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When do robo-advisors make us better investors? The impact of social design elements on investor behavior

Camila Back [a], Stefan Morana [b], Martin Spann [c,*]

[a] Camila Back, LMU Munich School of Management, University of Munich, D-80539 Munich, Germany
[b] Stefan Morana, Junior Professorship for Digital Transformation and Information Systems, Saarland University, D-66041 Saarbruecken, Germany
[c] Martin Spann, LMU Munich School of Management, University of Munich, D-80539 Munich, Germany

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ABSTRACT

Investors increasingly can obtain advice from “robo-advisors", artificial intelligence–enabled digitalized service agents. We study whether and why the provision of investment advice from a robo-advisor improves individuals’ investment decisions. In two consequential induced-value experiments, we analyze the well-documented disposition effect, which reflects investors’ greater propensity to realize past gains than past losses. We find that the availability of a robo-advisor reduces (i.e., mitigates) investors’ disposition effect (Study 1). Moreover, imbuing the robo-advisor with social design elements (e.g., a name and the ability to communicate using natural language) negatively affects investment behavior (i.e., increases the disposition effect). The extent to which investors seek advice mediates this effect, i.e., investors ask for advice to a lesser extent from a robo-advisor with, compared to without, social design elements (Study 2). Our findings advance our understanding of the benefits of artificial intelligence-enabled advisors for improving decision making. However, our results also imply increased psychological hurdles of asking for advice from human-like robo-advisors and highlight potential risks of imbuing them with social design elements, which has become a widespread practice to give robo-advisors a human touch.

1. Introduction

People often use mental shortcuts to make decisions, which may lead to deviations from rational behavior and ultimately to poor decision making (DellaVigna, 2009). The mistakes resulting from deviations from the standard theory have been the focus of extensive research in behavioral finance, particularly in relation to investment decisions (for an overview, see Bhattacharya et al., 2012) and have been shown to lead to substantial reductions in returns (e.g., Barber et al., 2009; Calvet et al., 2007). Therefore, researchers and policy makers are keenly interested in finding new ways to reduce mistakes and improve individuals’ investment decisions (OECD, 2017). Recent technological developments in artificial intelligence suggest a potential solution, in that robo-advisors (i.e., systems designed to provide automated investment advice) provide an effective means to scale access to financial advisory services at low costs (D’Acunto et al., 2019). Still, a widely open question concerns the role of robo-advisors in reducing investors’ mistakes. Particularly, robo-advisors, in contrast to human advisors, underlie many design decisions concerning the user experience with the system, which may impact investors’ take up (Capponi et al., 2022; D’Acunto and Rossi, 2021). Many companies that have introduced robo-advisors imbue them with social design elements, such as an avatar or a name (e.g., Bank of America’s Erica), seemingly to make them appear more “social”. However, the effects of these social design elements on investment decisions are not well understood. While some research suggests that adding social design elements to robo-advisors (e.g., a name) makes them appear less credible (Hodge et al., 2020), other studies have found a positive effect of social design elements on levels of trust towards the robo-advisor (Hildebrand and Bergner, 2021). As the pace of digitization continues to accelerate, we need a better sense of the relationship between industry efforts to substitute technology for human advisors and individuals’ own economic welfare. In this paper we seek to

* Corresponding author.
E-mail addresses: camila.back@lmu.de (C. Back), stefan.morana@uni-saarland.de (S. Morana), spann@lmu.de (M. Spann).

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answer the following research question: *How do robo-advisors with social design elements influence investment decisions, and to what extent are they able to mitigate investors' behavioral biases?*

We examine the effects of robo-advisors on individual investment decisions in two consequential induced-value experiments[1], in which participants receive advice and interact with a robo-advisor. We examine investors' mistakes by focusing on the so-called *disposition effect,* that represents an observed empirical regularity by which investors exhibit a greater propensity to sell "winners" compared with "losers" (Shefrin and Statman, 1985). In our experiments, the advice from the robo-advisor reflected a strategy aimed at maximizing expected profits and was adapted to each participant's portfolio allocation. With this experimental design, we can observe the effects of real interactions during a realistic user experience on participants' subsequent investment choices. For our experimental design, we adapt the main elements of Weber and Camerer's (1998) setup, in which participants must make a series of incentivized investment decisions across multiple rounds.[2] In the first study, we test the effect of a robo-advisor on investors' disposition effect. In the second study, we test whether imbuing the robo-advisor with social design elements impacts investors' disposition effect as well as the mediating role of investors' advice seeking behavior. To this aim, we implemented a robo-advisor with social design elements as well as a robo-advisor without social design elements.[3] The former had a name, communicated in natural language, and provided investment advice based on questions such as "Can you help me?" or "What assets should I buy?". In contrast, the latter only allowed users to click on a button to display the investment advice. Note that the content of the investment advice did not differ between operationalizations.[4] To test for the mediation, we additionally manipulated the request type. We distinguish between *endogenous* and *exogenous* requests. The former refers to a manifestation in which the robo advisor provided advice exclusively upon requests, i.e., receiving advice represents an endogenous choice. The latter is encompassed by robo-advisors that send advice automatically, without investors' active request, thus representing an exogenous choice.

The main results are threefold. First, we establish a mitigating effect of robo-advisors on the disposition effect. This effect is mainly driven by investors' behavior in the losses domain, i.e., investors with access to investment advice from a robo-advisor are less reluctant to sell assets at a loss compared to investors with no access to investment advice from a robo-advisor. Second, social design elements of a robo-advisor increase the disposition effect. In particular, investors with access to investment advice from a robo-advisor without social design elements are less subject to the disposition effect compared to investors with access to investment advice from a robo-advisor with social design elements. Third, the effect of social design elements is mediated by the extent to which advice is actually requested. We provide evidence for the mediating effect by controlling for the endogenous nature of advice requests. Specifically, we make recommendation requests exogenous and find that the effect of social design elements on the disposition effect vanishes if choices to receive advice are no longer endogenous, but exogenous.

Our paper contributes to three strands of the literature. First, it contributes to the literature on the impact of artificial intelligence-enabled technologies on economic decision making, particularly on their potential to reduce behavioral biases and increase individual welfare. Specific to the disposition effect, prior research has shown that implementing automatic selling mechanisms (Fischbacher et al., 2017; Weber and Camerer, 1998), or the use of a robo-advisor (D'Acunto et al., 2019) can improve financial performance, because they mitigate this disposition effect. Only few studies shed light on the role of the design elements aimed at improving users' experience in shaping investors' behaviors. As an exception, Frydman and Rangel (2014) investigate how the presentation of information on past purchases and whether the information is made salient impacts the disposition effect. Our study focuses on the impact of robo-advisors and the extent they are imbued with social design elements on the disposition effect. As such, we document the individual welfare consequences of interacting with technologies imbued with social design elements. Such aspects become increasingly important, given that technological advances (e.g., advances in artificial intelligence) come with greater freedom for designers and there is great potential (for both customers and firms) in improving our general understanding of the consequences of these decisions (Looney and Hardin, 2009).

Second, this study contributes to research pertaining the general effect of social design elements on customer behavior. We draw on the concept of Computers Are Social Actors (Reeves and Nass, 1996), whereby people apply social heuristics (e.g., politeness) in their interactions with technology, to understand potential impacts of social design elements on investment behaviors. Social design elements and their impact on consumer behavior have been the focus of extant research in domains other than finance. In a retail context, digital recommendation agents (e.g., for shopping recommendations) are expected to become the first and main point of contact for customers (Schanke et al., 2021). Therefore, there is great interest from researchers and practitioners alike to better understand the impact of design aspects of the user interface on the adoption and use of these technologies. Prior findings in this regard suggest mostly positive effects of social design elements, such as their ability to increase agents' persuasiveness (Holzwarth et al., 2006) as well as customers' willingness to share personal information (Schanke et al., 2021). Our findings relate to evidence pertaining to negative effects of social design elements. For example, Crolic et al. (2022) find that social design elements may lead to higher consumer expectations which may result in consumers' tendency to blame human-like (anthropomorphic) agents to a higher extent after a negative experience compared to non-human-like (non-anthropomorphic) agents. Our results suggest that social design elements may negatively affect investment behavior because they reduce the extent to which investors seek advice. These results thus highlight risks associated with imbuing agents with social design elements that may materialize before an interaction even takes place. In the context of financial investments, prior research suggests that investors who could benefit most from robo-advisors are less likely to request their advice in the first place (Ge et al., 2021). Our work enhances these findings by experimentally examining the drivers behind the observed reluctance of investors to seek advice as well as the subsequent economic consequences of their behavior.

