), they found two interesting outcomes (see Angelova and Regner 2013, p. 217). First, the higher the compensation, the more truthful the advice. Second, a compensation consisting of a voluntary prepayment and a bonus afterwards leads to more truthful advice compared to other compensation models. This is consistent over time because an advisor has an incentive not to lie due to the performance-based payment.

Hoechle et al. (2018) investigated, inter alia, how banks make profits with employed advisors and whether bank-owned products are preferred in investment advice decisions. They observed that bank products were more likely to be recommended, which could mean that bank advisors put the client's interest behind their employer's interest (see Hoechle et al. 2018, p. 4483).

Conflicts of interest: competition Bolton et al. (2007) examined conflicts of interest in financial advice in the context of competition and compared different scenarios, i.e., monopoly and competition, based on mathematical models related to the Bertrand model. They analyzed whether an advisor would recommend products of its own firm even if a product of another firm would be more suitable for a client in the context of competition, finding that competition reduces conflicts of interest (Bolton et al. 2007, p. 317f.). Gelman et al. (2021, p. 8) got similar outcomes, i.e. advisors who have a high local market power are more likely to engage in misconduct. Both results imply that the more competitive the advisory industry, the less conflicted the advisor.

Conflicts of interest: disclosure Results such as those of Chung and Harbaugh (2018, p. 534), who found that nontransparent incentives encourage advisors to provide biased advice to clients, motivated several authors to research whether disclosure of conflicts of interest could mitigate them.

Sah (2019) researched the effects of disclosure on conflicts of interest. She compared different perceptions of professional advisory norms, i.e. "self-interest" or "client first", in the context of financial advice and medical advice (see Sah 2019, p. 66). According to her, disclosure per se does not attenuate conflicts but professional norms in combination with disclosure can (see Sah 2019, p. 66). Thus, disclosure could be beneficial if it functions as a reminder for professional norms, when the norm "client first" is present in that industry. This means advisors behave differently in their advice giving, depending on the norm that is present in a specific environment, (see Sah 2019, p. 75f.). Especially, she found that while in the medical context the "client first" norm is more present, in the financial context it is often "self-interest", which might be grounded on the more severe effects of biased advice in the medical setting (see

Sah 2019, p. 71). She further discovered that non-expert advisors generally give more biased advice, whereas lesser, when reminded that the professional norm at place is "client first" (see Sah 2019, p. 75).

Cain et al. (2005, p. 22) and Cain et al. (2011, p. 849) observed that disclosure could have opposite effects than desired. Accordingly, disclosure of conflicts of interest, especially in a face-to-face conversation with a client, can create trust that can be abused by the advisor. Church and Kuang (2009) and Koch and Schmidt (2010) each repeated the experiment of Cain et al. (2005) and developed it further. For instance, Church and Kuang (2009, p. 521) found that advisors' conflicts do not increase with disclosure, but sanctions by clients may lessen conflicts because conflicted advisors fear the sanctions after disclosure. Opposingly, Gottschalk (2020, p. 23) came to the result that neither fines nor disclosure lessens biased advice, but rather increase conflicts. Ismayilov and Potters (2013, p. 319) discovered that disclosure has no significant impact on advice giving, i.e. it neither mitigates nor increases conflicts of interest. Chen and Richardson (2019) came to similar conclusions, additionally observing that disclosure has no impact on clients' purchase decision (see Chen and Richardson 2019, p. 179).

These mixed results suggest that it would be better not to focus only on regulatory enforced disclosure, but more on providing objective information to the clients that help them evaluate the recommendation (see Cain et al. 2011, p. 851), so that a client can distinguish between good and bad advice (see Inderst and Ottaviani 2012, p. 511).

Conflicts of interest: digital advice Contrary to the general assumption that RAs operate in a completely rational manner, not only human advisors but also RAs can be affected by conflicts of interest. Ji (2017, p. 1578) argued that RAs' conflicts of interest may be of even greater concern than human advisors because a RA typically advises significantly more clients than a human advisor.

Fein (2015) studied contractional information, i.e. user agreements and investment strategies, of three RAs to investigate to which extent RAs exhibit conflicts of interests. Her analysis revealed that RAs, like human advisors, are conflicted in their advice. For example, RAs often keep close relationships with brokers and banks in order to obtain favorable terms when executing their trades (see Fein 2015, p. 15). RAs also seek to recommend products that earn them the highest brokerage commission. This allows RAs, which are generally touted as low-cost, to indirectly increase their profits (see Fein 2015, p. 18). These findings are in line with Fisch et al. (2019, p. 26) and Bhatia et al. (2020, p. 7), who claim that RAs are often programmed for such a behavior.

Fiduciary duty

In some countries, legal regulations attempt to mitigate the problem of conflicts of interest by making a fiduciary duty mandatory. If advisors are subject to such an obligation, compliance with the fiduciary duty would be essential for their investment advisory decision. Financial advisors, acting under fiduciary duty, have to subordinate their own interests to those of their clients (see Rubin 2015, p. 525), thereby aiming at fulfilling their duty of care and loyalty (see Fein 2017, p. 2). The advisor's obligation may go as far as to refuse an explicit client request if the advisor recognizes that the request is contrary to the client's interests (see Rubin 2015, p. 542f).

Rubin (2015, p. 521) stated that the fiduciary duty should apply to all who provide customized advice to clients. An advisor can only meet this obligation if he or she has undergone appropriate training or a certification process, but this is often not the case, as there are hardly any legal requirements to do so (see Rubin 2015, p. 538).

Fein (2017) dealt in detail with the question of whether RAs can meet the obligations of fiduciary duty. She came to the conclusion that RAs cannot fulfill especially the duty of care (Fein 2017, p. 19). Addressing the criticism of Fein (2017), Lightbourne (2017, p. 665) instead came to the result that conflicts of interest arise equally for RAs as for human advisors, so that it is possible to program RAs in a way that they can meet the fiduciary duty. This is consistent with Duffy and Parrish (2021, p. 29) and Ji (2017, p. 1583).

Linnainmaa et al. (2015, p. 34) showed that conflicts of interest have only a minor impact on advice giving, which would imply that regulations that try to eliminate conflicts of interest would not have great importance.

Biases

Behavioral biases Biases can also influence investment advisory decisions. Behavioral biases are pervasive in the advisory industry, and not only do investors suffer from those, but many financial advisors do as well (see e.g. Baker et al. 2017, p. 25). Recommendations that are based on such biased and flawed judgments can seriously affect the quality of advice. For this reason, professional advisors must be aware of the various biases that anyone can fall prey in order to avoid them (see Baker et al. 2017, p. 25).

