Do Robo-Advisors Make Us Better Investors?

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Abstract

Investors increasingly can obtain assistance from "robo-advisors," artificial intelligence–enabled digitalized service agents imbued with anthropomorphic design elements that can communicate using natural language. The present article considers the impact of anthropomorphized robo-advisors on investment decisions, with a focus on their ability to mitigate investors' behavioral biases. We study the well-documented disposition effect, which reflects investors' greater propensity to realize past gains than past losses. In two induced-value laboratory experiments, the availability of a robo-advisor reduces (i.e., mitigates) investors' disposition effect. This relationship is mediated by two simultaneous (indirect) effects: the extent of requests for the robo-advisor's investment advice and perceptions of its socialness. These findings resonate with cognitive dissonance theory, which predicts that assigning responsibility to the advisor helps investors resolve a sense of discomfort that may arise after a financial loss. Anthropomorphic design elements alone are not sufficient to reduce the disposition effect, but they decrease investors' propensity to seek advice, which offsets the positive (indirect) effect of perceived socialness. These results have implications for the ongoing automation of advisory services, as well as for improving decision making, and suggest some further research directions.

Keywords: Robo-Advisors, Artificial Intelligence, Advice, Anthropomorphism, Disposition Effect.

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1 Introduction

Ample evidence suggests that people make mistakes when they deviate from rational prescriptions (DellaVigna 2009). Behavioral finance researchers study such mistakes extensively, particularly in relation to investment decisions (for an overview, see Bhattacharya et al. 2012). For example, the so-called *disposition effect* refers to an observed empirical regularity, by which investors exhibit a greater propensity to sell "winners" compared with "losers" (Shefrin and Statman 1985). Prior research suggests that these errors in judgment and decision making lead to substantial reductions in returns[1] (e.g., Barber and Odean 2000, Barber et al. 2009, Calvet et al. 2007). Therefore, researchers and policy makers are keenly interested in finding new ways to mitigate biases in investment decisions (Organisation for Economic Co-operation and Development [OECD] 2017).

Recent, important developments in artificial intelligence (AI) 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 (Agrawal et al. 2018, D'Acunto et al. 2019). Many companies that have introduced robo-advisors imbue them with anthropomorphic design elements, such as an avatar or name (e.g., Bank of America's Erica), seemingly to make them appear more "human" (Chung et al. 2020). However, the effects of anthropomorphic design elements on investment decisions are uncertain. Especially as the line between technology and humans grows increasingly blurred (Reed et al. 2012), we need a better sense of the relationship between industry efforts to substitute technology for human advisors and individuals' own economic welfare. Therefore, with this article we seek to answer the following research question: *How do robo-advisors with anthropomorphic design elements influence investment decisions, and to what extent are they able to mitigate behavioral biases such as the disposition effect?*

We examine the effects of robo-advisors on individual investment decisions in two induced-value laboratory experiments, which allows us to disentangle the impact of two separate characteristics of robo-advisors on the disposition effect, namely, their provision of investment advice and the degree to which they are anthropomorphized and perceived as a social entity. In this context, "anthropomorphism" refers to the process by which users assign the technology humanlike traits, motivations, or intentions (Epley et al. 2007). Imbuing robo-advisors with anthropomorphic design elements then might mitigate the disposition effect, if it increases users' perceptions of socialness, i.e., feelings of being with someone else (Wakefield et al. 2011).

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. We

[1] Calvet et al. (2007) estimate annual losses of 2.9 percentage points due to insufficient diversification alone.

design and implement a robo-advisor tool that participants can use to interact with the system, through a text-based chat window, and then receive investment advice. The implemented robo-advisor possesses a broad range of skills, ranging from engaging in small talk to providing current price information. Its investment advice reflected strategic efforts to maximize expected profits, 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. In one study, we compare investors' behavior with and without the availability of a robo-advisor. Then a second experiment features a comparable but nonanthropomorphic recommendation algorithm that provides the same investment advice as the robo-advisor.[2] The robo-advisor 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 recommending algorithm only allowed users to click on a button after which the investment advice was displayed on a window. By comparing investors' behavior in the presence of a robo-advisor versus a recommendation algorithm, we isolate the impact of anthropomorphic design elements on the disposition effect. We also 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. The analysis thus is based on a within–price sequence comparison approach.

The main results are twofold. First, we establish a negative (i.e., mitigating) effect of robo-advisors on the disposition effect and provide evidence of an underlying mechanism. Both the characteristics of the robo-advisors and users' perceptions of their socialness can reduce disposition effects. Specifically, we identify two parallel, indirect effects that together explain the impact of robo-advisors on the disposition effect. Second, two effects stemming from the use of anthropomorphic design elements offset each other. On the one hand, anthropomorphic design elements increase perceptions of socialness toward the advisor, which mitigate the disposition effect. Moreover, if they request advice, investors are more likely to follow suggests from an anthropomorphic robo-advisor compared with a (nonanthropomorphic) recommendation algorithm. On the other hand, investors seek advice from a recommendation algorithm more often than from an anthropomorphic robo-advisor. This greater propensity to seek advice also translates into a reduced disposition effect.

This study thus informs behavioral finance research pertaining to how the design architecture of technological support systems might reduce behavioral biases (e.g., Looney and Hardin 2009). Specific to the disposition effect, prior research has shown that decreasing the saliency of past purchase information (Frydman and Rangel 2014) and implementing automatic selling mechanisms (Fischbacher et al. 2017, Weber and Camerer 1998) can improve financial performance, because they mitigate this disposition effect. We add nuance to these findings with our investigation of some mechanisms underlying these effects.

[2] Note that throughout this article, 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).

Furthermore, our study relates to research into the role of advice in improving investment decisions. Advice is usually offered by third parties and may be biased by those advisors' own beliefs or agency conflicts, such that the advice ultimately might not align with the clients' own interests (Bhattacharya et al. 2012, Kling et al. 2019). Field evidence suggests that advice from human advisors even might hinder trading performance (e.g., Foerster et al. 2017, Hoechle et al. 2017). Investors thus may benefit more from unbiased advice from robo-advisors. Automated financial advice mitigates but does not fully eliminate suboptimal investment behavior (e.g., D'Acunto et al. 2019); we extend this insight, with experimental evidence, to clarify the extent to which robo-advisors should be imbued with anthropomorphic design elements to ensure investors' economic welfare. Finally, our methodological approach represents a contribution, in that it reveals how to isolate the effects of anthropomorphic design elements on investors' propensity to use advice, as well as their perceptions of socialness, and then how these factors affect investment decisions.

Our work also informs literature on judge–advisor systems (Bonaccio and Dalal 2006, Sniezek and Buckley 1995), which experimentally examines the effects of advisor-related aspects on advice-taking behavior. 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 anthropomorphic design elements to determine how advisor representations might determine both investors' propensity to seek advice and their responsiveness to it (Barham et al. 2018). Investors often adhere insufficiently little to expert advice, due to their self-centeredness (Yaniv 2004, Yaniv and Kleinberger 2000, Rader et al. 2017). Insufficient use of advice also appears in algorithmic forecasting settings (Prahl and van Swol 2017, Önkal et al. 2009), though prior studies in this domain restrict their analyses to individual responsiveness. By including design-related factors as potential drivers of advice-seeking behavior, we seek to extend such research. Just as people tend to ignore or fail to seek advice from human advisors because they want to maintain their autonomy and avoid feeling restricted in their desire for freedom (Brooks et al. 2015, Dalal and Bonaccio 2010, Usta and Häubl 2011), we posit that (anthropomorphic) design-related factors could prompt such considerations and influence investors' uses of advice offered by robo-advisors.

The remainder of this article is organized as follows: In the next section, we discuss the role of robo-advisors in shaping investment behavior related to the disposition effect. We provide explanations based on cognitive dissonance theory (Festinger 1957) and derive predictions, which we test in two experimental studies. 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 and some limitations. Finally, we conclude in Section 6.

2 Theory and Predictions

2.1 Cognitive Dissonance and the Disposition Effect

The disposition effect (i.e., investors' asymmetrical selling behavior in the domain of gains and losses) is a well-documented and extensively discussed behavioral pattern in behavioral economics 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 both individual investors (Odean 1998, Feng and Seasholes 2005) and institutional investors (zur Shapira and Venezia 2001), as well as experimental subjects (Weber and Camerer 1998, Lee et al. 2008). It applies beyond stock markets, for example, to real estate markets (Genesove and Mayer 2001), traded option markets (Poteshman and Serbin 2003), futures markets (Locke and Mann 2005), and online betting markets (Hartzmark and Solomon 2012). Although the existence of a disposition effect thus has robust empirical support, its drivers remain debated (Vaarmets et al. 2019).

Past research shows that the disposition effect is not motivated by rational motives, such as tax considerations, the desire to rebalance portfolios, or a reluctance to incur high trading costs (Odean 1998). Rather, it may be driven by preferences or beliefs (for discussions, see Ben-David and Hirshleifer 2012, Fischer and Maier 2019). A prominent preference-based explanation links the disposition effect to prospect theory (Tversky and Kahneman 1979), which predicts that investors express less willingness to take on risks after gains but more willingness to assume risk after they suffer losses. Despite its popularity, theoretical studies question whether the tendencies predicted by prospect theory can really produce a disposition effect (Barberis and Xiong 2009).