Third, this work also informs literature on the role of professional advice in improving investment decisions (Bhattacharya et al., 2012; Hoechle et al., 2017) and more generally on the antecedents of advice taking behavior in the context of human advisors (Bonaccio and Dalal, 2006; Sniezek and Buckley, 1995). Among human advisors, previous research shows that clients prefer advice from advisors who appear accurate, trustworthy, and accessible (Hofmann et al., 2009). When it comes to digital advisors, we consider the influence of social design elements to determine how advisor representations determine investors' propensity to seek advice (Barham et al., 2018). Building on work

[1] Induced-value experiments follow the key premises of induces-value theory (Smith 1976), whereby the proper provision of economic rewards induces characteristics pre-defined by the experimenter. The influence of subjective characteristics or preferences of the participants thus do not play a relevant role in determining the experimental outcomes.

[2] We control for potential price sequence effects by matching every participant in one treatment group with a participant from the other treatment group who experienced the same price sequence.

[3] A detailed description of the implemented social design elements is provided in Section 3.2. A more technical description of the system-implementation of the robo-advisors is provided in the Web Appendix.

[4] Note that throughout the paper, we restrict the term "advice" to a single type of advice, namely, a recommendation concerning which alternative the investor should choose; see Dalal and Bonaccio (2010).

related to individuals' motivations to seek advice (Brooks et al., 2015; Dalal and Bonaccio, 2010), we propose and empirically test how design-related factors aimed at increasing perceptions of socialness could influence these motives and impact the utilization of advice from digital advisors in the context of investment decisions.

The remainder of this paper is organized as follows: In Section 2, we discuss the role of robo-advisors in shaping investment behavior related to the disposition effect. Section 3 outlines our experimental design and the implementation of the robo-advisor. In Section 4, we present and discuss the results of the two experimental studies, followed by implications for research and practice as well as limitations in Section 5. Finally, we conclude in Section 6.

2. Theory and Hypotheses

2.1. The Effect of Investment Advice on the Disposition Effect

The disposition effect (i.e., investors' greater propensity to sell "winners" compared with "losers") is a well-documented and extensively discussed behavioral pattern in the behavioral finance literature. Scholars consider this pattern irrational, because the future performance of assets should be unrelated to investors' individual reference prices. The disposition effect has been observed for different types of investors (e.g., private and institutional investors), as well as different types of asset classes (e.g., stock markets and real estate markets, see Barberis and Xiong, 2009 for an overview).

Prior research that examines the role of professional advisors in reducing the disposition effect (Chang et al., 2016) relates it to the theory of cognitive dissonance (Akerlof and Dickens, 1982), which anticipates that people are reluctant to acknowledge mistakes and delay realizing losses because they want to avoid admitting that they made a poor choice in the first place (Dierick et al., 2019).[5] Advisors may help reduce investors' cognitive dissonance: If investors hold assets that have decreased in value and then receive the advice to sell from an independent source, they might be more willing to revisit their initial investment strategy and question their initial purchase decisions. This mechanism is related to rational learning models, including Bayesian updating of priors, and has been shown to help reduce the disposition effect (Seru et al., 2010). In this scenario, the provision of investment advice enables investors to alter their initial cognition (namely that they made a good investment), to remove dissonance and alleviate the feeling of discomfort that arises after experiencing a loss.

But, does this apply to the context of robo-advisors? Past research on human-computer-interaction documents numerous differences in how people interact with humans in contrast to machines (Pütten et al., 2010). For example, people ascribe different levels of responsibilities and blame after suboptimal outcomes to humans in contrast to machines (Gogoll and Uhl, 2018; Srinivasan and Sarial-Abi, 2021). Also, bidders' emotional reactions are mitigated in case of a digitized opponent in contrast to a human one (Teubner et al., 2015). Notwithstanding these differences, evidence also suggests that robo-advisors can be designed to take on the role of "social actors" (Nass and Moon, 2000). Therefore, as in the case of professional advice, receiving advice from a robo-advisor is likely to alleviate investors' sense of discomfort when facing a loss leading to a reduction in the disposition effect. Therefore, we posit:

Hypothesis 1. *Investment advice from a robo-advisor reduces the disposition effect.*

[5] Note that alternative explanations for the disposition effect have been proposed, including prospect theory or realization utility, for a discussion, see Ben-David and Hirshleifer (2012).

2.2. The Effect of Social Design Elements on the Disposition Effect

Researchers from a wide array of disciplines have studied the effects of imbuing technologies with social design elements on human behavior. We follow Feine et al. (2019) and define social design elements as a design feature salient to the user that presents a source of information and triggers a social reaction towards the technology. Social reactions in turn are emotional, cognitive, or behavioral reactions that follow social norms and are perceived as appropriate in the interaction with other humans. Social design elements such as the use of textual natural language aim at making the user of the technology feel as if the user of the technology is in the presence of someone else (Nass and Moon, 2000). Language, appearance, and interactivity constitute key social design elements for digital service providers (Feine et al., 2019; Wakefield et al., 2011). Language refers to the words used and how they are combined; we differentiate content, or *what* is said, from style, or *how* something is said (Feine et al., 2019). For example, adding greetings, self-disclosures, small talk, and a name are content-based social design elements, but using natural language and understanding complex sentences are associated with the language style. In terms of appearance, adding an avatar picture also can increase perceptions of socialness (e.g., Holzwarth et al., 2006). Finally, interactivity refers to the extent to which two-way communication is possible: When communication with technologies resembles interpersonal communication, it seems more interactive (Ha and James, 1998). People generally adopt social responses and perceive some level of socialness in interactions with digital service agents, even when they know they are interacting with machines and regardless of their familiarity and experience with the technology (Reeves and Nass, 1996; Wakefield et al., 2011). Furthermore, social design elements have shown to heighten these effects (Go and Sundar, 2019; Wang et al., 2007). Some authors even propose that strong perceived socialness is essential when designing digital assistants, because their main purpose is to compensate for a lack of human input (e.g., Wang and Benbasat, 2016).

Whilst many studies have established a positive link between perceived socialness and behavioral outcomes, negative effects also can arise, because imbuing AI-based agents with social design elements may undermine people's sense of autonomy (Kim et al., 2016). In the context of computer games, Kim et al. (2016) show that assigning humanlike traits to computerized game assistants, to whom individuals may ask for help or assistance during the game, leads to less enjoyment. This effect is explained by a decrease in individuals' perceived sense of autonomy during the game. In a robo-advisory setting, investors may ask for investment recommendations. From the perspective of the investor, receiving advice is accompanied by benefits such as a reduction of costs to achieve a desired outcome such as a higher return (Lee, 2002). At the same time, seeking advice may carry substantial psychological costs, arising from appearing inferior, incompetent or dependent on others (Brooks et al., 2015; Lee, 1997, 2002). Therefore, we posit that requesting advice resembles a trade-off between maximizing accuracy and maintaining autonomy (Dalal and Bonaccio, 2010). This trade-off may be contingent on the extent to which the advisor is perceived as a social actor, because investors' motive to maintain autonomy reduces their propensity to seek advice from an advisor with social design elements.

These theoretical considerations suggest that the availability of investment advice from a robo-advisor with social design elements might strengthen the disposition effect compared to the availability of advice from a robo-advisor without social design elements. Moreover, this effect may be explained by a lower propensity to request advice. We thus hypothesize:

Hypothesis 2a. *Imbuing robo-advisors with social design elements increases the disposition effect.*

Hypothesis 2b. *The effect of social design elements of robo-advisors on* *the disposition effect is mediated by the extent of advice requests.*

3. Methodology

We conduct two economically consequential between-subjects, value-induced experiments to test our hypotheses. With the first study, we assess the overall impact of robo-advisors on the disposition effect. The second study investigates the impact of social design elements on investors' perceptions and behaviors employing a 2 × 2 between-subjects design. First, we manipulate the extent to which social design elements are present. Second, we manipulate whether requesting investment recommendations is an exogenous or an endogenous choice. The second manipulation is aimed at testing advice requests as a potential mediator (Pirlott and MacKinnon, 2016). In this section, we elaborate on the base experimental design, which remains constant across treatment groups, then introduce our operationalization of the robo-advisor and the variations of the social design elements.