Baker et al. (2017) discussed a multitude of behavioral biases and their influence on the decision making of advisors theoretically. Accordingly, some advisors may utilize simple heuristics e.g. in their assessment of the client's risk tolerance, which rely often on stereotypes. In a general setting, advisors ranked risk assessment characteristics so that time horizon was listed as the most important characteristic, followed by liquidity needs, risk capacity, risk demand, and risk tolerance (see Grable et al. 2020, p. 14). However, when the advisors were confronted with different real-world scenarios, inconsistencies emerged. For example, it appeared that advisors were likely applying a simple portfolio allocation heuristic such as the "100—age" equity allocation rule, not taking into account other factors (see Grable et al. 2020, p. 20; Hubble and Grable 2019, p. 88). Hubble and Grable (2019) furthermore investigated the variation in portfolio allocation recommendations given by 200 financial advisors for five hypothetical scenarios, finding that even though the advisors were presented with the same client data, they gave varying recommendations (see Hubble and Grable 2019, p. 87f).

Another example is that advisors could be anchored by an initial piece of information that they use as reference point in making their decision, e.g. an initial stock price that has then changed (see Baker 2017, p. 25).

Besides, advisors' emotions and feelings affect the perception and thus the assessment of risks, which could result in biased advice. Among others, Baeckström et al. (2021, p. 732) observed a gender bias in financial advisory encounters i.e. advisors view their clients differently depending on their gender. For example, women are often perceived as less literate and less experienced in financial matters than male clients. Advisors are also more likely to recommend lower-risk portfolios to women, suggesting that advisors are influenced by certain gender stereotypes. Similarly, Söderberg (2012) identified significant differences between female and male advisors in how they evaluated their clients (see Söderberg 2012, p. 267). For example, she observed that male advisors in her sample rated their clients' responses higher than female advisors for almost all variables, which can be explained by the overconfidence bias that is typically stronger in men (see Söderberg 2012, p. 267).

While Söderberg (2012) examined ordinary clients, Baeckström et al. (2021) only considered millionaire clients in their study, resulting that the observed gender bias decreases as the client's wealth increases.

Other biases are e.g. the familiarity bias (the advisor prefers familiar options, which then leads to underdiversification), herding (the advisor discards its own thoughts and follows the recommendations of other advisors), the confirmation bias (advisors prefer and choose information that confirms their existing beliefs in their evaluation) and many more (see Baker et al. 2017).

Misguided beliefs of advisors It is also possible that advisors have misguided beliefs and make their decisions based on them. The research of van de Venter and Michayluk (2008) demonstrated that financial advisors become overconfident in their forecasting abilities with age and experience, which suggests that advisors give their recommendation not based on a rational analysis of what would be best for their clients but based on the advisor's own biased judgement (see van de Venter and Michayluk 2008, p. 554). Mullainathan et al (2012) showed that advisors do not dissuade their clients from investing in expensive actively managed products, but rather encourage them to do so (see Mullainathan et al. 2012, p. 18).

Hackethal et al. (2012, p. 510) found that advised portfolios show higher account turnover and perform worse in regard to the risk-return factor compared to non-advised portfolios. Moreover, they observed that this effect is more pronounced when advised by bank advisors than by independent advisors, which could be due to constraints imposed by the bank on its advisors (see Hackethal et al. 2012, p. 519). Confirming this puzzle, Foerster et al. (2017) demonstrated that advisors incorporate the client profile into their deliberations only to a limited extent and therefore do often not tailor portfolio recommendations to clients. They explained this behavior by comparing the portfolios of several thousand Canadian advisors to those of their clients, resulting that advisors incorrectly projected their own risk attitudes onto those of their clients (see Foerster et al. 2017, p. 1480). Results of Baeckström et al. (2021, p. 732) indicated similarly, that not only the client's portfolio impacts the advice, but especially personal traits of advisors.

The abovementioned findings are in line with the research results by Linnainmaa et al. (2021). They compared the trading behaviors and the investment performance of nearly 4000 Canadian advisors and their clients, resulting that the majority of financial advisors are lacking trading knowledge and are misguided in their beliefs. It furthermore turned out that both advisors and clients invest almost solely in active managed funds, that they choose similar return chasing strategies and that their portfolios are underdiversified with fairly high turnover and high costs (see Linnainmaa et al. 2021, p. 596f.). They supplementary found strong similarities between purchases of clients and co-clients of the same advisor (see Linnainmaa et al. 2021, p. 606). Strengthening this, they observed merely nonessential differences between "advisor-only" and "client-only" purchases, which suggests that the advisors act to the best of their knowledge and belief (see Linnainmaa et al. 2021, p. 610).

Additionally, they tested whether advisors trade contrary to their beliefs. Therefore, they regarded 400 post-career advisors, who continued to trade for themselves at their old firm. Thereby, Linnainmaa et al. (2021, p. 614) determined that even when there is no strategic benefit, advisors continue to invest in e.g. costly mutual funds, which implys that they were misguided in their beliefs.

Priolo et al. (2022) addressed a similar issue. Higher risk is generally rewarded with higher returns. Nevertheless, especially investors perceive this relationship as negative, mainly due to negative feelings associated with risk (see Priolo et al. 2022, p. 1f). They examined how financial advisors perceived the relationship between risk and return and found that the lower the experience and the higher the emotional intelligence of an advisor, the more negatively the relationship was perceived (see Priolo et al. 2022, p. 4). Thus, they identified that inexperienced advisors relied too much on their personal feelings when making decisions.

Regardless of whether advisors act under a fiduciary duty or whether conflicts of interest can be ruled out, the quality of advice would still be distorted if advisors have misguided beliefs. Consequently, mandatory professional education may solve the problem of poor advice (see Baker et al. 2017, p. 29; Bruhn and Asher 2020, p. 3316; Hubble and Grable 2019, p. 89; Linnainmaa et al. 2021, p. 613; Priolo et al. 2022, p. 5; Rubin 2015, p. 537f; Söderberg 2012, p. 268).

Biases of digital advisors Whereas human advisors are prone to various biases, algorithms have the potential to act rationally so that they are not influenced by emotions or feelings, if programmed properly (see Jung, et al. 2019, p. 416).

A rational portfolio selection would be consistent with Modern Portfolio Theory (hereafter "MPT"), dating back to Markowitz (1952), i.e., for a given risk, the expected return must be maximized and thus as close as possible to the efficient frontier (see, e.g., Hayes 2020, p. 572). Such MPT-based algorithms could eliminate emotional and cognitive biases of human advisors (see Hayes 2020, p. 572).