Another promising, belief-based explanation relates the disposition effect 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 (Zuchel 2001). More broadly, cognitive dissonance arises when a person holds two contradictory cognitions simultaneously, which creates a sense of discomfort that people may go to great lengths to mitigate (Festinger 1957). Pertaining to the disposition effect, cognitive dissonance may occur when an investor holds an asset that has decreased in value. An initial cognition reflects the investor's belief that there was a good reason to purchase the asset, but the subsequent cognition requires the divergent acknowledgment that the asset has decreased in value. Faced with such a dissonant cognition, investors seek self-justification and ways to reduce their discomfort, without relinquishing the original cognition. Thus they might delay the decision to sell an asset, refuse to admit the purchase was a mistake (Kaustia 2004), or delegate responsibility for the decision to someone else (Steffel et al. 2016). Kaustia (2010) advances similar arguments, based on self-justification and regret avoidance. If investors maintain their positive self-perception of their ability to make investment decisions and avoid selling an underperforming asset, it gives rise to the disposition effect (Kaustia 2010).

The tendency to self-justify initial beliefs is so strong that even when investors are presented with unequivocal and undeniable evidence that their beliefs are wrong, they remain convinced of their beliefs (Festinger 1957). No such dissonance occurs when the asset increases in value. Empirical studies affirm that cognitive dissonance also can function as an overarching theory to explain why the disposition effect might weaken, such as when Chang et al. (2016) determine that having a target to assign responsibility and blame (e.g., a mutual fund manager) reduces investors' discomfort with owning mutual fund that has decreased in value. On an individual level, investors with high levels of optimism and stubbornness, who are unlikely to acknowledge their past mistakes, appear more prone to the disposition effect (Cueva et al. 2017). Cognitive dissonance thus provides an explanation for investors' overall reluctance to realize losses, which creates an asymmetry relative to their desire to realize gains.

2.2 Disentangling the Effects of Investment Advice and Anthropomorphism

To address our research question, we investigate how the availability of investment advice from a robo-advisor may help reduce the discomfort that arises from dissonant cognitions. First, we discuss two characteristics of robo-advisors separately to identify distinct paths by which a robo-advisor might reduce the disposition effect. The first path captures an *advice effect* of investment advice, which is contingent on the extent to which advice is actually provided. The second path captures an *agency effect* and the influence of perceived socialness, depending on the extent to which the investor assigns blame for the outcome to the robo-advisor. In this context, "blame" entails directing negative feelings, elicited by an undesirable event (e.g., financial loss), toward the robo-advisor (Gurdal et al. 2013).

Advice generally has positive effects on individual decision making (e.g., Sniezek and Buckley 1995, Bonaccio and Dalal 2006, Rader et al. 2017), such that people with access to advice tend to outperform unadvised decision makers, in a variety of settings (e.g., Dalal and Bonaccio 2010, Yaniv 2004, Larrick and Soll 2006, Yaniv and Choshen-Hillel 2012). However, the extent to which decision accuracy improves also depends on factors such as the advisor's expertise, incentive schemes, and the level of congruence between the decision maker and the advisor (Hollenbeck et al. 1995, Sniezek et al. 2004). Moreover, even after receiving advice, people remain biased in the direction of their prior beliefs and systematically underweight advisors' opinions (e.g., Yaniv and Kleinberger 2000, Yaniv and Choshen-Hillel 2012). That is, people increase their decision-making accuracy by using advice—but not as much as they should.

The advice effect we predict is related to rational learning models (Yaniv and Milyavsky 2007, Charness et al. 2007), including Bayesian updating of priors. This mechanism may help reduce the disposition effect (Seru et al. 2010), because if investors hold assets that have decreased in value and then receive advice to sell, from an independent source, they might be more willing to revisit their initial investment strategy and question their initial purchase decisions. In this scenario, the provision of investment advice enables them to alter their initial cognition, to remove dissonance (Chang et al. 2016) and alleviate the feeling of discomfort. If they follow the advice and sell the asset, even in their loss domain, the disposition effect would diminish. In investigating investment decisions across multiple trading rounds, we operationalize this advice effect as the aggregate number of advice requests throughout the experiment.

The agency effect instead involves an attribution of blame to someone else for a loss, as an alternative mean to reduce feelings of discomfort elicited through cognitive dissonance. A robo-advisor may be particularly salient in this pathway, because blame attribution likely reflects perceptions of the advisor's socialness. If the advisor is perceived as a real person, with some level of agency, investors can more readily blame it for bad investment decisions. As research on mind perception demonstrates, people focus on others' experience and agency (Waytz et al. 2010, Gray et al. 2007), such that experience refers to an ability to experience things (i.e., sense and feel things), and agency implies an ability to act and plan. People generally attribute some degree of agency but little experience to robots (Gray et al. 2007).

In a judge–advisor system though, the judge (e.g., investor) retains agency, and the process of assigning blame may be unjustified (Gurdal et al. 2013). Such behaviors often target entities that are not responsible for the event, such as agents in a principle–agent relationship (Gurdal et al. 2013), advisors (Harvey and Fischer 1997), or spokespeople (Garofalo and Rott 2018). Moreover, negative emotions such as anger often increase tendencies to hold others responsible (Keltner et al. 1993). In a customer service setting, Hadi et al. (2019) provide evidence of a link between anthropomorphism and blame (which translates into dissatisfaction) in circumstances dominated by strong negative emotions. For financial investments, blame attribution might reduce cognitive dissonance (e.g., Chang et al. 2016, Zuchel 2001, Kaustia 2010), through a sort of reversed disposition effect in the case of managed funds. For example, by blaming a fund manager, investors can justify the choice to sell a losing asset, because they do not have to take responsibility or admit that they made a poor investment decision.

These theoretical considerations suggest that the availability of investment advice from a robo-advisor might reduce the disposition effect (P1). Two distinct paths, reflecting two characteristics of robo-advisors, should drive this effect (P2a and P2b), as we formalize here:

***P1**: Investors with access to investment advice from a robo-advisor exhibit a weaker disposition effect than investors without access to investment advice from a robo-advisor.*

***P2:** The mitigating effect of robo-advisors on the disposition effect is mediated by (a) the extent to which a robo-advisor's advice is requested (i.e., number of advice requests) and (b) perceptions of the robo-advisor's socialness.*

2.3 Anthropomorphic Design Elements

Researchers from a wide array of disciplines have studied the roots of anthropomorphism and its effects on human behavior (Epley et al. 2007). For example, studies in marketing show that anthropomorphizing a brand can increase brand loyalty, but anthropomorphizing products is less desirable (Aggarwal and McGill 2007, Chandler and Schwarz 2010). Information systems research also has established a positive link between anthropomorphism and technology use (e.g., Hess et al. 2009, Qiu and Benbasat 2009). Yet negative effects also can arise, whether from a feeling of eeriness if the technology becomes too humanlike (Wang et al. 2015) or because anthropomorphism undermines people's sense of autonomy (Kim et al. 2016).

The extent to which users ascribe technologies humanlike traits appears to depend on whether the user feels as if she or he is in the presence of someone else, which in turn reflects the social cues established by design features, such as the use of textual language (Nass and Moon 2000). For this study, we refer to cues that evoke anthropomorphism and perceptions of socialness (Gong 2008) as anthropomorphic design elements. Language, appearance, and interactivity constitute key anthropomorphic 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 anthropomorphic 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). But we propose that anthropomorphic design elements might heighten these effects. Some authors propose that strong perceived socialness is essential when designing digital assistants (Heerink et al. 2010, van Doorn et al. 2017), because their main purpose is to compensate for a lack of human input. Imbuing robo-advisors with anthropomorphic design elements, in the form of language, appearance, and interactivity cues, should increase perceptions of socialness (P3).

> ***P3****: The use of anthropomorphic design elements increases perceptions of the socialness of the robo-advisor.*

3 Methodology

We conduct two between-subjects, value-induced experiments to test our predictions. With the first study, we assess the overall impact of robo-advisors on the disposition effect, as well as disentangle the unique influences of the advice effect and the agency effect. Then we conduct a second study to investigate the impact of anthropomorphic design elements on investors' perceptions and behaviors. Keeping all else constant, we vary the level of anthropomorphism and measure its impact on investors' perceptions of socialness and the extent to which they request advice. 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 anthropomorphic design elements.[3]

3.1 Experimental Design

The general design of our economic 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 10 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.

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 two participants to each price path, then (2) randomly allocate participants 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. Reflecting a power analysis with effect size estimations based on a pretest, we targeted 240 participants (i.e., 120 participants per treatment group). As a conservative approach though, we simulated 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

[3] We preregistered both studies at Aspredicted.org. See https://aspredicted.org/blind.php?x=j9re59 for Study 1 and https://aspredicted.org/blind.php?x=k4923i for Study 2.

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 for each price path, to avoid order effects.

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

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

With the framework of market dynamics in Table 1, we can use a straightforward application of Bayesian updating in each period. For a rational investor, with the same priors for the probabilities of price increases, it is optimal to invest in the asset with the highest price, from a profit-maximizing perspective. The asset for which the price has increased most (or decreased least) offer 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,[4] on which the robo-advisor's advice is based.

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.[5] 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' perceptions of socialness, control variables, and demographics.

[4] 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.

[5] Web Appendix 2 provides the experimental instructions.

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 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. We used LimeSurvey to execute the web-based survey, running on a desktop computer. It provided instructions and collected several characteristics and perceptions included in our study. The trading game instead 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.[6] We integrated the entire trading game web-based application via an iFrame into LimeSurvey to store all the trading game data, using JavaScript (Web Appendix 3 contains screenshots of user interface across groups).

The operationalizations of the robo-advisor employed various anthropomorphic design elements, including the capability to interact with participants using natural written language. In addition, participants saw an avatar with a human embodiment, adopted from Wuenderlich and Paluch (2017). The robo-advisor introduced itself with the name Charles[7] and used personal pronouns (e.g., "I," "me"; Pickard et al. 2014). In terms of interactivity, its skills ranged from answering only context-unrelated questions (e.g., "How are you?" "What can you do?") to context-related questions without uncertainty (information requests in relation to past asset prices and the current value of the portfolio) to context-related questions with uncertainty. The printed instructions that each participant received included examples of questions they could ask the robo-advisor; the robo-advisor also disclosed these questions at the beginning of the experiment. Notably, the answers to context-related questions without uncertainty would not provide new information (i.e., it was already available through the user interface) and are certain, in the sense that their accuracy can be assessed immediately. The robo-advisor always gave accurate information to the participants. Context-related questions with uncertainty involve a request for advice, such as "Can you help me?" or "I need some advice," which triggers 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 Figure 1). 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 optimal

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[6] Web Appendix 5 provides a technical description of the robo-advisor application.