3.1. Experimental Design

The general design of our economically consequential experiments draws on Weber and Camerer (1998). Participants received an initial endowment of 2,000 experimental currency units and could trade six different assets (labeled A, B, C, D, E, and F) in ten consecutive trading rounds. The entire trading game consisted of 14 rounds. In rounds 0–2, investors were limited to observing the price development of the assets and were not allowed to trade. Trading assets began in period 3 and ended in period 12. Participants were not allowed to short sell the assets or to have a negative money account. The last round (period 13) determined the overall portfolio value, which in turn determined the payoff.[6]

Price sequence characteristics might influence investor behavior (e.g., primacy, recency), so we control for potential confounds by matching every participant in one treatment group with a participant from the other treatment group who experienced the same price sequence. Specifically, prior to the experiment, we simulated asset prices according to predetermined probability distributions (outlined subsequently). We then created a two-level randomization: (1) randomly allocate a group of participants to each price path, then (2) randomly allocate each participant assigned to the same price path to a treatment group. As established in prior research (e.g., Fischbacher et al., 2017), this design supports within–price sequence comparisons, without worrying about price sequence effects. We simulated a total of 150 unique price paths. In cases with an odd number of participants, we allocated one participant to a price path, who remained unmatched, such that no other participants viewed the same price sequence.

In round 0, the starting price for all tradeable assets was 100 experimental currency units. In each period, the price either increased by 6% or decreased by 5%, such that prices never stayed the same for two consecutive rounds. Participants saw the underlying stochastic processes for the different asset types ("++", "+", "O", "−", and "- -") and were aware of the underlying probabilities and number of assets per type. However, they did not know which asset corresponded to which type. Table 1 presents the probabilities of increases or decreases, by type, which remained constant across periods. The allocation of types and assets was randomly determined to avoid order effects. Hence, the chance that, for example, type "++" was assigned to the asset with label "A", was approximately 20%.

With the framework of market dynamics in Table 1, we can use a straightforward application of Bayesian updating in each period. For a rational (i.e., profit maximizing) investor, with the same priors for the probabilities of price increases, it is optimal to invest in the asset with the highest price. The asset for which the price has increased most (or decreased least) offers the highest probability of being type ++, and the asset for which the price has increased least has the highest probability of being type - -. A strategy to invest in the asset with the highest price thus represents the expected profit-maximizing strategy,[7] on which the robo-advisor's advice is based.

Table 1
Overview of asset types and probabilities of price increases and decreases.

Asset		Probability of Price Change	
Assets in the Market	Type	Increase	Decrease
1	++	60%	40%
1	+	55%	45%
2	O	50%	50%
1	-	55%	45%
1	- -	40%	60%

The experimental procedure consisted of several steps. First, participants read the experimental instructions and watched a prerecorded video, introducing the main features of the experimental interface and experimental task.[8] At the end of these instructions, they answered a set of control questions and received the correct answers, with brief explanations, regardless of their own answers. This step helps ensure participants' understanding of the trading interface and the dynamics of the trading game. Second, participants viewed the experimental interface and performed a series of investment decisions. At the end of the trading game, they learned the total amount they earned. Finally, we obtained participants' answers to post-experimental survey questions including manipulation checks, attention checks, control variables, and demographics.

3.2. The Robo-Advisor

To examine the effect of the availability of a robo-advisor on the disposition effect (Study 1), we employ a between-subjects design, in which participants were randomly assigned to one of two different treatment groups. In the robo-advisor group, investors could interact with and ask for investment advice from a robo-advisor through a chat window. The user interface in the control group did not incorporate a chat window. The trading game was implemented as a web-based application using HTML, CSS, and JavaScript. The robo-advisor is based on the Microsoft Bot Framework, integrated with the web chat feature of the bot framework in our trading game application.[9] We integrated the entire trading game application via an iFrame into the web-based experimental interface that included instructions and additional survey measures (see Fig. 1).

The operationalization of the robo-advisor employed various social design elements, including the capability to interact with participants using natural written language. In addition, a picture showing an avatar with a human embodiment was displayed. The robo-advisor introduced itself with the name Charles[10] and used personal pronouns (e.g., "I," "me"; Pickard et al., 2014). In terms of interactivity, its skills ranged from answering questions such as "How are you?", "What can you do?"

[6] We preregistered both studies at Aspredicted.org. Preregistrations, data and code are available at https://osf.io/z9jd5/?view_only=49a6f48a2549489d99d2bcf6a9a41153.

[7] Although this strategy is profit maximizing, it neglects budget constraints; specifically, investing in the asset with the highest probability of being type + may result in higher profits than not investing. This setting could apply if, for example, participants lack sufficient money to buy the asset with the highest price but can purchase the asset with the second highest price.

[8] The Web Appendix contains the experimental instructions for the first and second study respectively.

[9] The Web Appendix contains a technical description of the robo-advisor application.

[10] We choose the name Charles following previous research, e.g., Hodge et al. (2020).

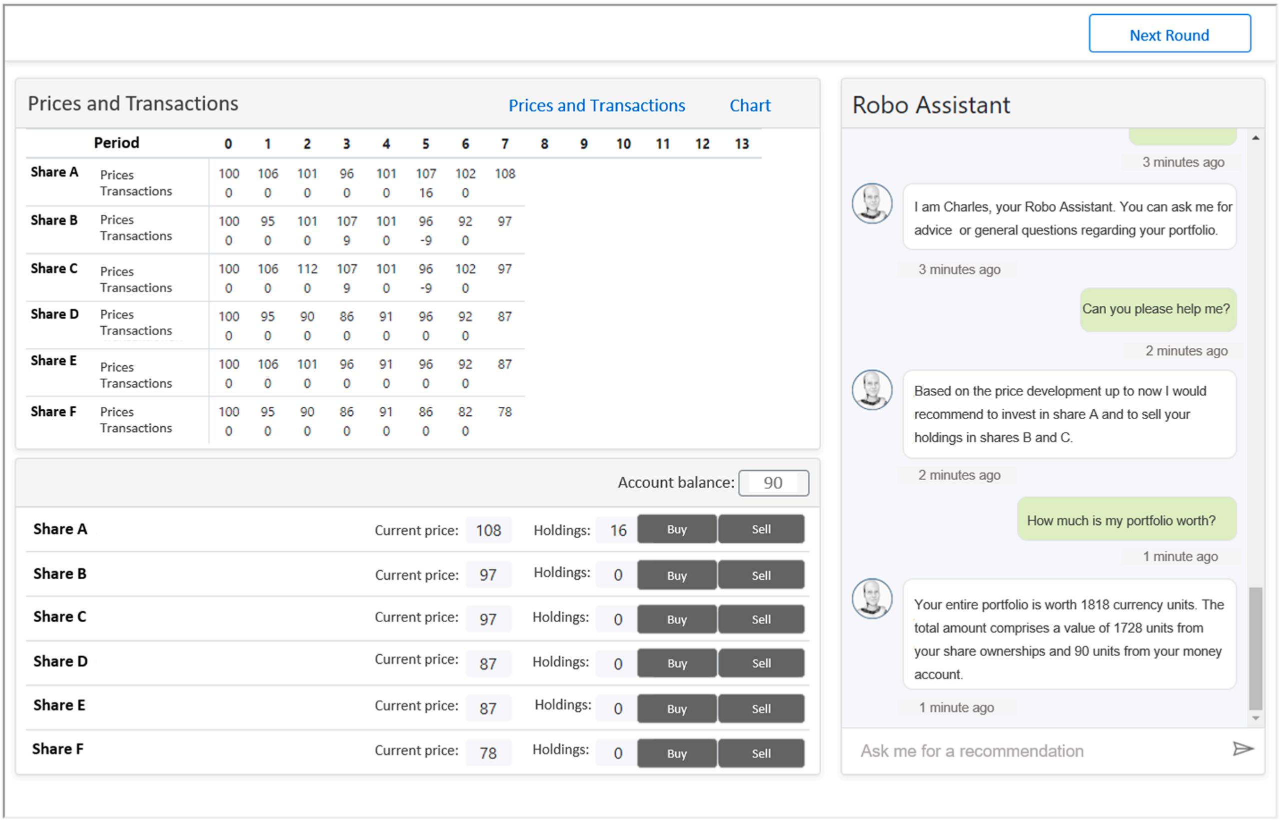

Fig. 1. User interface.
Notes: The screenshot shows the user interface in the treatment group with an exemplary price path and portfolio structure. The Web Appendix contains screenshots of the user interfaces for the other experimental groups.

and "How much is my portfolio worth?".[11] Particularly, participants were able to ask for advice. Messages such as "Can you help me?" or "I need some advice" triggered the provision of investment advice. The advice was always to invest in the asset with the highest price; if participants held other, lower-priced assets in their portfolios, the robo-advisor also advised selling them.