By analyzing the principles of 20 RAs that reflect approximately 90% of the market in the USA, Hayes (2020, p. 573f) showed that almost all of them follow MPT, which is consistent with the results of Beketov et al. (2018, p. 366).

Hayes (2020, p. 578) then compared the recommended portfolio constructions to the efficient frontier line, finding that they have little distance. After comparing robo-advisor performance with that of human advisors, it became clear that the products recommended by human advisors had a greater distance to the efficient frontier line than those of RAs (see Hayes 2020, p. 580). Such findings imply that RAs can be quite rational, which could reduce behavioral biases (see Uhl and Rohner 2018, p. 48).

D'Acunto et al. (2019, p. 2007) furthermore discovered that RA clients were less frequently exhibiting known biases, which may suggest that RAs can eliminate clients' biases (see D'Acunto et al. 2019, p. 2007). They found additionally that RAs for undiversified investors increase portfolio diversification and thereby reduce volatility, leading to slightly higher returns. For already diversified investors, however, there were no meaningful improvements (see D'Acunto et al. 2019, p. 2017f).

Contrastingly, Harrison and Samaddar (2020), who compared the performance of a real RA and a human advisor in different scenarios, observed that the human advisor outperformed the RA in every scenario considered (see Harrison and Samaddar 2020, p. 77). Although this result is certainly not generalizable, as the sample size is not representative, the result showed a very interesting case. It was noticeable that the RA did not take into account the individual characteristics of the clients, as it recommended the same strategy for each client scenario even if the age or the investment amount was changed. This means that the RA did not adapt its recommendation to an individual client (see Harrison and Samaddar 2020, p. 78). Strengthening this, Puhle (2019) analyzed five German RAs regarding their investment performance and asset allocation, finding that each considered RA underperformed the MSCI World Index (see Puhle 2019, p. 342f).

Tertilt and Scholz (2018, p. 81f) found that RAs made similar recommendations compared to human advisors. These finding might be caused by the fact that RAs mostly apply simple methodology to develop advice, and do not yet use all the previously presented methods of machine learning and artificial intelligence (see Beketov 2018). Bianchi and Brière (2021, p. 11f) explained three major reasons for this: technological constraints, regulatory constraints and transparency issues.

Even though RAs have the ability to perform data analysis that no human could ever do, RAs are still programmed by humans. Depending on the human impact, RAs can also have some weaknesses. Boreiko and Massarotti (2020) analyzed 53 RAs from Germany and from the USA, regarding different factors that may influence their investment recommendation. They found differences in the recommendations in the two countries for similar client profiles. They reasoned that different beliefs may be present in Germany and in USA, which could cause this puzzle (see Boreiko and Massarotti 2020, p. 7).

As RAs mainly use similar methodology for their client assessment and portfolio allocation, the problem of "herding" could arise in digital investment advisory decisions (see Ringe and Ruof 2021, p. 202).

The described studies imply that not only conventional advisors exhibit biases (see e.g., Linnainmaa et al. 2021), but algorithms may also lack clear trading knowledge if they are programmed by humans who hold misguided beliefs (see D'Acunto et al. 2019, p. 2006).

Discussion

The literature synthesis showed, that there are two main reasons why investment advice can be flawed or not tailored to the client. On the one hand, advisors may make mistakes in client profiling, e.g. in collecting or interpreting the data and provide incorrect advice on this basis. On the other hand, even if a correct client profile has been created, the advisor may give an inappropriate investment recommendation due to behavioral biases, misguided beliefs or when he or she is influenced by conflicts of interest.

Questionnaires designed to elicit the client profile are often insufficient to accurately assess the client (see e.g. Bhatia 2020, p. 7). Conventional advisors can more accurately identify clients' underlying motivations through the use of structured methods in face-to-face client interviews (see, e.g., Belkora 2015). In contrast to conventional advisors, RAs often have difficulty identifying their clients' investment motivations and risk tolerance because they lack emotional intelligence and personal interaction (see e.g. Jung et al. 2019, 412; Puhle 2019, p. 349). As a result, the advice given by RAs is often not tailored to the individual client's needs but more to an average client profile (see Faloon and Scherer 2017, p. 33f). Some suggestions have been made by literature on how to make client profiling more effective. Conventional advisors obtain a better client assessment when assisted by digital algorithms (see e.g. Kilic et al. 2017). Algorithms based on artificial intelligence and machine learning have the potential to determine the clients' risk tolerance and objectives more accurately (see Alsabah et al. 2021; Wang and Yu 2021). The use of such sophisticated algorithms in the future can overcome the weaknesses of questionnaire assessment. Additionally, the literature addressed various methods to find an optimized portfolio allocation that can be used by conventional advisors for their investment advisory decisions as well as in purely digital advice. Proposals were made in which algorithms compare the portfolio allocations of a large number of similar client profiles (see Zibriczky 2016; Musto et al. 2015; Leonardi et al. 2016). Other approaches aim at enabling algorithms to learn from historical market developments through machine learning and artificial intelligence and to react e.g. to future keywords in news announcements (see Geva and Zahavi 2014; Leow et al. 2021). The literature review revealed that digital advisory services, especially in the area of investment strategy development, will make a decisive impact in the future and could revolutionize the advisory industry. Furthermore, it was shown that not only conventional advisors but also RAs can be affected by conflicts of interest (see e.g. Fein 2015). This is mainly caused by the fact that operators, like banks or advisory firms, have a great influence on the programming of RAs and that this is done with a view to profit maximization. For instance, RAs often hold "relationships" with brokers or recommend products that earn them higher commissions (see Fein 2015, p. 15, Bhatia 2020, p. 7). A number of authors addressed the question whether conflicts of interest can be mitigated by disclosing them, finding opposing results (see e.g. Sah 2019; Chen and Richardson 2019). Regulations such as fiduciary duty affect conventional as well as digital investment advice and must be followed in both variants. It became apparent that conventional advisors can suffer not only from behavioral biases (see e.g. Baker et al. 2017), but also from misguided beliefs (see Linnainmaa et al. 2021). This has far-reaching consequences, as even an imposed fiduciary duty cannot prevent advisors from giving poor advice against their best beliefs. Some studies found that existing RAs are also affected by biases (see e.g. Boreiko and Massarotti 2020, p. 7; Ringe and Ruof 2021, p. 202).

Overall, the systematic literature review demonstrated that the determinants of investment advice are the same for conventional and digital advice, only the way advisors approach them differs.