[7] Adding a name increases perceptions of socialness (LaFrance 2014). The name "Charles" is associated with a high advice acceptance rate (Hodge et al. 2020).

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, the study scenario is realistic.

To assess the impact of anthropomorphic design elements on investors' perceptions and behaviors (Study 2), we also operationalize a recommendation algorithm, such that the comparison can reveal the impact of anthropomorphic design variations on the agency and advice effects. Thus the recommendation algorithm 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, as Figure 1 displays.

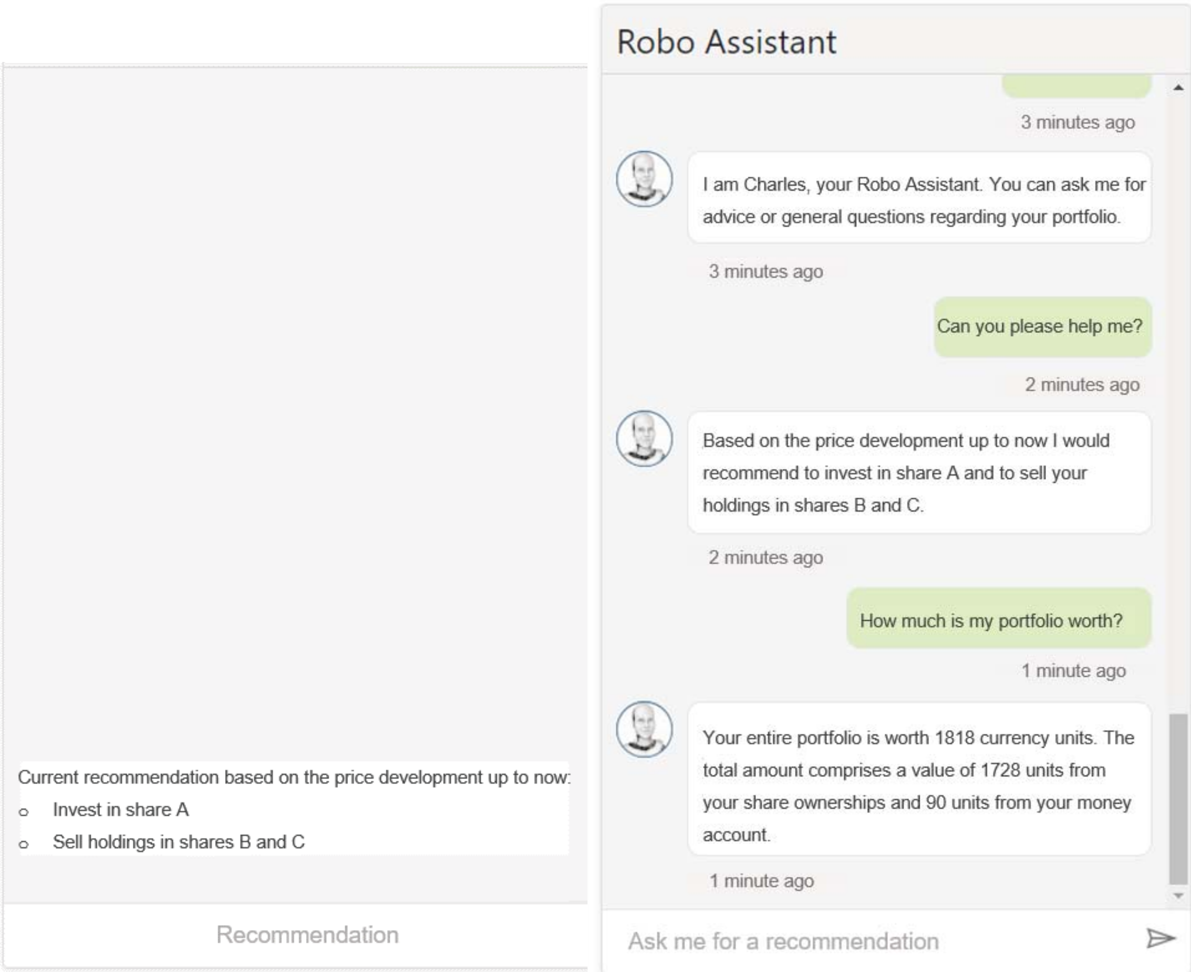

Figure 1: Screenshot of the advisor interface in the recommendation algorithm group (left) and in the robo-advisor group (right)

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. Furthermore, PGR and PLR do not appear systematically related (Weber and Welfens 2007). 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, we know little about how reference prices get selected (Baillon et al. 2020, Meng and Weng 2018). Therefore, following previous work (Weber and Welfens 2007, Fischbacher et al. 2017), we use weighted average purchase prices as the reference prices.[8] We then define PGR, PLR, and DE as follows:

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

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

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

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 DE would be 0.5. The DE 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 DE 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 DE of -1.

[8] 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.

In a postexperimental questionnaire, we also asked participants to complete multiple-item scales to measure each construct (see Web Appendix 1). Drawing on previous social response literature (Reeves and Nass 1996, Nass and Moon 2000), 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). We also included a three-item scale for self-accountability, or the extent to which participants felt accountable and responsible for the outcome of their investment decisions (Passyn and Sujan 2006). The questionnaire assessed trusting beliefs toward the advisor, in both the robo-advisor and the recommendation algorithm groups. 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). A one-item scale measures joy after a price increase and regret after a price decrease (Rau 2015). 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 (2007) elicitation task, financial literacy (Lusardi and Mitchell 2011), expertise with capital market products (adapted from Thompson et al. 2005), disposition to trust or general propensity to trust others (McKnight et al. 2002), sociability (i.e., "tendency to affiliate with others and to prefer being with others to remaining alone"; Cheek and Buss 1981, pg. 330), experience with text-based conversational agents (e.g., chatbots on websites), gender (using a male dummy), and age.

4 Experimental Studies

4.1 Study 1: Impact of Investment Advice from a 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,[9] and collected data from 195 participants matched on 98 unique price paths. 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 Experimental Design, 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

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

conversion rate of 400 experimental currency units to 1€ and rounded up to the nearest 50 cents). Participants took 45 minutes on average to complete the experiment, and the average income was 7.50€.

We conducted nonparametric Mann-Whitney tests to identify any significant deviations in the self-assessed control variables across groups but do not find any significant differences in terms of risk-taking behavior, loss aversion, financial literacy, expertise with capital market products, disposition to trust, sociability, experience with chatbots, or 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 ($p = 0.023$). We therefore control for age in all subsequent analyses.

4.1.1 Results

We begin by addressing whether the availability of investment advice from a robo-advisor causally reduces the disposition effect, then present evidence on the mechanism underlying this effect. We also discuss participants' portfolio choices in more detail.

4.1.1.1 Advice from a Robo-Advisor and the Disposition Effect

Table 2 provides an overview of the DE measure; the means of the observed variables, including the number of interactions and the resulting final payout; and the means of self-assessed perceptions of socialness across treatments. Investors in the robo-advisor group sent 6.2 messages on average.[10] 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 call advice requests. Of the 97 participants randomly assigned to the robo-advisor group, 77 requested advice at least once. Participants in the robo-advisor group also earned more portfolio points (2,136.43) than participants in the control group (2,062.14), which resulted in an average increase of 2.7% in relation to the overall payout (Wilcoxon signed-rank test, $z = -2.096$, $p = 0.036$). Consistent with P1, participants in the robo-advisor group exhibit lower disposition effects than participants in the control group (Wilcoxon signed-rank test, $z = 2.955$, $p = 0.003$).

[10] In the questionnaire, we included a question to check whether participants were able to identify the name of the robo-advisor; more than 90% correctly identified "Charles" as the robo-advisor's name.

Table 2: Summary of main outcome variables across treatment groups

		Treatment	
		Control	Robo-Advisor
Disposition Effect	DE	0.06 (0.28)	−0.07 (0.32)
	PLR	0.14 (0.17)	0.23 (0.26)
	PGR	0.20 (0.21)	0.16 (0.16)
Requests	Advice requests	—	3.74 (3.33)
	Other requests	—	2.45 (3.04)
Anthropomorphism	Perceived socialness	4.64 (1.10)	5.16 (1.12)
Payout	Asset portfolio	1,325.00 (753.67)	1,601.30 (809.52)
	Total portfolio	2,062.14 (209.82)	2,136.43 (271.05)
	Total payout (in €)	7.40 (0.55)	7.57 (0.71)
No. of observations		98	97

Note: This table reports the means and standard deviations (in parentheses). For the disposition effect, the results refer to 97 (96) observations in the control (robo-advisor) group for which the disposition effect is defined.

To determine whether the reduction is driven by an increase in realized losses (i.e., through PLR) or a decrease in realized gains (i.e., through PGR), we separate the two components. The robo-advisor reduces the disposition effect by increasing investors' proportion of losses realized (Wilcoxon signed-rank test, $z = -2.844$, $p = 0.005$). Moreover, the difference between the population mean ranks for the proportion of gains realized is insignificant (Wilcoxon signed-rank test, $z = 0.653$, $p = 0.514$). Consistent with previous findings (Weber and Welfens 2007, Fischbacher et al. 2017), the correlation between PRL and PGR in the robo-advisor group, as well as in the control group, is insignificant (Sperman's $\rho_{\text{robo-advisor}} = -0.071$, $p_{\text{robo-advisor}} = 0.492$; Sperman's $\rho_{\text{control}} = 0.111$, $p_{\text{control}} = 0.280$). Thus, we establish a first result:

> **Result 1**: The disposition effect is significantly lower in the robo-advisor group than in the control group, mainly driven by an increase in the proportion of losses realized.