In addition, participants read that the investment advice was based on an algorithm that incorporates information on past price developments (see the right-hand side of Fig. 2). They had no specific information about the target or reasoning process of the algorithm (e.g., profit-maximizing strategy), but nor did the participants have any reason to believe the advice was not in their best interests. The robo-advisor recommended which shares to buy as well as which shares to sell according to the same underlying profit-maximizing logic. The recommendation about which shares to sell was personalized, as the robo-advisor accounted for the current individual portfolio composition. The optimal descriptions of how robo-advisors work remains a highly debated topic (SEC, 2017), and currently, a broad range of practices exist for providing information to investors, many of which do not proactively disclose the processes by which the advisor developed the investment advice (Litterscheidt and Streich, 2020). Therefore, we consider that the study scenario is realistic.

To assess the impact of social design elements on investors' perceptions and behaviors (Study 2), we also operationalize a robo-advisor without social design elements, such that the comparison can reveal the impact of social design variations on the disposition effect. Thus, the robo-advisor without social design elements does not display a picture, has no name and does not introduce itself, and limits participants' interactions with the system to clicking on a "Recommendation" button to receive investment advice. The content of the advice and the information about its derivation were the same in both conditions (see Fig. 2). To test the proposed mediator (i.e., the extent to which advice is actually requested), we additionally develop versions of the robo-advisor (with and without social design elements) in which advice is provided exogenously in the beginning of each trading round. We thus can distinguish between the request type being either exogenous or endogenous. The main idea is to test whether the endogenous nature of actively requesting and receiving advice plays a role in determining the effectiveness of robo-advisors in reducing the disposition effect.

3.3. *Measures*

We followed Odean's (1998) proposed approach to measure the disposition effect (DE), which we define as the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR). A reduction in DE can stem from an increase in PLR, a decrease in PGR, or both (Fischbacher et al., 2017). An asset enters the domain of gains (losses) if its current price is above (below) a certain reference price. Despite extensive research into the impact of reference prices on individual behavior and decision making, little is known about how reference prices get selected (Meng and Weng, 2018). Therefore, following previous work (Fischbacher et al., 2017), we use weighted

[11] Notably, the answers to questions related to the portfolio or past prices would not provide new information (i.e., the information was already available through the user interface) and their accuracy can be assessed immediately.

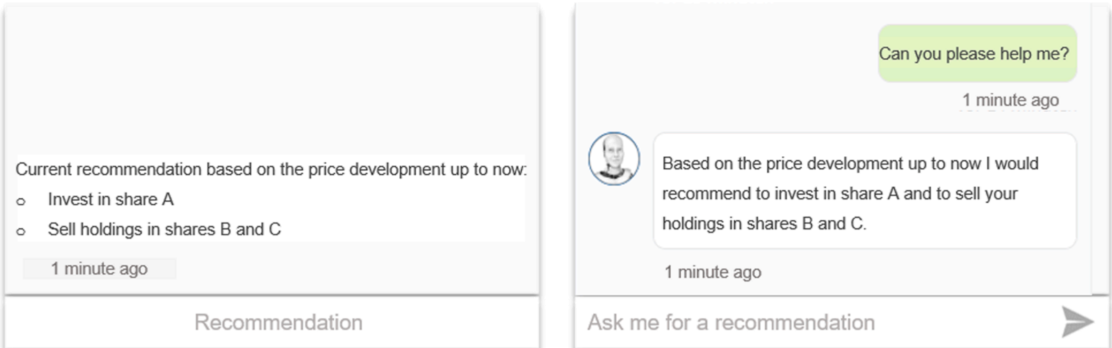

Fig. 2. Screenshot of the interface of the robo-advisor with social design elements (right) and without social design elements (left).

average purchase prices as the reference prices.[12] We then define PGR, PLR, and DE as follows:

$$Proportion\ of\ Gains\ Realized\ (PGR) = \frac{Realized\ Gains}{Realized\ Gains + Paper\ Gains}, \tag{1}$$

$$Proportion\ of\ Losses\ Realized\ (PLR) = \frac{Realized\ Losses}{Realized\ Losses + Paper\ Losses},\ \ and \tag{2}$$

$$Disposition\ Effect\ (DE) = PGR - PLR. \tag{3}$$

That is, realized gains (losses) correspond to the units of assets an investor sells at a gain (loss), compared with the reference price (i.e., weighted average purchase price). Paper gains (losses) correspond to the units of assets an investor holds in the gains (losses) domain that are not sold. The sum of realized and paper gains (losses) corresponds to the total number of possibilities to sell at a gain (loss). Assume an investor buys 10 units of asset A in round 3 and sells those 10 units in round 6. The price of asset A decreases from round 3 to 4, then increases from round 4 to 5 and again increases from round 5 to 6, such that in rounds 5 and 6, it exceeds the initial purchase price. In this case, the investor realizes 0 losses (out of 10 possibilities to sell at a loss) and 10 gains. The number of possibilities to sell at a gain equals 20, so the calculated disposition effect would be 0.5. The disposition effect measure ranges from -1 to 1. Intuitively, if an investor always avoids selling at a loss but constantly sells at a gain, both paper gains and realized losses would equal 0, so the disposition effect would equal 1. At the other extreme, if an investor constantly sells losses and holds on to gains, realized gains and paper losses would equal 0 in the preceding equations, producing a disposition effect of -1. Note that in our setting a profit-maximizing investment strategy yields a disposition effect that varies with the price development of the assets and is most often negative. We examine whether participants exhibit a disposition effect in general by comparing the investment behavior of participants in the control group relative to this benchmark and assess the influence of the experimental treatments on the disposition effect by focusing on between-group comparisons. Note that we cannot measure the disposition effect if an investor never has the possibility to sell at a gain (loss), since PGR (PLR) is not defined in this case.

In a post-experimental questionnaire, we measured control variables (see Web Appendix), demographics as well as attention and manipulation checks: Drawing on previous social response literature (Nass and Moon, 2000; Reeves and Nass, 1996), we assessed perceptions of socialness with seven adjectives: friendly, helpful, intelligent, polite, informative, likeable, and interactive (see also Wakefield et al. 2011, Wang et al. 2007). The questionnaire also assessed trusting beliefs toward the robo-advisor. This multidimensional construct comprises a four-item scale for competence, a three-item scale for benevolence, and a four-item scale for integrity (McKnight et al., 2002). Furthermore, we elicited several self-assessed control variables: risk-taking behavior in economic decisions (Dohmen et al., 2011), level of loss aversion determined with Gächter et al.'s (2021) elicitation task, financial literacy (Lusardi and Mitchell, 2011), expertise with financial market products (adapted from Thompson et al. (2005)), disposition to trust or general propensity to trust others (McKnight et al., 2002), and sociability (i.e., "tendency to affiliate with others and to prefer being with others to remaining alone"; Cheek and Buss, 1981, pg. 330). We also asked for basic demographic information such as gender, age, and level of education.