Limitations and future search

Through the applied systematic literature search the selection bias could be reduced to a minimum. However, as in every literature review, it cannot be completely ensured that each relevant publication could be found. A search in other databases or an extension of the inclusion criteria could have led to more identified publications. However, the aim of this systematic literature review was mainly to identify the determinants that are crucial for investment advisory decisions and to discuss them. More detailed insights could be gained by subjecting each determinant to its own systematic literature review. In any case, with 97 publications considered, it was possible to provide a solid overview of the literature regarding the determinants of investment advisory decisions.

My literature analysis revealed that no study was conducted with only certified financial advisors. Such studies could result in different outcomes and could thereby provide suggestions for regulators. Although regulatory determinants were not the focus of this work, it became apparent that legal regulations adapted to digital investment advice do not yet fully exist. Furthermore, there are almost no studies comparing the performance of RAs with conventional advisors. Once future generations of RAs give investment advice decisions based on ML and AI, it will be important to investigate whether this will lead to more personalized investment advice and better performance. Research will still have a lot to contribute in these fields.

Conclusion

This systematic literature review was conducted to identify the determinants of conventional and digital investment advisory decisions. Therefore, 97 relevant publications were included in this thesis. Five main determinants of advisory decisions were identified and analyzed in detail. These were found to be the same for conventional and digital advice, with only the way advisors approach them differing. It became salient that conflicts of interest are omnipresent in the advisory business and can hardly be eliminated completely no matter of the advisory model. It was shown that conventional advisors in particular suffer from misguided beliefs, which means that even if advisors are subject to a fiduciary duty or are required to disclose their conflicts of interest, they can still give poor advice if they suffer from biases. RAs, which are often touted as operating completely rational and being free of emotions, can also be influenced by conflicts of interest and can suffer from biases like traditional advisors as they are still programmed by humans. RAs are often associated with topics such as artificial intelligence or machine learning, although contrary to expectations, RAs are based only on simple algorithms at this stage. There are two ways to improve investment advice in the future. One is to make professional training mandatory for conventional advisors, the other is to address the identified and current deficiencies in digital investment advice through the use of machine learning and artificial intelligence. IT experts should collaborate with highly skilled financial experts in programming RAs. It remains to be seen which of the two options will be realized faster and will be more successful in the future.

Appendix 1: Literature search report

Friday, 18. March 2022—11:00 am CET

Opened database IEEE Xplore (https://ieeexplore.ieee.org/)

Activated "Advanced Search", switched to "Command Search"; IEEE allows only 7 wildcards (*), thus, little adaptations were necessary;

Search nuance 1: Robo-advisors' decision: ("Digital advi*" OR "Robo* advi*") AND ("decision*" OR "recommendation") AND ("investment*" OR "Financ*") = > Records: 9; Screening regarding titles and abstracts: 1 excluded (content); 8 remaining.

Search nuance 2: Conventional advisors' decision: ("Financ* advi*" OR "Financ* advice" OR "Conventional advi*" OR "human advi*" OR "In* Person advi*") AND ("recommendation" OR "decision*") AND ("investment*" OR "Financ*") = > Records: 8; Screening regarding titles and abstracts: 4 excluded (content); 4 remaining.

Search nuance 3: Comparison: ("robo* advi*" OR "human advi*" OR "conventional advi*" OR "person advi*") AND ("compar*" OR "similarit*" OR "difference*") = > Records:4; Screening regarding titles and abstracts: 2 excluded (content); 2 remaining.

Opened database Scopus (https://www.scopus.com/)

Activated "Advanced Search", switched to "Enter query string";

Search nuance 1: Robo-advisors' decision: ("Digital advi*" OR "Robo* advi*") AND ("decision*" OR "recommendation") AND ("investment*" OR "Financ*").

=> Records: 437; 4 excluded (language); 383 excluded (content); 50 remaining.

Saturday, 19. March 2022—10:00 am CET & Sunday, 20. March 2022—10:00 am

Opened database Scopus (https://www.scopus.com/)

Activated "Advanced Search", switched to "Enter query string";

Search nuance 2: Conventional advisors' decision: ("Financ* advi*" OR "Financ* advice" OR "Conventional advi*" OR "human advi*" OR "In* Person advi*") AND ("recommendation" OR "decision*") AND ("investment*" OR "Financ*") = > Records: 2936; 31 excluded (language); 2811 excluded (content); 94 remaining.

Sunday, 20. March 2022—13:00 am CET

Opened database Scopus (https://www.scopus.com/)

Activated "Advanced Search", switched to "Enter query string";

Search nuance 3: Comparison: ("Digital advi*" OR "robo* advi*" OR "human advi*" OR "conventional advi*" OR "In* person advi*") AND ("compar*" OR "similarit*" OR "difference*") AND ("investment*" OR "Financ*") = > Records: 406; 5 excluded (language); 380 excluded (content); 21 remaining.

Monday, 21. March 2022—09:00 am CET

Opened SSRN (https://www.ssrn.com)

Activated "Advanced Search"; Searched in Title, Abstract, Keywords & Full Text.

Search nuance 1: Robo-advisors' decision: ("Digital advi*" OR "Robo* advi*") AND ("decision*" OR "recommendation") AND ("investment*" OR "Financ*")

= > Records: 0; 0 excluded (content); 0 remaining.

Search nuance 2: Conventional advisors' decision: ("Financ* advi*" OR "Financ* advice" OR "Conventional advi*" OR "human advi*" OR "In* Person advi*") AND ("recommendation" OR "decision*") AND ("investment*" OR "Financ*") = > Records: 0; 0 excluded (language); 0 excluded (content); 0 remaining.

Search nuance 3: Comparison: ("Digital advi*" OR "robo* advi*" OR "human advi*" OR "conventional advi*" OR "In* person advi*") AND ("compar*" OR "similarit*" OR "difference*") AND ("investment*" OR "Financ*") = > Records: 0; 0 excluded (language); 0 excluded (content); 0 remaining.

Search nuance: Uncategorized search: "Robo-advice" Records: 254; 3 excluded (language); 238 excluded (content); 13 remaining.

Search nuance: Uncategorized search: "Digital advice" Records: 40; 1 excluded (language); 36 excluded (content); 3 remaining.

Search nuance: Uncategorized search: "Financial advi*" Records: 44; 0 excluded (language); 40 excluded (content); 4 remaining.