This effect relates to investors' selling behavior in the losses domain, which provides support for an explanation based on cognitive dissonance theory. In line with this theory, we posited that the availability of a robo-advisor reduces the discomfort that arises from owning an asset that has decreased in value, but no dissonance emerges if the asset increases in value, so we expected no difference in selling behavior in the gain domain, across treatment groups. Alternative explanations (e.g., realization utility, prospect theory) instead would imply a symmetric effect for PLR and PGR.

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[11] (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, $p < 0.001$). 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 ($t(96) = 2.09$, $p = 0.039$), but participants in the robo-advisor group produce a disposition effect measure that is significantly lower than 0, that is, a reversed disposition effect ($t(95) = -2.156$, $p = 0.034$). 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.

4.1.1.2 Mediation Analysis

Next, we assess the indirect effects of robo-advisors on the disposition effect according to both the number of advice requests and the perceptions of socialness (P2a and P2b). Using standard approaches for testing multiple mediation models (Preacher and Hayes 2008), we tease apart their individual indirect effects. First, we fit an ordinary least squares (OLS) regression equation to estimate the overall effect of robo-advisors on the DE measure, while accounting for the control variables (Equation 4). Second, we fit another OLS regression equation to assess the effect of robo-advisors on perceptions of socialness (Equation 5). Third, the number of advice requests is overdispersed (mean = 1.86; variance = 9.02), so we fit a negative binomial regression model to estimate the effect of robo-advisors on the number of advice requests (Gardner et al. 1995) (Equation 6). Fourth, we estimate the effect of robo-advisors on the DE measure, controlling for the number of advice requests and perceptions of socialness (Equation 7). Formally:

$$DE = a_0 + a_1 RoboAdvisor + \bar{a}_2 C + \varepsilon_1, \tag{4}$$

$$PerceivedSocialness = b_0 + b_1 RoboAdvisor + \bar{b}_2 C + \varepsilon_2, \tag{5}$$

$$\ln(AdviceRequests) = c_0 + c_1 RoboAdvisor + \bar{c}_2 C + \varepsilon_3, \tag{6}$$

$$DE = d_0 + d_1 RoboAdvisor + d_2 PerceivedSocialness + d_3 AdviceRequests + \bar{d}_4 C + \varepsilon_4, \tag{7}$$

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 and b_2 are vectors of the same length. Table 3 shows the results of the pathwise regressions of Equations 4 to 7.

[11] The DE measure is specified for 80 of the 98 price paths and ranges from −1 to 0.25.

Table 3: Pathwise regressions for disposition effects, advice requests, and perceptions of socialness

Model	(4)	(5)	(6)	(7)
Dependent Variable	DE	AdviceRequests	PerceivedSocialnes	DE
Treatment effect				
RoboAdvisor	−0.1447***	18.3552***	0.4416***	−0.0051
	(0.0491)	(0.1786)	(0.1680)	(0.0601)
Mediators				
AdviceRequests				−0.0366***
				(0.0111)
PerceivedSocialness				−0.0360*
				(0.0199)
Controls				
Risk aversion	−0.0130	−0.1375**	−0.0362	−0.0240
	(0.0161)	(0.0675)	(0.0555)	(0.0155)
Loss aversion	0.0345	−0.1475	−0.3019**	0.0199
	(0.0287)	(0.1739)	(0.1446)	(0.0267)
Disposition to trust	−0.0038	0.1075	0.0473	0.0076
	(0.0173)	(0.0682)	(0.0651)	(0.0157)
Sociability	−0.0288	0.0707	0.0848	−0.0209
	(0.0203)	(0.0789)	(0.0843)	(0.0189)
Financial sophistication	0.0243	0.0260	0.0833	0.0344
	(0.0488)	(0.1667)	(0.1895)	(0.0473)
Financial expertise	0.0005	0.0896	0.0189	0.0056
	(0.0188)	(0.0755)	(0.0798)	(0.0173)
Experience chatbots	−0.0407	0.2403**	0.0807	−0.0223
	(0.0281)	(0.1052)	(0.0987)	(0.0248)
Male	0.0051	−0.5239***	−0.4018*	−0.0485
	(0.0446)	(0.1706)	(0.2081)	(0.0446)
Age	−0.0010	−0.0084	−0.0063	−0.0014
	(0.0051)	(0.0207)	(0.0154)	(0.0041)
# trades	−0.0003	0.0148***	−0.0006	0.0007
	(0.0010)	(0.0033)	(0.0033)	(0.0011)
Duration	0.0002***	0.0004	0.0002	0.0003***
	(0.0001)	(0.0004)	(0.0003)	(0.0001)
Constant	0.1787	−18.2152***	4.7677***	0.2763
	(0.2215)	(0.8791)	(0.7866)	(0.2175)
Observations	193	193	193	193
R-squared	0.1235		0.1240	0.2101
Pseudo R-squared		0.3309		

Note: The first, third, and fourth columns contain the OLS regression results. The second column provides the results of a negative binomial regression (overdispersion parameter $\ln(\alpha) = -1.0381$, which is significantly different from 0, $p < 0.01$). Web Appendix 1 contains detailed specifications of all control variables. Regressions exclude two observations from participants whose DE is undefined. Robust standard errors are in parentheses and clustered on 98 unique price paths. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In Table 3, Model 4 confirms the nonparametric Wilcoxon sign-rank test: After accounting for control variables, the robo-advisor significantly reduces the disposition effect. Models 5 and 6 indicate positive and significant effects of the availability of a robo-advisor on the number of advice requests[12] and perceptions of socialness, respectively. After controlling for these variables, the direct effect of the robo-advisor on the disposition effect becomes insignificant, in line with commonly used methods to test for mediation (Baron and Kenny 1986).

Indirect effects can be determined according to the product of coefficients approach (Rucker et al. 2011). The indirect effect of perceived socialness, according to the specifications in Models 5 and 7, is given by the product of the coefficients $b_1 * d_2$. Following recent efforts to identify mediation effects when the relationships of the variables are nonlinear (in our case, the relationship between the number of advice requests and the treatment variable), we calculate the conditional indirect effects for selected values of $RoboAdvisor$ (e.g., Hayes and Preacher 2010, O'Rourke and Vazquez 2019, Geldhof et al. 2018, Coxe and MacKinnon 2010). The path between the treatment variable and the number of advice requests is the first partial derivative, with respect to $RoboAdvisor$, of the loglinear regression Equation 6—that is, the marginal effect of $RoboAdvisor$ on the prediction function for $AdviceRequests$. The following expression gives the indirect effect of the number of advice requests:

$$c_1 e^{c_0 + c_1 RoboAdvisor + \bar{c}_2 C + \varepsilon_3} * d_3. \tag{8}$$

We next tested for the statistical significance of the indirect effects, using bootstrapped confidence intervals (CIs) to accommodate the nonnormal distribution of the indirect effect (Preacher and Hayes 2008). As Table 4 shows, the CIs do not include 0, in support of P2a and P2b. Two separate paths exist and explain the mechanism underlying the reduction in the disposition effect due to the presence of a robo-advisor.

Table 4: Significance testing for indirect effects

Indirect effect over perceived socialness		
General formula	Indirect effect	95% bootstrapped CI
$b_1 * d_2$	−0.016	−0.050, −0.001
Conditional indirect effect over the number of advice requests		
$RoboAdvisor = 1$		
$c_1 e^{c_0 + c_1 RoboAdvisor + \bar{c}_2 C + \varepsilon_3} * d_3$	−1.961	−3.308, −0.695

Note: Bias-corrected bootstrapped CIs based on 1,000 iterations are reported. Conditional mediated effects assume values of C fixed at its mean, reported only for the robo-advisor treatment group, because the conditional indirect effect for the control group is 0 by design.

[12] By design, participants in the control group were not able to request investment advice.

We summarize these findings in our second result:

> **Result 2**: The effect of the availability of a robo-advisor on the disposition effect is mediated by (a) perceptions of socialness and (b) the number of advice requests.

4.1.1.3 Investors' Portfolio Choices

We next examine the effect of robo-advisor advice on the allocation of wealth. Overall, investors in the robo-advisor group hold more of their wealth in risky assets ($M_{robo\text{-}advisor} = 0.75$, $M_{control} = 0.64$, $t(193) = -2.141$, $p = 0.034$). Whereas investors in general tend to value their current liquidity higher than possible gains in the future, due to hyperbolic discounting or inertia (Laibson 1997, Bhattacharya et al. 2012), our findings suggest that robo-advisors may help reduce this bias. In our experimental research setting, investing more translates into an increase in overall profits, because the expected value of the portfolio of risky assets is positive. Therefore, robo-advisors help increase investors' profits by both reducing mistakes that might lead to the disposition effect and increasing investors' overall propensity to invest in risky assets. Stated differently, participants in the robo-advisor group earned more portfolio points by investing better and investing more. Comparing the relative impact of these effects on the profit increase in the robo-advisor group versus the control group reveals a stronger effect of the reduction in the disposition effect.[13]