4. Experimental Studies

4.1. Study 1: Impact of Investment Advice from Robo-Advisor on the Disposition Effect

To assess the overall impact of investment advice from a robo-advisor on investors' behavior, and in particular whether they exhibit a disposition effect, the first study uses a between-subjects design with a control group and a robo-advisor group. We conducted the experiment in December 2019, in the experimental lab of a large European university,[13] and collected data from 195 participants (median age = 23, proportion of male participants = 62%) matched on 98 unique price paths.[14] Each computer in the lab was located in a separate cubicle and preconfigured to assign the participant to either the control or the robo-advisor group, with a predefined (randomly assigned) price path. As outlined in Section 3.1, every participant in the control group was matched with a participant in the robo-advisor group who experienced the same price path. Randomization also took place at the participant level, because when they entered the lab, participants drew a random card with a cubicle number. Participants received 2€, along with any earnings from the trading game (we used a conversion rate of 400 experimental currency units to 1€ and rounded up to the nearest 50 cents). Participants took 10 minutes on average to complete the trading game, and the average income was 7.50€.

The treatment and control group were balanced in terms of attitude

[12] For comparability, we calculate the DE measure with reference prices based on the highest, lowest, first, and last purchase price. The main findings are robust to these different operationalizations of the reference price. Most empirical studies on the disposition effect (cf. Meng and Weng 2018) do not discuss expectation-based reference points, and thus neither do we.

[13] Karlsruhe Decision & Design Lab (KD2Lab).

[14] We determined a target sample size of 102 participants per group based on an a priori power analysis with a significance level of 0.05 to achieve a statistical power of 0.9 for detecting an effect size of 0.3.

towards risk, loss aversion, financial literacy, expertise with capital market products, disposition to trust, sociability, and gender. In the control group, participants had a median age of 22 years, whereas in the robo-advisor group, the median age was 23 years (Mann-Whitney U test, z = -2.173, p = 0.030). We therefore control for age in all subsequent analyses.

4.1.1. Results

We first address whether the availability of investment advice from a robo-advisor causally reduces the disposition effect. Table 2 provides an overview of the disposition effect measure; the means of the observed variables, including the number of interactions and the resulting final payout.[15] Investors in the robo-advisor group sent 6.2 messages on average. Roughly 60% of the total interactions were messages that prompted investment advice (e.g., “Can you help me?”, “Should I buy asset A?”, “Advice”), which we define as advice requests. Of the 96 participants randomly assigned to the robo-advisor group, 76 requested advice at least once. Participants in the robo-advisor group also earned more portfolio points (2,136.65) than participants in the control group (2,059.75), which resulted in an average increase of 2.7% in relation to the overall payout. The descriptive evidence further suggests that, consistent with our first hypothesis, participants in the robo-advisor group exhibit lower disposition effects compared to participants in the control group (DE = -0.07 in the robo-advisor group compared to DE = 0.06 in the control group). Furthermore, this reduction appears to be driven by an increase in realized losses (i.e., through PLR) rather that by decrease in realized gains (i.e., through PGR). Indeed, we find that the robo-advisor increases investors’ proportion of losses realized (Wilcoxon signed-rank test, z = −2.797, p = 0.005) whereas the difference between the population mean ranks for the proportion of gains realized across groups remains insignificant (Wilcoxon signed-rank test, z = 0.676, p = 0.499).

The disposition effect also might occur in the presence of other influences, so we test for two theoretical benchmarks. First, the disposition effect might be informed by the choice to follow a profit-maximizing strategy and invest in the asset with the highest price. This strategy yields an average negative disposition effect[16] (M = −0.45, SD = 0.34). Participants in both the control group and, to a lesser extent, the robo-advisor group exhibit a disposition effect relative to this first benchmark (Wilcoxon signed-rank test, $z_{\text{robo-advisor}} = 6.666$, $z_{\text{control}} = 7.326$, $p < 0.001$). Second, random trading behavior would result in an average disposition effect of 0. Relative to 0, participants in the control group indicate a disposition effect (Wilcoxon signed-rank test, z = 1.932, p = 0.053), but participants in the robo-advisor group produce a disposition effect measure that is significantly lower than 0, that is, a reversed disposition effect (Wilcoxon signed-rank test, z = -1.934, p = 0.053). These benchmarks offer some insights into our results, yet we remain mainly interested in assessing the effect of the robo-advisor relative to our empirical benchmark, the disposition effect in the control group.

Second, we fit an ordinary least squares (OLS) regression to assess the effect of the robo-advisor on the disposition effect (Hypothesis 1). Formally, we fit the following model:

$$DE = a_0 + a_1 RoboAdvisor + a_2^T C + \varepsilon, \tag{4}$$

where *RoboAdvisor* is a dummy variable that indicates whether the participant is assigned to the robo-advisor group, C is a vector of the control variables, and a_2 is a vector of the same length. Table 3 shows the results from the estimation tasks. Column 1 shows the overall treatment effect on the disposition effect without any controls. The effect is significant and negative (i.e., mitigating). Column 2 shows the estimation results from model (4) including attitude towards risk, loss aversion, disposition to trust, financial sophistication, expertise with financial market products, and age as control variables. We see that the coefficient for *RoboAdvisor* remains negative and significant, in supports of Hypothesis 1.

4.1.2. Discussion

These results demonstrate the potential benefit of robo-advisors for investment decisions. On the one hand, we find that the availability of their unbiased investment advice significantly reduces investors’ disposition to hold on to assets losing value for too long. Based on an analysis on investors’ portfolio choices, we also find evidence that robo-advisors increase the overall share of wealth invested in risky assets[17] (75% on average in the robo-advisor group compared to 64% on average in the control group). Compared to the control group, participants in the robo-advisor group invested more in the highest priced asset (Wilcoxon signed-rank test, z = −5.286, p < 0.001) as well as less in the lowest priced asset (Wilcoxon signed-rank test, z = 3.739, p < 0.001). Moreover, participants in the robo-advisor group earned significantly more portfolio points than participants in the control group (average difference of 76.90 portfolio points, Wilcoxon signed rank test, z = -2.057, p = 0.040). Due to the design of our trading environment, a significant difference in the disposition effect likely translates into greater differences in total portfolio points over longer time horizons. On the other

Table 2
Summary of main outcome variables across treatment groups.

		Treatment	
		Control	Robo-Advisor
	No. of observations	97	96
DispositionEffect	DE	0.06 (0.28)	−0.07 (0.32)
	PLR	0.14 (0.17)	0.23 (0.26)
	PGR	0.20 (0.22)	0.16 (0.16)
Requests	Advice requests	—	3.71 (3.33)
	Other requests	—	2.45 (3.04)
Payout	Asset portfolio	1,317.96 (754.33)	1,608.98 (810.20)
	Total portfolio	2,059.75 (209.58)	2,136.65 (272.46)
	Total payout (in €)	7.39 (0.55)	7.57 (0.72)

Notes: This table reports the means and standard deviations (in parentheses). For the disposition effect, the results exclude 2 observations for which the DE is undefined.

Table 3
Effect of robo-advisors on the disposition effect.

Model	(4) without controls	(4) with controls
RoboAdvisor	-0.1290***	-0.1302**
	(0.0448)	(0.0506)
AdviceRequests		
Controls	No	Yes
Constant	0.0574**	0.0795
	(0.0286)	(0.1545)
Observations	191	191
R-squared	0.044	0.066

Notes: Regressions exclude two observations from participants whose DE is undefined. Robust standard errors are in parentheses and clustered on 98 unique price paths. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The regression with controls includes attitude towards risk, loss aversion, disposition to trust, financial sophistication, expertise with financial market products, and age as covariates.

[15] As outlined in the preregistration, we excluded 2 participants who failed at least two out of three attention checks in the post-experimental survey.

[16] The DE measure is specified for 80 of the 98 price paths and ranges from −1 to 0.25. The DE measure is undefined if a profit-maximizing investor never has the possibility to sell at a gain or a loss.