Appendix 2: Overview of the Results of the Literature Search

			Databases and other sources									
			Scopus		IEEE Xplore		SSRN		Backword search		Forward search	
ID	Nuance	Search string	Hits	Relevant	Hits	Relevant	Hits	Relevant	Hits	Relevant	Hits	Relevant
1	Robo-advisor' decision	("Digital advi*" OR "Robo* advi*") AND ("decision*" OR "recommendation") AND ("investment*" OR "Financ*")	437	27	9	4	0	0	0	0	0	0
2	Conventional advisors' decision	("Financ* advi*" OR "Financ* advice" OR "Conventional advi*" OR "human advi*" OR "In* Person advi*") AND ("recommendation" OR "decision*") AND ("investment*" OR "Financ*")	2936	54	8	2	0	0	0	0	0	0

			Databases and other sources									
			Scopus		**IEEE Xplore**		**SSRN**		**Backword search**		**Forward search**	
ID	**Nuance**	**Search string**	**Hits**	**Relevant**	**Hits**	**Relevant**	**Hits**	**Relevant**	**Hits**	**Relevant**	**Hits**	**Relevant**
3	Comparison	("Digital advi*" OR "robo* advi*" OR "human advi*" OR "conventional advi*" OR "In* person advi*") AND ("compar*" OR "difference*") AND ("investment*" OR "Financ*")	406	9	4	1	0	0	0	0	0	0
4	Uncategorized search	Keyword search	0	0	0	0	338	10	0	0	0	0
5	Uncategorized search	Forward and backword search	0	0	0	0	0	0	21	19	4	2
		Sum per database	3779	90	21	7	338	10	21	19	4	2
		Total number of relevant literature selected from 4163 scanned documents	With duplicates Without duplicates		107 76	+	Forward search Backward search		2 19	Total: 97		

Notes to Appendix

Appendix 1 provides information on the hits achieved:

Sum Hits Scopus: 437 + 2936 + 406 = 3779 | of which 27 + 54 + 9 = 90 were relevant

Sum Hits IEEE Xplore: 9 + 8 + 4 = 21 | of which 4 + 2 + 1 = 7 were relevant

Sum Hits SSRN: 0 + 338 = 338 | of which 10 were relevant

Hits from other sources (backward and forward search) could be obtained through full-text analysis

Backward search: 21 | of which 19 were relevant

Forward search 4 | of which 2 were relevant

= > 3779 + 21 + 338 + 21 + 4 = 4163 publications were scanned;

= > Relevant database publications: 90 + 7 + 10 = 107 (including duplicates)

= > After cleaning duplicates 76 relevant database publications remained

Consequently, 97 (=76+2+19) publications were included in this systematic literature review.

Further insights into the systematic literature evaluation and assessment can be found in the Excel spreadsheet attached to the thesis.

Abbreviations

AI	Artificial intelligence
CFA	Chartered financial analyst
CFP	Certified financial planner
Et al.	Et alia/and others
E.g.	Exempli gratia/for example
IT	Information technology
I.e.	Id est/that is
MiFID	Markets in financial instruments directive
ML	Machine learning
MPT	Modern Portfolio theory
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
RA	Robo-advisor
USA	United States of America
XAI	Explainable artificial intelligence

Author contributions

FW did all the works for this review article himself The author read and approved the final manuscript.

Declarations

Competing interests

The author declares that he has no competing interests.

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References

Adam M, Toutaoui J, Pfeuffer N, Hinz O (2020) Investment decisions with robo-advisors: the role of anthropomorphism and personalized anchors in recommendations. In: Proceedings of the 27th European conference on information systems (ECIS). https://aisel.aisnet.org/ecis2019_rp/33

Ahn W, Lee HS, Ryou H, Oh KJ (2020) Asset allocation model for a robo-advisor using the financial market instability index and genetic algorithms. Sustainability 12(3):849–864. https://doi.org/10.3390/su12030849

Alsabah H, Capponi A, Lacedelli OR, Stern M (2021) Robo-advising: learning investors' risk preferences via portfolio choices. J Financ Econom 19(2):369–392. https://doi.org/10.1093/jjfinec/nbz040

Angelova V, Regner T (2013) Do voluntary payments to advisors improve the quality of financial advice? An experimental deception game. J Econ Behav Organ 93:205–218. https://doi.org/10.1016/j.jebo.2013.03.022

Baeckström Y, Marsh IW, Silvester J (2021) Variations in investment advice provision: a study of financial advisors of millionaire investors. J Econ Behav Organ 188:716–735. https://doi.org/10.1016/j.jebo.2021.05.008

Baker HK, Filbeck G, Ricciardi V (2017): How behavioural biases affect finance professionals. Eur Financ Rev 25–29. https://ssrn.com/abstract=2899214

Beketov M, Lehmann K, Wittke M (2018) Robo advisors: quantitative methods inside the robots. J Asset Manag 19(6):363–370. https://doi.org/10.1057/s41260-018-0092-9

Belkora J (2015) Evaluating client discovery interviews at a financial advisory firm. J Wealth Manag 18(1):9–23. https://doi.org/10.3905/jwm.2015.18.1.009

Bhatia A, Chandani A, Chhateja J (2020) Robo advisory and its potential in addressing the behavioral biases of investors—a qualitative study in Indian context. J Behav Exp Finance 25:100281. https://doi.org/10.1016/j.jbef.2020.100281

Bianchi M, Briere M (2021) Robo-advising: Less AI and more XAI? SSRN Electron J. https://doi.org/10.2139/ssrn.3825110

Black F, Litterman R (1992) Global portfolio optimization. Financ Anal J 48(5):28–43

CFP Board (2019) Code of Ethics and Standards of Conduct, Certified Financial Planner Board of Standards, Inc., [online]. https://www.cfp.net/-/media/files/cfp-board/standards-and-ethics/cfp-code-and-standards.pdf. Accessed 25 April 2022

Bolton P, Freixas X, Shapiro J (2007) Conflicts of interest, information provision, and competition in the financial services industry. J Financ Econ 85(2):297–330. https://doi.org/10.1016/j.jfineco.2005.06.004

Boreiko D, Massarotti F (2020) How risk profiles of investors affect robo-advised portfolios. Front Artif Intell 3:60. https://doi.org/10.3389/frai.2020.00060

Bruhn A, Asher A (2020) The primacy of ethics in the provision of financial advice. Account Finance 61(2):3305–3327. https://doi.org/10.1111/acfi.12703

Cain DM, Loewenstein G, Moore DA (2005) The dirt on coming clean: perverse effects of disclosing conflicts of interest. J Leg Stud 34(1):1–25. https://doi.org/10.1086/426699

Cain DM, Loewenstein G, Moore DA (2011) When sunlight fails to disinfect: understanding the perverse effects of disclosing conflicts of interest. J Consum Res 37(5):836–857. https://doi.org/10.1086/656252

Chen L, Liu K, Wang Y, Zhang H (2018) A portfolio selection model for robo-advisor. In: 2018 5th IEEE international conference on cloud computing and intelligence systems (CCIS), pp 693–698. https://doi.org/10.1109/ccis.2018.8691258