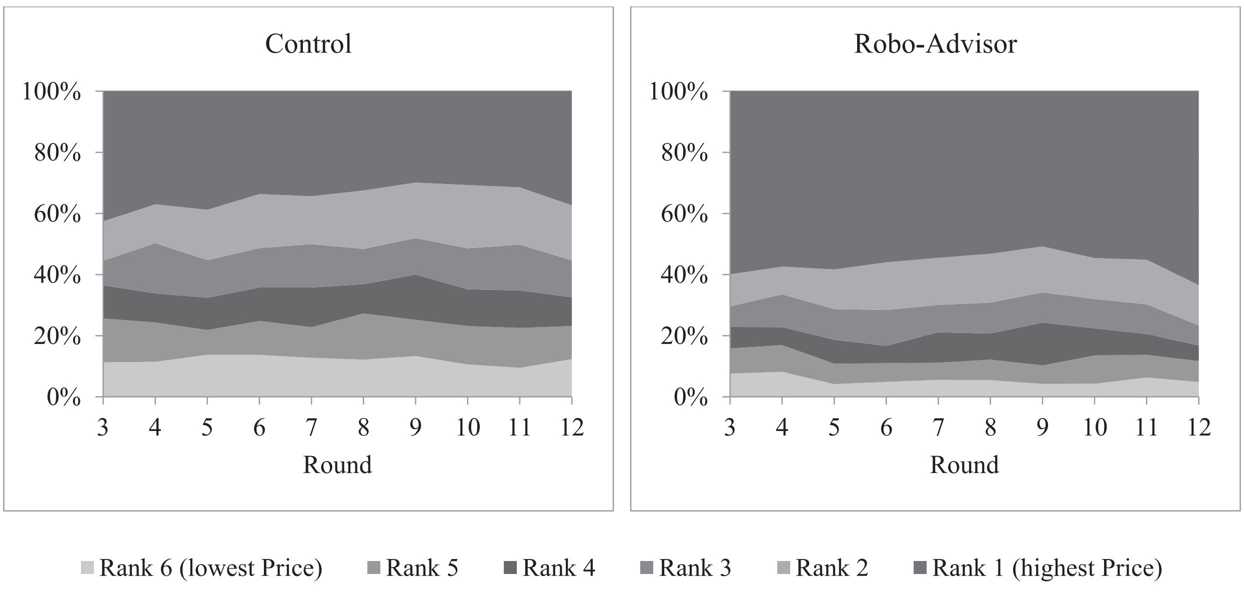

Figure 2: Average share of the invested amount in ranks relative to the budget invested in risky assets (y-axis) across trading rounds (x-axis)

[13] Assuming a difference of 220 portfolio points invested in risky assets and the actual average asset return in the control group of 0.49%, roughly 14% of the profit increment would result from an increase in the share of risky assets in the portfolio, while 86% comes from the reduction in the disposition effect.

To better illuminate the allocation of wealth, we examine specific allocations across the different assets. Figure 2 shows the portfolio allocation by rank across treatment groups. All assets are ranked in each period according to the price level, such that rank 1 represents the highest price and rank 6 represents the lowest. If two or more assets have the same price, they share the same rank, and the rank below is empty. For example, if assets A and B have the highest price in a particular period, both are assigned rank 1, and rank 2 remains empty. The average share of the invested amount in the asset with the lowest rank (i.e., highest price) relative to the amount invested in risky assets is higher in the robo-advisor group (56.3%) than in the control group (34.8%, Wilcoxon signed-rank test, $z = -5.286$, $p < 0.001$). Moreover, the average share of the invested amount in the asset with the highest rank (i.e., lowest price) is lower in the robo-advisor group (5.6%) than in the control group (12.1%, Wilcoxon signed-rank test, $z = 3.739$, $p < 0.001$). Note that the greater tendency to hold an asset with the highest price among the robo-advisor group, compared with the control group, remains consistent over time. The effect of the availability of a robo-advisor on the disposition effect thus does not appear likely to be subject to time-trend effects.

4.1.2 Discussion

These results demonstrate the potential benefit of robo-advisors for investment decisions. The availability of their unbiased investment advice significantly reduces investors' disposition to hold on to assets losing value for too long. Moreover, participants in the robo-advisor group earned significantly more portfolio points than participants in the control group (average difference of 74.29 portfolio points). 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. Furthermore, robo-advisors help facilitate investors' decisions to sell an asset at a loss but also increase the overall share of wealth invested in risky assets. This aspect is important, considering investors' tendency to underinvest persistently due to hyperbolic discounting (Laibson 1997). Moreover, we find support for both agency and advice effects. The presence of a robo-advisor increases perceptions of socialness, which then diminishes the disposition effect; the extent to which advice is sought (and received) also simultaneously reduces the disposition effect.

This experimental design allows us to establish a causal effect of the availability of investment advice from a robo-advisor on the disposition effect. In the second study, we also assess the impact of anthropomorphism achieved through design elements on investors' attitudes and behavior toward the advisor. Moreover, we explore the impact of anthropomorphic design elements on investment decisions, by comparing the impact of the availability of (the same) investment advice from an anthropomorphic robo-advisor versus a nonanthropomorphic recommendation algorithm.

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

In this between-subjects experiment, participants were randomly assigned to either the robo-advisor group or the recommendation algorithm group. The experimental instructions do not differ meaningfully from Study 1 but were slightly adapted for participants in the recommendation algorithm group. We included one additional open-ended question in the postexperimental questionnaire, regarding participants' investment strategy, to clarify their decision-making process and the potential influence of the availability of investment advice. We conducted the experiment in May 2020, with 259 participants from a large European university,[14] using the ORSEE software (Greiner 2015). They received a link to the experiment and completed it online, using their own PCs. We implemented a randomization algorithm in the survey, such that it randomly assigned participants to the robo-advisor group or recommendation algorithm group 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 a participant from the other treatment group, 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 200 experimental currency units to 1€ and rounded up to the nearest 50 cents). Participants took about 45 minutes to complete the experiment, and the average income was 12.30€. The nonparametric Mann-Whitney tests to identify any significant deviations between the treatment groups did not reveal any significant differences in terms of risk-taking behavior, level of loss aversion, financial literacy, expertise with capital market products, disposition to trust, sociability, experience with chatbots, gender, or age.

4.2.1 Results

We report the effect of anthropomorphic design elements on the disposition effect and discuss the mechanism underlying this effect, then consider how anthropomorphism shapes investors' advice-seeking and advice-following behavior in the following sections.

4.2.1.1 Anthropomorphic Design Elements and the Disposition Effect

Table 5 summarizes our results. In line with P3, perceptions of socialness are higher in the robo-advisor group than the recommendation algorithm group,[15] as also confirmed by the Mann-Whitney test ($z = 2.449$, $p = 0.014$). Moreover, the results suggest a negligible difference in the DE between the recommendation algorithm and the robo-advisor group. Differences in the proportion of gains and losses realized, the resulting DE measure, and final payoffs are insignificant across treatment groups. Although the number of advice requests in the recommendation algorithm group is higher than in the robo-advisor group (χ^2(17, n

[14] MELESSA laboratory of LMU Munich.

[15] More than 92% of the participants in the robo-advisor group correctly identified "Charles" as its name.

= 259) = 34.588, p = 0.007), when we account for other forms of requests, participants interacted more with the robo-advisor than the recommendation algorithm (χ^2(21, n = 259) = 32.424, p = 0.053).

Table 5: Summary of main outcome variables across treatment groups

		Treatment	
		Recommendation Algorithm	Robo-Advisor
Main Outcomes	DE	−0.03 (0.32)	−0.02 (0.27)
	PLR	0.21(0.25)	0.18 (0.19)
	PGR	0.18 (0.18)	0.16 (0.17)
Requests	Advice requests	4.71 (3.74)	3.19 (3.67)
	Other requests	—	2.02 (3.68)
Anthropomorphism	Perceived socialness	4.94 (1.06)	5.25 (1.10)
Payout	Asset portfolio	1,513.81 (851.53)	1,552.69 (808.82)
	Total portfolio	2,118.8 (305.51)	2,108.55 (249.29))
	Total payout (in €)	12.30 (0.89)	12.27 (0.74)
No. of observations		129	130

Note: This table reports the means and standard deviations (in parentheses). For the disposition effect, the results refer to the 123 (127) observations in the recommendation algorithm (robo-advisor) group for which the DE is defined.

Intuitively, anthropomorphism may give rise to two behavioral effects. On the one hand, it could hinder participants from requesting advice in the first place. On the other hand, if the robo-advisor is perceived as more social, it may be more susceptible to blame for a bad outcome. Therefore, we consider how perceived socialness affects participants' propensity to follow advice, which may increase the blame assigned to the advisor.

4.2.1.2 Mediation Analysis

To assess the overall effect of anthropomorphic design elements on the disposition effect, we fit Equations 4–7 with the new treatment variable $RecommendationAlgorithm$. In Table 6 and in line with the χ^2 test result, Model 5 shows a positive effect of the recommendation algorithm on the number of advice requests. Furthermore, the treatment of being assigned to the recommendation algorithm has a negative and significant effect on perceptions of socialness. This pattern is consistent with opposing mediation, or indirect effects of opposing signs, which results in a nonsignificant overall effect (O'Rourke and MacKinnon 2018).