[17] For a comprehensive discussion on investors’ tendency to underinvest due to hyperbolic discounting or inertia, see Gomes et al. (2020).

hand, investors do not fully exploit the economic potential of receiving (and following) the advisor's recommendations as we can see from comparing investors' investment behavior to the portfolio maximizing strategy. Investors' decision making is thus prone to mistakes, even with the aid of a robo-advisor. This finding underlies the need for better understanding how the design of robo-advisors might affect their use to improve investors' welfare. We are thus interested in examining the role of design elements in overcoming potential barriers that may hinder investors to seek advice in the first place. To this aim, in the second study we assess the impact of social design elements by comparing the impact of the availability of (the same) investment advice from a robo-advisor with vs. without social design elements. Moreover, given that the extent to which advice is requested is endogenous in our first experiment, we test the mediating role of the number of advice requests by testing for the effect of request type by varying between endogenous and exogenous recommendation requests.

4.2. Study 2: Impact of Social Design Elements on the Disposition Effect

This experiment follows a 2 (robo-advisor with vs. without social design elements) x 2 (endogenous vs. exogenous requests) between-subjects design. Participants were randomly assigned to one of four experimental groups as shown in Table 4. The experimental instructions are shown in the Web Appendix. They are consistent with Study 1 but were slightly adapted for participants in the new treatment groups.[18] We conducted the experiment in June 2021, with 407 participants (median age = 23, proportion of male participants = 27%) from a large European university,[19] using the ORSEE software (Greiner, 2015). Participants received a link to the experiment and completed it online, using their own PCs. We implemented a randomization algorithm such that it randomly assigned participants to the different treatment groups after ensuring that they met the necessary technical requirements (e.g., access via PC and not mobile device, browser version, browser configuration). Analogous to Study 1, participants were randomly allocated to 1 of 130 unique price paths and matched with participants from the other three treatment groups, who considered the same price developments. They received 6€, which was added to any earnings from the trading game (we used a conversion rate of 350 experimental currency units to 1€ and rounded up to the nearest 50 cents). Participants took about 8.3 minutes to complete the trading game, and the average income was 12.30€. We find no strong association between the treatment groups and the variables for attitude towards risk, level of loss aversion, financial literacy, expertise with capital market products, disposition to trust, sociability, gender, or age.

4.2.1. Results

We report the effect of social design elements on the disposition effect and discuss the mechanism underlying this effect. Table 5 summarizes our results.[20] The levels of the disposition effect suggest a difference between social design elements and no social design elements for endogenous requests (i.e., Group 1 and Group 2), but no difference for exogenous (i.e., Group 3 and Group 4). Moreover, the results in relation to advice seeking behavior suggest that social design elements decrease the extent to which advice is requested (M = 3.14, SD = 3.09 in the group with social design elements vs. M = 5.51, SD = 5.12 in the group without social design elements). Furthermore, a smaller share of participants in Group 2 (12.5%) compared to Group 1 (29.5%) did not request investment advice throughout the experiment. Note that when we account for other types of requests (e.g., small talk), participants interacted similarly often with the robo-advisor with and without social design elements. There is no evidence of differences across groups in the average number of advice requests if requests are endogenous or exogenous. In the groups with endogenous requests, investors ascribed higher levels of perceived socialness to the robo-advisor with social design elements compared to the robo-advisor without social design elements (Mann-Whitney U test, $z = 1.996$, $p = 0.046$). Moreover, a measure for investors' awareness in relation to exogenous recommendations requests revealed that exogenous (vs. endogenous) recommendations had the desired effect in that investors were fully aware that, independent on their preferences, they received recommendations at the beginning of each trading round (Mann-Whitney U test, $z = -16.725$, $p < 0.001$).

Table 4
Experimental Groups (Study 2).

		Robo-Advisor	
		Social Design Elements	No Social Design Elements
Recommendation Requests	Endogenous	Group 1 ($n_1 = 95$)	Group 2 ($n_2 = 96$)
	Exogenous	Group 3 ($n_3 = 99$)	Group 4 ($n_4 = 98$)

Table 5
Summary of main outcome variables across treatment groups.

		Treatments			
		Endogenous Requests		Exogenous Requests	
Social Design Elements		Yes	No	Yes	No
	No. of obs.	95	96	99	98
DispositionEffect	DE	-0.05 (0.31)	−0.11 (0.28)	-0.13 (0.30)	-0.11 (0.30)
	PLR	0.20 (0.22)	0.23 (0.25)	0.25 (0.24)	0.23 (0.23)
	PGR	0.14 (0.18)	0.12 (0.14)	0.12 (0.14)	0.13 (0.17)
Requests	Advice requests	3.14 (3.09)	5.51 (5.12)	10.77 (1.58)	10.76 (1.55)
	Other requests	1.67 (2.57)	-	0.91 (1.90)	-
Payout	Asset portfolio	1,497.03 (817.53)	1,687.91 (687.61)	1,642.98 (786.53)	1,647.76 (785.88)
	Total portfolio	2,117.69 (277.26)	2,097.43 (288.88)	2,126.34 (306.40)	2,143.14 (309.92)
	Total payout (in €)	12.29 (0.79)	12.24 (0.82)	12.32 (0.87)	12.40 (0.91)

Notes: This table reports the means and standard deviations (in parentheses). For the disposition effect, the results excludes 5 observations for which the DE is undefined.

Next, we want to assess the overall effect of social design elements on the disposition effect as well as the mediating role of advice requests. First, we estimate the overall effect of social design elements on the disposition effect (model 5 below). Second, we assess the effect of social design elements on the number of advice requests (model 6 below). Third, we estimate the effect of social design elements on the disposition effect, controlling for the number of advice requests (model 7 below).

[18] We included one additional open-ended question in the post-experimental questionnaire which revealed consistent results with our intended manipulations.

[19] MELESSA laboratory of LMU Munich.

[20] As outlined in the preregistration, we excluded 19 participants who failed at least two out of three attention checks in the post-experimental survey.

For all three models, we fit OLS regressions.[21] Formally:

$$DE = a_0 + a_1 SocialDesignElements + a_2^T C + \varepsilon_1, \tag{5}$$

$$AdviceRequests = b_0 + b_1 SocialDesignElements + b_2^T C + \varepsilon_2, \tag{6}$$

$$DE = c_0 + c_1 SocialDesignElements + c_2 AdviceRequests + c_3^T C + \varepsilon_3, \tag{7}$$

where *SocialDesignElements* is a dummy variable that indicates whether the participant is assigned to a group with a robo-advisor with or without social design elements, *AdviceRequests* is the total number of advice requests, C is a vector of the control variables, and a_2, b_2, and c_3 are vectors of the same length. We are furthermore interested in exploiting the second randomized dimension, i.e., endogenous vs. exogenous recommendation requests, to assess the conditional mediating effect of advice requests. Specifically, we are interested in examining the effect of social design elements on advice requests (and subsequently on the disposition effect) contingent on the extent to which advice requests are endogenous or exogenous. Therefore, we estimate the following OLS models which account for the interaction between social design elements and endogenous requests:

$$DE = \alpha_0 + \alpha_1 SocialDesignElements + \alpha_2 Endogenous + \alpha_3 SocialDesignElements \times Endogenous + \alpha_4^T C + \varepsilon_4, \tag{5'}$$

$$AdviceRequests = \beta_0 + \beta_1 SocialDesignElements + \beta_2 Endogenous + \beta_3 SocialDesignElements \times Endogenous + \beta_4^T C + \varepsilon_5, \tag{6'}$$

where *Endogenous* is a dummy variable that indicates whether the participant is assigned to a group where requests are endogenous in contrast to exogenous, C is a vector of the control variables, and α_4 and β_4 are vectors of the same length. Attitude towards risk, loss aversion, disposition to trust, sociability, financial sophistication, expertise with financial market products, and gender are included as control variables.

Table 6 shows the results from estimating models (5)-(7) as well as models (5')-(6'). The interaction effects of models (5') and (6') are plotted in Fig. 3.

The first column of Table 6 suggest no overall effect from social design elements on the disposition effect. However, after including the interaction term (model 5′) we establish a partially significant positive effect from social design elements on the disposition effect contingent on requests being endogenous (Hypothesis 2a). We next turn our attention to the pathwise regressions which are pivotal in determining the mediating role of advice requests Hayes and Preacher, 2010). Concerning the first path, results from model ((6) suggest that social design elements have a significant negative effect on advice requests. As intended, the results from model (6') show that endogeneity in requests blocks the effect of social design elements on the extent to which advice is sought. The last column shows the results from the second path whereby advice requests negatively impact the disposition effect.