Chen P, Richardson M (2019) Conflict of interest, disclosure and vertical relationships: an experimental analysis. Econ Pap A J Appl Econ Policy 38(3):167–181. https://doi.org/10.1111/1759-3441.12245

Chung W, Harbaugh R (2018) Biased recommendations from biased and unbiased experts. J Econ Manag Strategy 28(3):520–540. https://doi.org/10.1111/jems.12293

Church BK, Kuang XJ (2009) Conflicts of interest, disclosure, and (costly) sanctions: experimental evidence. J Legal Stud 38(2):505–532. https://doi.org/10.1086/596117

Coombs C, Redman A (2018) The impact of robo-advice on financial advisers: a qualitative case study. In: UK academy for information systems conference proceedings 2018. https://aisel.aisnet.org/ukais2018/17

Cooper WW, Kingyens AT, Paradi JC (2014) Two-stage financial risk tolerance assessment using data envelopment analysis. Eur J Oper Res 233(1):273–280. https://doi.org/10.1016/j.ejor.2013.08.030

Cordell DM (2001) RiskPACK: how to evaluate risk tolerance. J Financ Plan 14(6):36

Crawford VP, Sobel J (1982) Strategic information transmission. Econometrica 50(6):1431–1451. https://doi.org/10.2307/1913390

D'Acunto F, Prabhala N, Rossi AG (2019) The Promises and pitfalls of robo-advising. Rev Financ Stud 32(5):1983–2020. https://doi.org/10.1093/rfs/hhz014

D'Acunto F, Rossi AG (2021) Robo-advising. In: The Palgrave handbook of technological finance, pp 725–749. https://doi.org/10.1007/978-3-030-65117-6_26

Damrongsakmethee T, Neagoe V-E (2020) Stock market prediction using a deep learning approach. In: 2020 12th International conference on electronics, computers and artificial intelligence (ECAI), pp 1–6. https://doi.org/10.1109/ecai50035.2020.9223142

Day M-Y, Lin J-T (2019) Artificial intelligence for ETF market prediction and portfolio optimization. In: Proceedings of the 2019 IEEE/ACM international conference on advances in social networks analysis and mining, pp 1026–1033. https://doi.org/10.1145/3341161.3344822

Day M-Y, Cheng T-K, Li J-G (2018) AI robo-advisor with big data analytics for financial services. In: 2018 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM), pp 1027–1031. https://doi.org/10.1109/asonam.2018.8508854

Deo S, Sontakke N (2021) Usability, user comprehension, and perceptions of explanations for complex decision support systems in finance: a robo-advisory use case. Computer 54(10):38–48. https://doi.org/10.1109/mc.2021.3076851

Dong Z-L, Zhu M-X, Xu F-M (2021) Robo-advisor using closed-form solutions for investors' risk preferences. Appl Econ Lett. https://doi.org/10.1080/13504851.2021.1937495

Duffy S, Parrish S (2021) You say fiduciary, I say binary: a review and recommendation of robo-advisors and the fiduciary and best interest standards. Hastings Bus Law J 17(1):3

Deloitte GmbH (2016) Cost-income ratios and robo-advisory, why wealth managers need to engage with robo-advisors. https://www2.deloitte.com/content/dam/Deloitte/de/Documents/financial-services/Robo-Advisory-in-Wealth-Management.pdf. Accessed 08 March 2022

ESMA (2018) Guidelines on certain aspects of the MiFID II suitability requirements, European Securities and Markets Authority. https://www.esma.europa.eu/sites/default/files/library/esma35-43-1163_guidelines_on_certain_aspects_of_mifid_ii_suitability_requirements_0.pdf. Accessed 25 April 2022

Faloon M, Scherer B (2017) Individualization of robo-advice. J Wealth Manag 20(1):30–36. https://doi.org/10.3905/jwm.2017.20.1.030

Fang F, Ventre C, Basios M, Kanthan L, Martinez-Reg D, Wu F, Li L (2022) Cryptocurrency trading: a comprehensive survey. Financ Innov 8(1):1–59. https://doi.org/10.1186/s40854-021-00321-6

Fein ML (2015) Robo-advisors: a closer look. SSRN Electron J. https://doi.org/10.2139/ssrn.2658701

Fein ML (2017) Are robo-advisors fiduciaries? SSRN Electron J. https://doi.org/10.2139/ssrn.3028268

Fisch JE, Marion L, Turner JA (2019): The emergence of the robo-advisor. In: The disruptive impact of FinTech on retirement systems, pp 13–37. https://doi.org/10.1093/oso/9780198845553.003.0002

Foerster S, Linnainmaa JT, Melzer BT, Previtero A (2017) Retail financial advice: Does one size fit all? J Finance 72(4):1441–1482. https://doi.org/10.1111/jofi.12514

Gu CS, Hsieh HP, Wu CS, Chang RI, Ho JM (2019) A fund selection robo-advisor with deep-learning driven market prediction. In: 2019 IEEE international conference on systems, man and cybernetics (SMC), pp 2845–2850. https://doi.org/10.1109/smc.2019.8914183

García-Crespo Á, López-Cuadrado JL, González-Carrasco I, Colomo-Palacios R, Ruiz-Mezcua B (2012) SINVLIO: using semantics and fuzzy logic to provide individual investment portfolio recommendations. Knowl Based Syst 27:103–118. https://doi.org/10.1016/j.knosys.2011.08.012

Gelman M, Khan Z, Shoham A, Tarba SY (2021) Does local competition and firm market power affect investment adviser misconduct? J Corp Finance 66:101810. https://doi.org/10.1016/j.jcorpfin.2020.101810

Geva T, Zahavi J (2014) Empirical evaluation of an automated intraday stock recommendation system incorporating both market data and textual news. Decis Support Syst 57:212–223. https://doi.org/10.1016/j.dss.2013.09.013

Gonzalez-Carrasco, Israel; Colomo-Palacios, Ricardo; Lopez-Cuadrado, Jose Luis; Garc ́ıa-Crespo, Ángel; Ruiz-Mezcua, Belén (2012): PB-ADVISOR: A private banking multi-investment portfolio advisor, in: *Information Sciences*, vol. 206, pp. 63–82. doi:https://doi.org/10.1016/j.ins.2012.04.008.