Table 6: Pathwise regressions on disposition effects, advice requests, and perceptions of socialness

Model	(4)	(5)	(6)	(7)
Dependent Variable	DE	AdviceRequests	PerceivedSocialnes	DE
Treatment effect				
RecommendationAlgorithm	0.0129	0.4957***	−0.3191**	0.0357
	(0.0366)	(0.1147)	(0.1245)	(0.0364)
Mediators				
AdviceRequests				−0.0239***
				(0.0054)
PerceivedSocialness				−0.0339**
				(0.0159)
Controls				
Risk aversion	0.0127	−0.0022	0.0564	0.0140
	(0.0144)	(0.0438)	(0.0517)	(0.0134)
Loss aversion	0.0133	0.0908	−0.1219	0.0161
	(0.0213)	(0.0775)	(0.0824)	(0.0224)
Disposition to trust	−0.0221	0.0745	0.1563***	−0.0109
	(0.0168)	(0.0484)	(0.0502)	(0.0163)
Sociability	−0.0284	0.0229	0.0111	−0.0286
	(0.0191)	(0.0511)	(0.0592)	(0.0177)
Financial sophistication	−0.0158	−0.1067	−0.2193	−0.0298
	(0.0518)	(0.1413)	(0.1771)	(0.0485)
Financial expertise	0.0089	−0.0334	0.0228	0.0056
	(0.0141)	(0.0436)	(0.0530)	(0.0129)
Experience chatbots	−0.0265	0.1574*	0.2448***	−0.0061
	(0.0196)	(0.0818)	(0.0859)	(0.0186)
Male	0.0578	−0.2265*	−0.0800	0.0342
	(0.0471)	(0.1206)	(0.1782)	(0.0447)
Age	−0.0009	0.0016	−0.0077	−0.0008
	(0.0034)	(0.0105)	(0.0144)	(0.0038)
# trades	−0.0026***	0.0109***	0.0040	−0.0013
	(0.0010)	(0.0029)	(0.0030)	(0.0010)
Duration	0.0000	0.0005***	0.0002	0.0001
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Constant	0.2469	−0.3590	4.1062***	0.3550**
	(0.1492)	(0.4544)	(0.5365)	(0.1558)
Observations	250	250	250	250
R-squared	0.0862		0.1332	0.1741
Pseudo R-squared		0.0359		

Note: The first, third, and fourth columns contain the results from the OLS regressions. The second column provides the results from negative binomial regression (overdispersion parameter $\ln(\alpha) = 0.3801$ is significantly different from 0, $p < 0.05$). Web Appendix 1 contains detailed specifications for the control variables. Regressions exclude 9 observations from participants whose DE is undefined. Robust standard errors are in parentheses and clustered on 130 unique price paths. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We calculated the indirect effects over the number of advice requests and perceived socialness, as in Study 1. We also identified bootstrapped CIs for the sum of the indirect effects. As Table 7 shows, the CIs for the indirect effects do not include 0, which provides further support for the existence of two, directionally inconsistent, separate paths that explain the mechanism underlying the effect of omitting anthropomorphic design elements on the disposition effect. In the lower part of Table 7, the sum of indirect effects is insignificant in the nontreatment condition and slightly negative in the treatment condition, implying that the number of advice requests has a stronger indirect effect than perceived socialness does.[16]

Table 7: Significance testing for indirect effects

Indirect effect over perceived socialness		
General formula	Indirect effect	95% bootstrapped CI
$b_1 * d_2$	0.011	0.001, 0.032
Conditional indirect effect over the number of advice requests		
$RecommendationAlgorithm = 1$		
$c_1 e^{c_0 + c_1 RecAlg + \bar{c}_2 C + \varepsilon_3} * d_3$	−0.055	−0.111, −0.022
$RecommendationAlgorithm = 0$		
$c_1 e^{c_0 + c_1 RecAlg + \bar{c}_2 C + \varepsilon_3} * d_3$	−0.033	−0.057, −0.016
Conditional sum of indirect effects		
$RecommendationAlgorithm = 1$		
$c_1 e^{c_0 + c_1 RecAlg + \bar{c}_2 C + \varepsilon_3} * d_3 + b_1 * d_2$	−0.044	−0.101, −0.008
$RecommendationAlgorithm = 0$		
$c_1 e^{c_0 + c_1 RecAlg + \bar{c}_2 C + \varepsilon_3} * d_3 + b_1 * d_2$	−0.022	−0.046, 0.002

Note: Bias-corrected bootstrapped confidence intervals based on 1,000 iterations are reported. Conditional indirect effects assume the values of C are fixed at its mean.

This evidence indicates that anthropomorphic design elements are not sufficient for improving investment decisions and reducing the disposition effect. Furthermore, in line with P2b and the Study 1 results, we find evidence of an agency effect. The extent to which a digital advisor induces a feeling of social presence mitigates investors' disposition effect. As we predicted, perceived socialness also increases the saliency of the robo-advisor as someone to blame. Participants in the robo-advisor group indicated lower levels of self-accountability than participants in the recommendation algorithm group ($M_{\text{robo-advisor}} = 4.51$, $M_{\text{recommendation-algorithm}} = 4.79$, $t(257) = -2.078$, $p = 0.039$), in support of the notion that anthropomorphic design elements can mitigate feelings of being accountable or responsible for the outcome of investment

[16] In support of theoretical considerations regarding the agency effect, we find a positive correlation coefficient between perceived socialness and PLR (Spearman's $\rho = 0.108$, $p = 0.088$). The correlation coefficient between perceived socialness and PGR is slightly negative and insignificant (Spearman's $\rho = -0.085$, $p = 0.175$).

decisions. In Section 4.2.1.3, we delve into this effect to examine the relationship between perceived socialness and investors' responsiveness to advice.

Furthermore, we find a counterbalancing effect of anthropomorphic design elements. Specifically, they significantly reduce the number of advice requests and thereby mitigate the advice effect. Homing in on participants' advice-seeking behavior, fewer participants in the recommendation algorithm group (15 of 129) than in the robo-advisor group (41 of 130) did not request investment advice throughout the experiment. Moreover, the average number of advice requests from participants who asked at least once for advice was slightly (but insignificantly) lower in the robo-advisor group (4.663) than in the recommendation algorithm group ((5.372), $\chi^2(16, n = 202) = 21.072$, $p = 0.176$). Our third result accordingly note:

> **Result 3:** The relationship between the use of anthropomorphic design elements and the disposition effect is mediated by two directionally inconsistent indirect effects: (1) a negative indirect effect through perceptions of socialness and (2) a positive indirect effect through the number of advice requests.

4.2.1.3 The Impact of Anthropomorphism on Advice-Seeking and Advice-Following Behavior

The goal of this subsection is twofold. First, we seek to understand why increased perceptions of socialness reduce the disposition effect. In previous sections, we have argued that increasing perceptions of socialness facilitates assigning blame to the advisor, which reduces cognitive dissonance. In this section, we test whether the mere presence of the robo-advisor is sufficient to evoke this effect. Second, we analyze why investors seek more advice from a recommendation algorithm than from a robo-advisor.

To better understand the role of perceived socialness, we consider if and how responsiveness to advice can reduce the disposition effect. Moreover, we examine the impact of anthropomorphism on the extent to which investment decisions are influenced by advice, provided it is requested by the participant. We operationalize investors' responsiveness as the weight given to the advice (Bonaccio and Dalal 2006, Barham et al. 2018). Drawing from judge–advisor system literature (Sniezek and Buckley 1995, Bonaccio and Dalal 2006), our measure of the weight of advice (WOA) at the subject level is:

$$WOA_i = \frac{1}{|\Lambda_i|} \sum_{t \in \Lambda_i} \frac{judge\ final\ estimate_{i,t}}{advisor\ recommendation_{i,t}}, \tag{9}$$

where the set $\Lambda_i = \{3 \leq t \leq 12,\ adv_{i,t} > 0\}$ contains the investment rounds in which the total number of advice requests $adv_{i,t}$ from a participant i in period t is greater than 0. Then $|\Lambda_i|$ refers to the number of elements in Λ_i. The final decision of judge (i.e., participant) i in period t is given by $judge\ final\ estimate_{i,t}$, operationalized as participant i's share of the entire available budget (both the amount available from selling other assets in the portfolio and the amount in the money account) invested in the highest valued asset at time t. The investment advice from the robo-advisor is to invest all of the available budget into the asset(s) with the highest price. Therefore, $advisor\ recommendation_{i,t}$ is measured as participant i's maximum share of budget investable in highest valued asset in period t.[17] The WOA measure ranges from 0 (participant's share of wealth at the end of the period[s] in which advice is requested amounts to 0) to 1 (participant invests the highest possible amount in the highest-valued asset throughout the period[s] in which advice is requested).

We calculated this measure for the 89 (113) participants in the robo-advisor (recommendation algorithm) group who requested advice at least once. A higher average WOA measure emerges from the robo-advisor group (0.53) than the recommending algorithm group (0.48), though the difference is statistically insignificant ($t(200) = 1.134$, $p = 0.26$). Moreover, WOA correlates positively with perceptions of socialness (Spearman's $\rho = 0.186$, $p = 0.008$). Together, these results indicate that imbuing the robo-advisor with anthropomorphic design elements increases investors' feeling of being in the presence someone else but also can influence the weight that received advice carries with investors.[18] A greater WOA in our setting automatically translates into a reduction of the disposition effect. The disposition effect of participants in the robo-advisor group who did not request advice does not differ from that of participants in the recommendation algorithm group who also did not request advice ($M_{robo\text{-}advisor} = 0.098$, $M_{recommendation\text{-}algorithm} = 0.087$, $t(54) = 0.175$, $p = 0.862$). Instead, these participants differed in their perceptions of socialness ($M_{robo\text{-}advisor} = 5.233$, $M_{recommendation\text{-}algorithm} = 4.438$, $t(55) = 2.219$, $p = 0.031$).

Investors sought more advice from the recommendation algorithm, and we propose three potential motives: differences in perceptions of effort, a potential reduction of attention driven by the use of anthropomorphic design elements, and differences in attitudes due to variations in anthropomorphism. First, participants in the robo-advisor group had to write a message into the chat window, whereas participants in the recommendation algorithm group clicked a button to trigger investment advice. 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 slightly higher in the robo-advisor group than in the recommendation algorithm group, which suggests that perceived effort does not hamper their interactivity. This explanation is unlikely to explain our findings.

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[17] The variable $advisor\ recommendation_{i,t}$ always takes a value equal to or slightly lower than 1, due to budget constraints.