As in commonly used methods to test moderated mediation, we calculate the statistical significance of indirect effects according to the product of coefficients approach (Hayes and Preacher, 2010; Rucker et al., 2011) conditional on levels of endogenous vs. exogenous request types. The product of coefficients $(\beta_1 + \beta_3) * c_2$ gives the indirect effect conditional on endogenous requests. The product of coefficients $\beta_1 * c_2$ gives the indirect effect conditional on exogenous requests. Table 7 reports bootstrapped CIs for the conditional indirect effect of social design elements via advice requests. By experimentally manipulating the extent to which investors have to actively seek advice, we test the validity of the number of advice requests as a mediator. Specifically, limiting endogenous choices by providing recommendations exogenously represents a *blockage manipulation* which should neutralize the effect of the mediator (Pirlott and MacKinnon, 2016). The CI for the indirect effect for endogenous requests is positive and does not include zero. In contrast, the indirect effect for exogenous requests is insignificant. This result is in line with Hypothesis 2b and implies that social design elements impact the disposition effect conditionally on investors having to actively request recommendations.

4.2.2. Discussion and Tests of Alternative Explanations

The results from our second study provide meaningful insights into the mechanism by which the design of robo-advisors can influence investors' selling behavior. We find a positive (i.e., strengthening) indirect effect of the use of social design elements through the extent of advice requests on the disposition effect. Investors sought more advice from the robo-advisor without social design elements compared to the robo-advisor with social design elements and we posited that this behavior may reflect investors' motivation to maintain autonomy (Dalal and Bonaccio, 2010) and preserve their self-esteem (Usta and Häubl, 2011). Asking for advice from a robo-advisor with social design elements, which may be perceived as having a certain level of agency (Gray et al., 2007; Waytz et al., 2010), may decrease investors' perceptions of their own personal agency to a greater extent compared to asking advice from a robo-advisor without social design elements. Therefore, social design elements may decrease investors' receptivity to assistance; in extreme cases, investors might even feel so threatened that they never seek advice.

We discuss three alternative explanations for the observed effect: differences in perceptions of effort, differences in the extent to which the technology is perceived as trustworthy, and differences in the level of investor sophistication. First, participants had to write a message into the chat window to ask for an investment recommendation from the robo-advisor with social design elements, whereas a click on a button triggered an investment recommendation from the robo-advisor without social design elements. Even though the robo-advisor responded even to short messages such as "Advice" or "Help," participants might have perceived greater required effort, compared with a simple click, which could potentially reduce the number of advice requests. However, the total amount of requests (advice and other types) is not significantly different in both treatment groups (Mann-Whitney U test, $z = 1.075$, $p = 0.282$), which suggests that perceived effort does not hamper their interactivity. On a similar vein, social design elements (e.g., allowing participants to ask a wide range of questions) could have a distracting effect and requires subjects to focus more on what to do and what to ask. Specifically, participants may trade-off making requests that do not prompt investment advice with requests that do. However, the correlation coefficient between advice requests and messages about other topics (e.g., "What can you do?", "What is the return on my portfolio?") is slightly positive and insignificant (Spearman's $\rho = 0.087$, $p = 0.232$), which suggests that participants' tendency to request advice is independent of whether they engaged in other interactions with the advisor. Taken together, our findings do not support an explanation based on perceived effort.

Second, social design elements have been shown to increase trust towards advisors. For example, Hildebrand et al. (2021) show that conversational robo-advisors increase perceptions of trust compared to static, non-conversational robo-advisors. In a retail context, Schanke et al. (2021) provide evidence for a positive effect of social design elements on consumers' willingness to disclose personal information and subsequent (positive) impact on conversions. In contrast, Hodge et al. (2020) finds a negative effect on naming robo-advisors on their credibility. Furthermore, a positive link between advisor trustworthiness and advice utilization is well established in the literature on judge–advisor systems (e.g., Sniezek and van Swol, 2001). In the post-experimental

[21] Acknowledging that the number of advice requests is an overdispersed count variable (mean = 4.15, variance = 19.41), we find consistent results for the mediation analysis after estimating model (6) with a negative binomial regression in the Web Appendix.

Table 6
Pathwise regressions on disposition effects over advice requests.

Model Dependent variable	(5) DE	(5') DE	(6) AdviceRequests	(6') AdviceRequests	(7) DE
SocialDesignElements	0.0155	-0.0314	-1.2270***	0.0402	-0.0064
	(0.0336)	(0.0463)	(0.3536)	(0.2451)	(0.0317)
Endogenous		0.0002		-5.2244***	
		(0.0403)		(0.5256)	
SocialDesignElements × Endogenous		0.0945*		-2.4914***	
		(0.0554)			
AdviceRequests					-0.0179***
					(0.0032)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	0.0116	0.0175	6.7391***	8.8022***	0.1323
	(0.1122)	(0.1143)	(1.5777)	(1.2629)	(0.1088)
Observations	383	383	383	383	383
R-squared	0.0159	0.0282	0.0376	0.5362	0.0891

Notes: This table shows the results from OLS regressions for the models as specified in the headers. Control variables include attitude towards risk, loss aversion, disposition to trust, sociability, financial sophistication, financial expertise and gender (see Web Appendix). Regressions excludes 5 observations from participants whose DE is undefined. Robust standard errors are in parentheses and clustered on 102 price paths. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

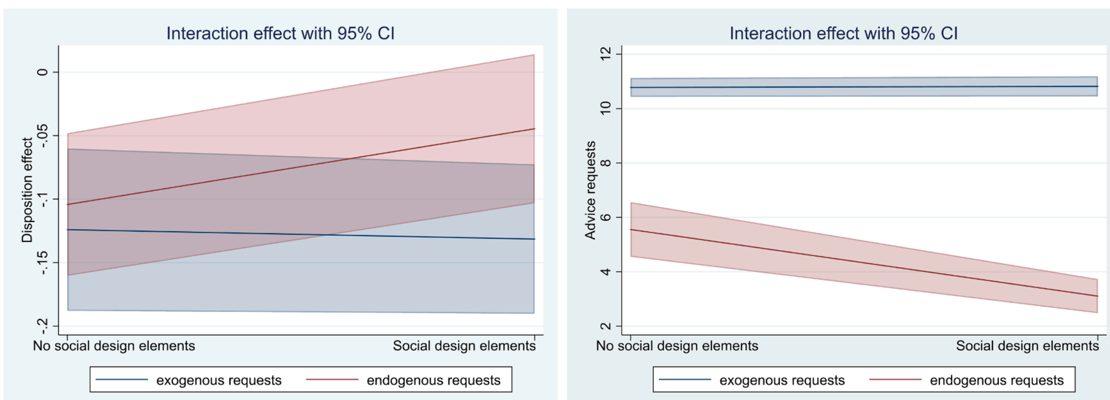

Fig. 3. Interaction effects with 95% CIs.

Table 7
Significance tests for indirect effects of social design elements on the DE via advice requests.

	Conditional indirect effect	Bootstraped standard error	95% bootstrapped CI
Endogenous Requests	0.044	0.013	0.022, 0.073
Exogenous Requests	-0.001	0.004	−.0041, 0.007

Notes: Bias-corrected bootstrapped confidence intervals based on 1,000 iterations are reported.

survey, we assessed a measure of trusting beliefs toward the advisor (see Web Appendix for the list of used scale items) and find only small, statistically insignificant differences in trusting beliefs driven by social design elements (Mann-Whitney U test, z = -1.191, p = 0.234). Differences in trusting beliefs therefore are unlikely to explain the difference in advice seeking behavior.

Third, there is a non-negligible number of participants who never requested advice from the robo-advisor. In particular, more participants never requested advice from the robo-advisor with (cf. without) social design elements. It is possible that these participants are more sophisticated investors who are less prone to the disposition effect. However, we find that those participants in Group 1 (endogenous request and robo-advisor with social design elements) who never requested advice have a slightly higher disposition effect (DE = 0.102) compared to those participants in Group 2 (endogenous request and robo-advisor without social design elements) who never requested advice (DE = 0.090) (Mann-Whitney U test, z = -0.266, p = 0.790). Overall, the difference in the extent (and lack) of assistance sought due to motives related to maintaining autonomy offers a good potential explanation for the (negative) impact of social design elements on the extent to which investors ask for advice.