Gottschalk F (2020) Regulating markets with advice: an experimental study. Oxford Bull Econ Stat 83(1):1–31. https://doi.org/10.1111/obes.12383

Grable JE, Hubble A, Kruger M (2020) Do as I say, not as I do: an analysis of portfolio development recommendations made by financial advisors. J Wealth Manag 22(4):62–73. https://doi.org/10.3905/jwm.2019.1.089

Hackethal A, Haliassos M, Jappelli T (2012) Financial advisors: a case of babysitters? J Bank Financ 36(2):509–524. https://doi.org/10.1016/j.jbankfin.2011.08.008

Harrison JP, Samaddar S (2020) Who is better at investment decisions: man or machine? J Wealth Manag 23(3):70–84. https://doi.org/10.3905/jwm.2020.1.119
Hayes A (2020) Enacting a rational actor: roboadvisors and the algorithmic performance of ideal types. Econ Soc 49(4):562–595. https://doi.org/10.1080/03085147.2020.1782054
Hens T, Mayer J (2018) Decision theory matters for financial advice. Comput Econ 52(1):195–226. https://doi.org/10.1007/s10614-017-9668-6
Hoechle D, Ruenzi S, Schaub N, Schmid M (2018) Financial advice and bank profits. Rev Financ Stud 31(11):4447–4492. https://doi.org/10.1093/rfs/hhy046
Hubble A, Grable JE (2019) The efficient frontuzzle: what investment risk profiling still fails to solve. J Invest 28(6):73–90. https://doi.org/10.3905/joi.2019.1.098
Inderst R, Ottaviani M (2012) Financial advice. J Econ Lit 50(2):494–512. https://doi.org/10.1257/jel.50.2.494
Investopedia (2021) What is investment advice? Investopedia. https://www.investopedia.com/terms/i/investment-advice.asp Retrieved 25 April 2022
Ismayilov H, Potters J (2013) Disclosing advisor's interests neither hurts nor helps. J Econ Behav Organ 93:314–320. https://doi.org/10.1016/j.jebo.2013.03.034
Jansen C, Fischer R, Hackethal A (2008) The influence of financial advice on the asset allocation of individual investors. SSRN Electron J. https://doi.org/10.2139/ssrn.1102092
Ji M (2017) Are robots good fiduciaries? Regulating robo-advisors under the investment advisers act of 1940. Columb Law Rev 117:1543–1584. https://doi.org/10.2139/ssrn.3036722
Jung D, Dorner V, Glaser F, Morana S (2018) Robo-advisory digitalization and automation of financial advisory. Bus Inf Syst Eng 60(1):81–86. https://doi.org/10.1007/s12599-018-0521-9
Jung D, Dorner V, Weinhardt C, Pusmaz H (2018) Designing a robo-advisor for risk-averse, low-budget consumers. Electron Mark 28(3):367–380. https://doi.org/10.1007/s12525-017-0279-9
Jung D, Glaser F, Köpplin W (2019) Robo-advisory: opportunities and risks for the future of financial advisory. Contrib Manag Sci. https://doi.org/10.1007/978-3-319-95999-3_20
Kilic M, Heinrich P, Schwabe G (2015) Coercing into completeness in financial advisory service encounters. In: Proceedings of the 18th ACM conference on computer supported cooperative work and social computing, pp 1324–1335. https://doi.org/10.1145/2675133.2675289
Kilic M, Dolata M, Schwabe G (2017) Why do you ask all those questions? Supporting client profiling in financial service encounters. In: Proceedings of the 50th Hawaii international conference on system sciences | 2017, pp 4695–4704. https://doi.org/10.24251/HICSS.2017.572
Kinder G, Galvan S (2005) EVOKE: a life planning methodology for the coming revolution in client relationships. J Financ Plan 18(4):46–55
Koch C, Schmidt C (2010) Disclosing conflicts of interest—Do experience and reputation matter? Account Organ Soc 35(1):95–107. https://doi.org/10.1016/j.aos.2009.05.001
Lachance ME, Tang N (2012) Financial advice and trust. Financ Serv Rev 21:209–226
Leonardi G, Portinale L, Artusio P, Valsania M (2016) A smart financial advisory system exploiting case-based reasoning. In: 2nd International workshop on personalization and recommender systems in financial services, FINREC, vol 1606, pp 33–40. https://iris.uniupo.it/retrieve/handle/11579/74737/20693/FINREC2016.pdf. Retrieved 25 April 2022
Leow EKW, Nguyen BP, Chua MCH (2021): Robo-advisor using genetic algorithm and BERT sentiments from tweets for hybrid portfolio optimization. Expert Syst Appl 179:115060. https://doi.org/10.1016/j.eswa.2021.115060
Lightbourne J (2017) Algorithms and fiduciaries: existing and proposed regulatory approaches to artificially intelligent financial planners. Duke Law J 67:651
Linnainmaa JT, Melzer BT, Previtero A (2021) The misguided beliefs of financial advisors. J Financ 76(2):587–621. https://doi.org/10.1111/jofi.12995
Linnainmaa JT, Melzer BT, Previtero A (2015) Costly financial advice: conflicts of interest or misguided beliefs. CiteSeerx. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.725.8958. Retrieved 25 April 2022
Lippi A, Lozza E, Poli F, Castiglioni C (2021) How does the emotional meaning associated with money and financial advisor's characteristics impact investors' risk-taking? J Neurosci Psychol Econ 14(4):207–221. https://doi.org/10.1037/npe0000150
Litterscheidt R, Streich DJ (2020) Financial education and digital asset management: what's in the black box? J Behav Exp Econ 87:101573. https://doi.org/10.1016/j.socec.2020.101573
Lozza E, Castiglioni C, Bonanomi A, Poli F (2022) Money as a symbol in the relationship between financial advisors and their clients: a dyadic study. Int J Bank Market 40(4):613–630. https://doi.org/10.1108/ijbm-04-2021-0124
Markowitz H (1952) Portfolio selection. J Financ 7(1):77–91. https://doi.org/10.2307/2975974
Metzler DR, Neuss N, Torno A (2022) The digitization of investment management—an analysis of robo-advisor business models. In: Wirtschaftsinformatik 2022 proceedings, vol 2. https://aisel.aisnet.org/wi2022/finance_and_blockchain/finance_and_blockchain/2. Retrieved 25 April 2022
Morana S, Gnewuch U, Jung D, Granig C (2020) The effect of anthropomorphism on investment decision-making with robo-advisor chatbots. In: Proceedings of the 28th European conference on information systems (ECIS). https://aisel.aisnet.org/ecis2020_rp/63. Retrieved 25 April 2022
Mullainathan S, Noeth M, Schoar A (2012) The market for financial advice: an audit study. Natl Bureau Econ Res. https://doi.org/10.3386/w17929
Musto C, Semeraro G, Lops P, de Gemmis M, Lekkas G (2015) Personalized finance advisory through case-based recommender systems and diversification strategies. Decis Support Syst 77:100–111. https://doi.org/10.1016/j.dss.2015.06.001
Nguyen LTM, Gallery G, Newton C (2016) The influence of financial risk tolerance on investment decision-making in a financial advice context (2016). Austral Account Bus Financ J 10(3):3–22. https://doi.org/10.14453/aabfj.v10i3.2
Oxford English Dictionary (2022) Oxford English Dictionary—Advisor, Oxford University Press. https://www.oed.com/view/Entry/291088. Retrieved 25 April 2022

Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, Chou R, Glanville J, Grimshaw JM, Hróbjartsson A, Lalu MM, Li T, Loder EW, Mayo-Wilson E, McDonald S, McGuinness LA, Stewart LA, Thomas J, Tricco AC, Welch VA, Whiting P, Moher D (2021) The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. Int J Surg 88:105906. https://doi.org/10.1016/j.ijsu.2021.105906

Phoon K, Koh F (2018) Robo-advisors and wealth management. J Altern Invest 20(3):79–94. https://doi.org/10.3905/jai.2018.20.3.079

Priolo G, Vacondio M, Bernasconi SM, Rubaltelli E (2022) Beware the inexperienced financial advisor with a high trait emotional intelligence: psychological determinants of the misperception of the risk-return relationship. Personal Individ Differ 188:111458. https://doi.org/10.1016/j.paid.2021.111458

Puhle M (2019) The performance and asset allocation of German robo-advisors. Soc Econ 41(3):331–351. https://doi.org/10.1556/204.2019.41.3.4

Ringe WG, Ruof C (2021) Robo advice—legal and regulatory challenges. Routledge Handb Financ Technol Law. https://doi.org/10.4324/9780429325670-11

Rosenberg E (2019) I spent 10 years working in finance and I'm convinced robo-advisers are better than human advisers for 5 reasons. Business Insider. https://www.businessinsider.com/personal-finance/robo-advisors-are-better-than-human-financial-advisors-2019-7?international=true&r=US&IR=T. Retrieved 25 April 2022

Rubin GD (2015) Advisers and the fiduciary duty debate. Bus Soc Rev 120(4):519–548. https://doi.org/10.1111/basr.12073

Rühr A (2020) Robo-advisor configuration: an investigation of user preferences and the performance-control dilemma. In: Twenty-eighth European conference on information systems (ECIS2020). https://aisel.aisnet.org/ecis2020_rp/94/. Retrieved 25 April 2022

Sah S (2019) Conflict of interest disclosure as a reminder of professional norms: clients first! Organ Behav Hum Decis Process 154:62–79. https://doi.org/10.1016/j.obhdp.2019.07.005

Scherer B, Lehner S (2021) What drives robo-advice? SSRN Electron J. https://doi.org/10.2139/ssrn.3807921

Schumaker RP, Chen H (2009) Textual analysis of stock market prediction using breaking financial news. ACM Trans Inf Syst 27(2):1–19. https://doi.org/10.1145/1462198.1462204

Sebastião H, Godinho P (2021) Forecasting and trading cryptocurrencies with machine learning under changing market conditions. Financ Innov 7(1):1–30. https://doi.org/10.1186/s40854-020-00217-x

Snelbecker GE, Roszkowski MJ, Cutler NE (1990) Investors' risk tolerance and return aspirations, and financial advisors' interpretations: a conceptual model and exploratory data. J Behav Econ 19(4):377–393. https://doi.org/10.1016/0090-5720(90)90024-2

So MKP (2021) Robo-advising risk profiling through content analysis for sustainable development in the Hong Kong financial market. Sustainability 13(3):1306. https://doi.org/10.3390/su13031306

Söderberg IL (2012) Gender stereotyping in financial advisors' assessment of customers. J Financ Serv Market 17(4):259–272. https://doi.org/10.1057/fsm.2012.24

Spatt CS (2020) Conflicts of interest in asset management and advising. Ann Rev Financ Econ 12(1):217–235. https://doi.org/10.1146/annurev-financial-110118-123113

Statista (2022) Robo-advisors—worldwide, statista. https://www.statista.com/outlook/dmo/fintech/digital-investment/robo-advisors/worldwide?currency=usd. Retrieved 25 April 2022

Stendardi EJ, Graham JF, O'Reilly M (2006) The impact of gender on the personal financial planning process. Humanomics 22(4):223–238. https://doi.org/10.1108/08288660610710746

Streich DJ (2021) Risk preference elicitation and financial advice taking. J Behav Finance. https://doi.org/10.1080/15427560.2021.1974444

Tertilt M, Scholz P (2018) To advise, or not to advise—how robo-advisors evaluate the risk preferences of private investors. J Wealth Manag 21(2):70–84. https://doi.org/10.3905/jwm.2018.21.2.070

Thanki H, Baser N (2021) Determinants of financial risk tolerance (FRT): an empirical investigation. J Wealth Manag 24(2):48–64. https://doi.org/10.3905/jwm.2021.1.144

Torno A, Schildmann S (2020) What do robo-advisors recommend? An analysis of portfolio structure, performance and risk. Lecture notes in business information processing, pp 92–108. https://doi.org/10.1007/978-3-030-64466-6_6

Uhl MW, Rohner P (2018) Robo-advisors versus traditional investment advisors: an unequal game. J Wealth Manag 21(1):44–50. https://doi.org/10.3905/jwm.2018.21.1.044

Van de Venter G, Michayluk D (2008) An insight into overconfidence in the forecasting abilities of financial advisors. Aust J Manag 32(3):545–557. https://doi.org/10.1177/031289620803200309

Wang H, Yu S (2021) Robo-advising: enhancing investment with inverse optimization and deep reinforcement learning. In: 2021 20th IEEE international conference on machine learning and applications (ICMLA), pp 365–372. https://doi.org/10.1109/icmla52953.2021.00063

Wang PY, Liu CS, Yang YC, Huang SH (2019) A robo-advisor design using multiobjective RankNets with gated neural network structure. In: 2019 IEEE international conference on agents (ICA), pp 77–78. https://doi.org/10.1109/agents.2019.8929188

Xue J, Zhu E, Liu Q, Yin J (2018) Group recommendation based on financial social network for robo-advisor. IEEE Access 6:54527–54535. https://doi.org/10.1109/access.2018.2871131

Xue J, Liu Q, Li M, Liu X, Ye Y, Wang S, Yin J (2018) Incremental multiple kernel extreme learning machine and its application in robo-advisors. Soft Comput 22:3507–3517. https://doi.org/10.1007/s00500-018-3031-2

Zibriczky D (2016) Recommender systems meet finance: a literature review. In: 2nd International workshop on personalization and recommender systems in financial services. https://doi.org/10.13140/RG.2.1.1249.2405

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