[18] We also assessed a measure of trusting beliefs toward the advisor, which can increase responsiveness to advice (e.g., Sniezek and van Swol 2001). We observe small, statistically insignificant differences in trusting beliefs toward the advisor across groups ($M_{robo\text{-}advisor} = 4.53$, $M_{recommendation\text{-}algorithm} = 4.42$, $t(257) = 0.657$, $p = 0.512$). However, when we examine the three dimensions of trusting beliefs (benevolence, integrity, and competence) independently, we find that participants in the robo-advisor group report higher trusting beliefs on the benevolence dimension than those in the recommendation algorithm group ($M_{robo\text{-}advisor} = 4.60$, $M_{recommendation\text{-}algorithm} = 4.18$, $t(257) = 2.258$, $p = 0.025$).

Second, digital agents in customer service settings arguably decrease consumers' cognitive load (Brachten et al. 2020), but anthropomorphic elements (e.g., allowing participants to ask a wide range of questions) could have a distracting effect and increase participants' cognitive load (Yang and Shen 2018). In our study context, perhaps participants trade off making requests that do not prompt investment advice with requests that do. However, the correlation coefficient between the number of advice requests and the number of messages about other topics (e.g., "What can you do?" "What is the return on my portfolio?") is slightly positive (Spearman's $\rho = 0.126$, $p = 0.043$). This finding suggests that participants tended to request advice to a greater extent if they also engaged in other interactions with the advisor. It thus cannot explain why participants might be more reluctant to request advice from a robo-advisor than a recommendation algorithm.

Third, theory suggests that individual receptivity to assistance may reflect both a motivation to maximize decision accuracy and maintain autonomy (Dalal and Bonaccio 2010). Giving up control over an investment decision may threaten self-esteem too (Usta and Häubl 2011). Asking for advice from an anthropomorphic advisor (which has a certain level of agency) may decrease investors' perceptions of their own personal agency. Therefore, anthropomorphic design elements may decrease investors' receptivity to assistance; in extreme cases, investors might even feel so threatened that they never seek advice. The difference in the extent of assistance sought due to motives related to maintaining autonomy offers a good potential explanation for the (negative) impact of anthropomorphic design elements on the number of advice requests.

Thus, simply increasing perceptions of socialness may not be sufficient to mitigate investors' disposition effect. Although increasing perceived socialness likely increases the weight investors assign to the advice, which increases their propensity to assign blame to the advisor, it does not translate into a greater propensity to follow the advisor's advice. Increasing anthropomorphism also keeps investors from seeking advice in the first place. It is therefore crucial to find an optimal level of anthropomorphic design elements to maximize both advice-seeking and advice-following behaviors.

4.2.2 Discussion

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 negative (i.e., mitigating) indirect effect of the use of anthropomorphic design elements through perceived socialness on the disposition effect. Moreover, anthropomorphic design elements render the advisor more susceptible to being blamed for a loss. In particular, participants in the robo-advisor group feel less accountable for their actions than participants in the recommendation algorithm group. Thus, notwithstanding the positive effects of anthropomorphizing technology on investment decisions, we find important behavioral consequences that may have counterbalancing effects, including reduced propensity to seek advice, which can strengthen the disposition effect. In reviewing potential explanations for this effect, we affirm an account based on investors' reduced propensity to seek advice due to the representation of the advisor (anthropomorphic vs. not).

We also can draw two conclusions from a qualitative analysis of participants' textual descriptions of their investment strategy (see Web Appendix 4). First, investors tend to assign humanlike characteristics to robo-advisors (e.g., described as "smart" and as making the participant feel safe). Second, we find a systematic difference in the extent to which investors are open to advice. Specifically, anthropomorphism may hinder participants from being influenced by the advisor, which leads to increased reactance and a lower propensity to seek advice in the first place. Notably, our results suggest that robo-advisors offer great potential in addressing investors' mistakes, but they also highlight the relevant boundaries to their effectiveness for reducing the disposition effect.

5 General Discussion

Our theoretical contributions are twofold. First, we contribute to behavioral finance literature by shedding light on the drivers and mechanisms of the disposition effect in the context of online advisory services. We affirm cognitive dissonance as an explanation of this disposition effect. In this regard, we extrapolate previous findings about the role of fund managers in facilitating investors' decisions in loss domains (Chang et al. 2016) to robo-advisors. These technologies increasingly are being designed to provide investment advice but also to appear human, reflecting a general notion that people dislike and mistrust algorithms (Logg et al. 2019). In examining the impact of these joint objectives (providing advice and appearing more human), our study highlights some risks of neglecting the potential negative outcomes of anthropomorphizing technology. Our methodical approach and controlled conditions help disentangle the effects of anthropomorphism versus the influences of the investment advice itself.

A long-standing debate exists about whether the disposition effect is driven by preferences or beliefs (Ben-David and Hirshleifer 2012, Fischer and Maier 2019). We derive predictions from cognitive dissonance theory, which suggests a belief-based explanation. Essentially, we argue that delaying the realization of losses represents a way for investors to reduce their feelings of discomfort after learning that an asset has decreased in value. Robo-advisors influence investors' beliefs in two ways: They learn from the investment advice, and then they feel as though they can assign blame and responsibility to the robo-advisor, regardless of its actual responsibility (Gurdal et al. 2013).

We briefly elaborate on alternative, preference-based explanations (e.g., shift in reference points away from purchase prices to current prices, prospect theory) which would predict a symmetric effect of an increase in the proportion of losses realized and a decrease in the proportion of gains realized. Yet we find that the reduction in the disposition effect, due to the availability of a robo-advisor, results solely from an increase in the proportion of losses realized, in support of an explanation based on cognitive dissonance theory. Moreover, we rule out the possibility that preferences change due to greater utility realized from stronger emotional reactions in the presence of an advisor. Despite previous findings that investment decisions lead to more pronounced disposition effect due to stronger feelings of regret after a loss and joy after a gain (Rau 2015), in our study, the measures of joy and regret do did not differ across groups. We thus cannot support a preference-based explanation.

Second, our experimental design reveals heterogeneity in participants' advice-seeking behavior. It extends 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, Tomaino et al. 2020) foster responsiveness to algorithmic advice. To the best of our knowledge, this study is the first to examine the impact of anthropomorphic design elements of robo-advisors on the extent to which advice is sought and followed, as well as its subsequent effect on economic performance (i.e., investment decisions). We replicate previous results about the positive effect of advice on decision accuracy (Rader et al. 2017), then further identified effects of anthropomorphic design elements on advice-seeking behavior, as well as on the 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 anthropomorphized, because investors' motive to maintain autonomy reduces their propensity to seek advice from an advisor with anthropomorphic design elements. We also offer suggestive evidence of a positive effect of anthropomorphic design elements on the extent to which investors follow advice, measured as the weight the advice carries in investors' decisions.

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. Anthropomorphic design elements are popular currently (Hodge et al. 2020), and robust empirical evidence indicates that anthropomorphizing technology can foster social connections and increase outcomes such as likeability or ease of use (Epley et al. 2007, Qiu and Benbasat 2009). Our results add to this evidence: Anthropomorphizing technology through design elements can increase financial welfare by enhancing investors' responsiveness to the advice. However, this effect may be counterbalanced by a reduction in investors' propensity to ask for advice.

This study focuses on one instance of robo-advisory applications, characterized by a high degree of user control (i.e., investors must proactively ask for investment advice and retain full agency over the decision). If user control were diminished (e.g., investment advice automatically pops up), investors might benefit more from anthropomorphism. When users must proactively seek advice (as often occurs in real life), managers should account for the potentially unwanted side effects of anthropomorphizing technology. An optimal degree of anthropomorphism would combine some anthropomorphic design elements to leverage the agency effect with alternative types of advice. For example, insights for how to make an investment decision or social support (e.g., acknowledging difficulty of a decision) might help investors to feel less restricted in their freedom, thereby increasing their propensity to seek advice (Dalal and Bonaccio 2010). Furthermore, guiding investors in how to make a decision, instead of mandating the decisions to make, might foster greater willingness to cooperate with the advisor, which also may be strengthened by perceptions of socialness (Greiner et al. 2014). Such insights also might apply in other industries, such as health care and insurance, that involve objectively measurable outcomes. The potential of well-designed automated advisory services for these industries and their consumers is tremendous.

Such generalizability is not guaranteed though and should be tested further. Other avenues for research might address some limitations of our study as well. First, the experimental subjects were primarily university students, such that the results might not generalize to other demographic groups. A more representative sample of potential users of robo-advisory services would offer greater external validity. Second, we tested our predictions in controlled experiments, and participants only interacted for a limited time with the system. Laboratory settings and real interactions with robo-advisor tools differ in important ways, and factors that emerge during longer relationships with the advisor or increased familiarity with the technology could affect the results (Rader et al. 2017). That said, we note that 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. The validity of our results also 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 should test the proposed mechanisms in a field experiment. 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 (Goodman and Flaxman 2017). 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 and advice-following behaviors thus represents a fruitful research avenue. Fourth, we observe significantly fewer advice requests to the robo-advisor compared with the recommendation algorithm and hope that continued research will address the impact of anthropomorphic systems on investors' sense of restricted autonomy, as well as the subsequent behavioral (and economic) consequences.

6 Conclusions

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 (Ariely and Jones 2008). 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 (Looney and Hardin 2009, Agnew 2010). The shift toward automation thus 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. 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 anthropomorphic 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 real economic costs.