5. General Discussion

Our main contributions are threefold. First, we contribute to existing literature by assessing whether access to a robo-advisor mitigates the disposition effect (i.e., whether they make us better investors). While previous studies have established a diminishing effect of robo-advisors on the disposition effect (e.g., D'Acunto et al., 2019), our methodological approach and controlled conditions help shedding light on investors' actual advice seeking behavior as well as the mechanism by which the different components of the disposition effect (PLR and PGR) drive the effect. Consistent with cognitive dissonance as an explanation, we find that the effect is driven by investors' selling behavior in the losses domain. In this regard, we extrapolate previous findings about the role of fund managers in facilitating investors' decisions to realize losses (Chang et al., 2016) to robo-advisors.

Second, digitized text-based assistants are increasingly being designed to provide customer service but also to appear human, reflecting a general notion that people dislike and mistrust algorithms (Go and Sundar, 2019). In examining the impact of social design elements, our study highlights some risks of neglecting the potential negative outcomes of making the technology appear "more social" in the context of robo-advisory systems. Moreover and relating back to the theory of cognitive dissonance, robo-advisors may mitigate the sense of discomfort that arises after learning that an investment decision led to losses. Particularly, the extent of social design elements might play a role in reducing this sense of discomfort. This finding therefore also advances prior findings in the context of digital recommendation agents documenting users' discomfort stemming from stimuli such as social design elements (Spatola and Agnieszka, 2021). Users are well aware of the fact that they are interacting with a technology, and social design elements may be perceived as inconsistent with this knowledge and lead to a state of discomfort.

Third, we offer a novel explanation to understand why social design elements negatively impact investment behavior: investors are hindered in their propensity to seek advice in the first place and are thereby unable to fully utilize the potential of the robo-advisor in order to increase their welfare. Our experimental design offers a clean way to test the validity of this explanation. We hereby extend previous research on individual motives and propensities to seek advice, by revealing the effects of advisor-related aspects in a digital context. Previous studies suggest that increased levels of perceived control (Dietvorst et al., 2018) or transparency (Yeomans et al., 2019) foster responsiveness to algorithmic advice. To the best of our knowledge, this study is the first to examine the impact of social design elements of robo-advisors on the extent to which advice is sought, as well as its subsequent effect on economic performance (i.e., investment decisions). We further identified effects of social design elements on advice-seeking behavior, as well as on the trade-off between maximizing accuracy and maintaining autonomy (Dalal and Bonaccio, 2010).

These results have important implications for the automation of financial services and for efforts to mitigate behavioral biases. Various features of the investment interface might "debias" investors and mitigate the disposition effect, such as using automatic selling devices (Fischbacher et al., 2017) or reducing the salience of past price information (Frydman and Rangel, 2014). We propose another option; unbiased investment advice can function as another debiasing tool. Algorithms often outperform human decision makers (Bigman and Gray, 2018), and incorporating advice even to a limited extent improves decision making (Larrick and Soll, 2006). Decision makers' tendency to discount advice notwithstanding (Yaniv and Kleinberger, 2000), we show that algorithm-based investment advice significantly reduces the disposition effect. Providing potential investors with an opportunity to seek unbiased algorithmic advice carries a low cost for companies, improves investment decisions, and may even increase overall satisfaction with the service provider (Huang and Rust, 2017).

In designing these digital advisors, companies also can leverage our findings. Social design elements are popular currently (Hodge et al., 2020), and robust empirical evidence indicates that making technology appear more social can foster social connections and increase outcomes such as likeability or ease of use (Qiu and Benbasat, 2009). Our results show that this strategy may represent a double-edged sword: It may lead to a stronger relationship toward the advisor and increase experiential outcomes, but it also increases the psychological cost associated with advice seeking. Our results offer one instance as to how the negative effect of social design elements may be diminished, namely by diminishing user control (i.e., by making recommendation requests exogenous). Also, this strategy could also help mitigating mistakes resulting from overconfidence, since overconfident investors may be more inclined to believe that they do not need to seek advice. Alternatively, decreasing the psychological costs associated with asking advice may be achieved by leveraging different types of advice. For example, advising on *how* to make an investment decision or the provision of social support (e.g., acknowledging difficulty of a decision) are types of advice that might help investors feel less restricted in their freedom, thereby increasing their propensity to seek advice (Dalal and Bonaccio, 2010). In addition, designing default options to minimize the cost associated with seeking advice might represent a fruitful strategy. From a policy perspective, offering automated and unbiased advice (e.g., targeted at increasing savings) only works if investors utilize it, which is not always the case. Such insights might also apply in other industries, such as health care and insurance, which involve objectively measurable outcomes. The potential of well-designed automated advisory services for these industries and their consumers is tremendous.

There are several avenues for future research such as testing the generalizability of our findings for other domains of automated advisory services such as consumption- (e.g., money management money apps such as Personal Capital), tax- (e.g., Betterment's "Tax Loss Harvesting+" algorithm), or healthcare-related decisions (e.g., health coaching apps such as Healthie). Additional avenues for research might address some limitations of our study as well. First, the experimental subjects were recruited from a university subject pool across various study majors, but the results may not generalize to all demographic groups or professional investors. Second, we tested our hypotheses in controlled experiments where participants interacted for a limited time with the trading system. Many advisory applications, such as financial planning tools, are designed to provide advice with little user input and within a short time frame, similar to the robo-advisor implemented in our experiments. However, there is evidence for a diminishing impact of social design elements on usage continuance after post-adoption in the context of speech-based digital agents (e.g., Apple's Siri or Amazon's Alexa) (Moussawi et al., 2022). Future research may thus study the effect of social design elements on economic decision making provided longer-term relationships and increased familiarity with the technology. Further, our results benefitted from the implementation of a robo-advisor capable of interacting with participants in natural language and of responding to a wide range of questions. Still, further research could test the proposed mechanisms in a field setting. Third, we did not provide participants with detailed information about the inner workings of the robo-advisor. This "black box" is common to decision-making algorithms; the high degree of algorithmic complexity in many applications makes resolving this issue difficult. More transparency regarding the reasoning process of robo-advisors may translate into increased use of their advice. Understanding whether and how disclosures shape advice-seeking behaviors thus represents a fruitful research avenue. Relatedly, our results raises interesting ethical considerations in relation to digital investment advisory services which may be further investigated. For example, an important ethical consideration represents customers' needs to comprehend the financial services that are being offered (Shanmuganathan, 2020). Looking for ways to increase investors' knowledge could involve reducing investors' hurdles to seek advice in the first place (e.g., overconfidence). This aspect further highlights the potential reach of our findings.

6. Conclusion

The complexity of decisions that directly affect individual welfare (e.g., financial, insurance, health care) has increased in recent years, and improving decision making represents a critical challenge for society (Soll et al., 2015). In complex environments, people can derive significant benefits from receiving unbiased advice that helps them make more rational decisions (Hoechle et al., 2017). For example, in a financial context, retirees often struggle to manage their pensions or contribution plans on their own; advisory services might help both current and future retirees make more profitable investment decisions (Gomes et al., 2020; Looney and Hardin, 2009). Hence, the shift toward automation, facilitated through advances in artificial intelligence, could enable a broader range of consumers to access advisory services at a low cost, suggesting the vast relevance of understanding the effects of digital advisors and their design features. This goes beyond (risky) investment decisions, since automated advisory systems are being adopted across many different domains such as taxes or healthcare care (Panesar, 2019). Moreover, automated advisory applications can increase customers' perceptions of the value of advisory services, which could translate into a competitive advantage for service providers that establish them. Our findings, highlighting how robo-advisors can facilitate difficult investment decisions and how social design elements influence consumers' perceptions of the advisory system and advice-seeking behavior, thus offer a step toward a better understanding of the benefits of new technological developments in terms of reducing behavioral biases that can impose substantial economic costs.

Data availability

Data and code are available at https://osf.io/z9jd5/.

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Supplementary materials

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