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Web Appendix for "Do Robo-Advisors Make Us Better Investors"

Web Appendix 1: Measurement Scales

Construct	Items	Reference	Study 1 [a)]	Study 2
Perceptions of socialness	How well do the following items describe the user interface of the experiment? - helpful - intelligent - polite - informative - interactive (7 point Likert scale ranging from 'not at all' to 'very much')	Wang and Benbasat (2009) Wakefield et al. (2011)	Mean: 4.90 Std. Dev.: 1.13 Cronbach's alpha: 0.87	Mean: 5.10 Std. Dev.: 1.09 Cronbach's alpha: 0.87
Self-accountability	How accountable do you feel with regards to the outcome of the portfolio? How accountable are you in protecting your investments from price decreases? How strongly do you feel that it is your responsibility to protect your portfolio from price decreases? (7 point Likert scale ranging from 'not at all accountable' to 'very accountable')	Passyn and Sujan (2006)	Mean: 4.50 Std. Dev.: 1.11 Cronbach's alpha: 0.65	Mean: 4.65 Std. Dev.: 1.11 Cronbach's alpha: 0.62
Trusting beliefs [b)] Dimensions: - Competence (items 1-4) - Benevolence (items 5-7) - Integrity (items 8-11)	The robo-advisor is competent and effective in providing advice. The robo-advisor performs its role of giving advice very well. Overall, the robo-advisor is a capable and proficient advice provider. In general, the robo-advisor is very knowledgeable. I believe that the robo-advisor would act in my best interest. If I required help, the robo-advisor would do its best for me. The robo-advisor is interested in my well-being, not just its own. The robo-advisor is truthful in its dealings with me. I would characterize the robo-advisor as honest. The robo-advisor would keep its commitments. The robo-advisor is sincere and genuine. (7 point Likert scale ranging from 'strongly disagree' to 'strongly agree')	McKnight et al. (2002)	Mean: 4.68 Std. Dev.: 1.15 Cronbach's alpha: 0.93	Mean: 4.48 Std. Dev.: 1.31 Cronbach's alpha: 0.94

Rejoice	How much rejoice did you feel when you owned shares which had increased in value compared to the previous period? (7 point scale ranging from 'no rejoice' to 'strong rejoice')	Rau (2015)	Mean: 5.36 Std. Dev.: 1.31	Mean: 5.50 Std. Dev.: 1.29
Regret	How much regret did you feel when you owned shares which had decreased in value compared to the previous period? (7 point scale ranging from 'no regret' to 'strong regret')	Rau (2015)	Mean: 4.40 Std. Dev.: 1.71	Mean: 4.54 Std. Dev.: 1.73
Attitude towards risk	How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? (7 point scale ranging from 'completely unwilling to take risks' to 'completely willing to take risks')	Dohmen et al. (2011)	Mean: 4.07 Std. Dev.: 1.57	Mean: 4.02 Std. Dev.: 1.59
Loss aversion [c)]	Assume that for each of the ten questions a coin is thrown. The coin can either land at "heads" or "tail". To answer each of the ten questions you will either have to choose "accept" or "reject". 1.) If the coin shows "heads" you will lose 2€; if it shows "tail" you will win 10€. … 10.) If the coin shows "heads" you will lose 11€; if it shows "tail" you will win 10€.	Gächter et al. (2007)	Mean: 1.68 Std. Dev.: 0.74 Min: 0.83 Max: 5	Mean: 1.74 Std. Dev.: 0.79 Min: 0.83 Max: 5
Financial sophistication [d)]	Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? [More than $102 / Exactly $102 / Less than $102 / Do not know / Refuse to answer] Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? [Exactly the same / Less than today / Do not know / Refuse to answer] Please tell me whether this statement is true or false. 'Buying a single company's stock usually provides a safer return than a stock mutual fund' [True / False / Do not know / Refuse to answer]	Lusardi and Mitchell (2011)	Share of financial sophisticated participants: 63%	Share of financial sophisticated participants: 75%
Expertise with capital market products	How familiar are you with capital market products? (7 point scale ranging from 'not familiar at all' to 'very familiar') I know a lot about investing in capital market products. (7 point scale ranging from 'strongly disagree' to 'strongly agree') How frequently do you invest in capital market products? (7 point scale ranging from 'never' to 'all the time')	Thompson et al. (2005)	Mean: 2.48 Std. Dev.: 1.32 Cronbach's alpha: 0.89	Mean: 2.82 Std. Dev.: 1.67 Cronbach's alpha: 0.94

Experience with text-based conversational agents (e.g., chatbots)	How often do you use chatbots (e.g. on websites)? (5 point scale ranging from ‘never’ to ‘every day’)	Self-developed measure	Mean: 1.77 Std. Dev.: 0.79	Mean: 1.83 Std. Dev.: 0.78
Disposition to trust	My typical approach is to trust new information technologies until they prove to me that I shouldn’t trust them. I usually trust in information technology until it gives me a reason not to. I generally give an information technology the benefit of the doubt when I first use it. (7 point Likert scale ranging from ‘strongly disagree’ to ‘strongly agree’)	McKnight et al. (2002)	Mean: 4.15 Std. Dev.: 1.45 Cronbach’s alpha: 0.86	Mean: 4.31 Std. Dev.: 1.31 Cronbach’s alpha: 0.82
Sociability	I like to be with people. I welcome the opportunity to mix socially with people. I prefer working with others rather than alone. I find people more stimulating than anything else. (dropped) I'd be unhappy if I were prevented from making many social contacts. (7 point Likert scale ranging from ‘strongly disagree’ to ‘strongly agree’)	Cheek and Buss (1981)	Mean: 5.19 Std. Dev.: 1.05 Cronbach’s alpha: 0.77	Mean: 5.03 Std. Dev.: 1.16 Cronbach’s alpha: 0.80

Notes: [a)] Results for trusting beliefs include only observations from the robo-advisor group (n=97). All other constructs include all 195 observations.
[b)] For participants in the recommendation algorithm group, we referred to “the algorithm that provides advice” instead of “the robo-advisor”.
[c)] Loss aversion coefficient is calculated as the quotient of potential gains and the potential losses of the first lottery which is no longer accepted (switching point). The measure ranges from 5 (= 10/2), if the first lottery is rejected) to 0.91 (= 10/11), if only the last lottery is rejected. We assumed a measure of 0.83 (=10/12) if the subject did not reject any of the lotteries.
[d)] We measure financial sophistication as a binary variable equal to one if participants answered all three questions correctly, see also Bursztyn, Ederer, Ferman, and Yuchtman (2014).

Web Appendix 2: Experimental Instructions

Instructions[1]

In the following, we present a full translation of the instructions for the control group. Instructions for the robo-assistant and recommendation algorithm are identical, except for the highlighted text in grey, which is added for these treatment groups. We further indicate the differences between the robo-advisor group and the recommendation algorithm group by "[]".

Dear participant,

Welcome to this experiment. We thank you for your interest in our research. The entire duration of the experiment will be approximately 45 minutes. The experiment is divided into two parts. The first part consists of an economic decision-making experiment. The second part consists of a questionnaire. You will be able to earn money based on your decisions. At the end you will be forwarded to an external survey where you can enter the required information for the disbursement of the earned amount.

Please do not conduct the experiment on a mobile device (cell phone or tablet). Only laptops or PCs are allowed. To be able to participate in the study, please use the browser Firefox or Google Chrome. We recommend the latest version. All other browsers are not supported and you will not be able to participate! In addition, a resolution of at least 1920 x 1080 pixels on your device is recommended in order for the next pages to be displayed correctly. Please conduct the experiment in full screen mode (press the F11 key on your keyboard).

For participating in this experiment you will receive a fixed and a variable amount of money. The fixed amount is 6€. The variable amount of money depends on your decisions during the experiment. It is therefore important that you read the following instructions carefully.

For the payment of the total amount earned you have the choice between a bank transfer or a transfer via PayPal. At the end of the experiment you will be redirected to a new survey where you will be asked to enter the data required for the chosen transfer modality. The data entered here will not be linked to the data obtained in the experiment. The entire amount will be transferred to your account within the next ten working days.

During the entire experiment you are not allowed to communicate with other participants, use mobile phones or start other programs on the computer. If we subsequently discover that you have violated any of

[1] The translated instructions (from German) from the second study are shown. Instructions for the first study are identical expect for the paragraphs in relation to the technical restrictions and the availability of different payment methods for disbursement (which were omitted for a laboratory setting) as well as the slightly different fixed fee and conversion rate.

these rules, we will unfortunately have to exclude you from the experiment and all its payouts. If you have any questions, please use the contact field at the bottom left of each page. An experiment coordinator will be available at all time during the session and will respond to your questions as soon as possible. You will receive an answer within a few minutes.

In the experiment itself, we do not talk about euro, we talk about experimental monetary units. The number of experimental monetary units you receive in the experiment are converted into euro with the following exchange rate at the end of the experiment:

350 experimental monetary units = 1€

Your payout will be rounded up to 50 eurocents and you will be told the exact payout amount at the end of the experiment.

The following pages explain the experiment in detail. You will also see a video that explains the interface and shows your decision options during the experiment.

The Experiment

This experiment is about trading shares. The experiment consists of 14 periods (period 0 to 13). In the first periods you cannot trade. Instead you observe the price developments of the shares. In period 3 to period 12 you can buy and sell 6 different shares (share A to share F). To this end, you will receive 2000 experimental monetary units. You may hold shares in your portfolio until the end. In the last period, the portfolio of shares is valued according to the last available prices.

Please observe the following rules for trading units:

- Your balance cannot be negative, i.e. you can buy additional units if your balance exceeds the price of the unit you wish to buy.
- Short sales are not permitted, i.e. you can only sell shares that you own.

Your Robo-Assistant

In this experiment you are supported by a Robo-Assistant named Charles. Charles is a computer program designed to answer basic questions about your portfolio and the price movements of the shares. In addition, the Robo-Assistant can make investment recommendations based on an algorithm.

[Investment recommendations

In this experiment you have the possibility to ask for an investment recommendation. The investment recommendations are based on an algorithm.]

Price development

Each of the six shares has a starting price of 100 in period 0, after which the price of each share changes. The price either increases by 6% or decreases by 5% from one period to the next, i.e. the prices of the shares change in each period.

The price changes of the shares are determined randomly. Therefore, all price changes of all shares are independent of your buying/selling decisions. The same applies to all buy/sell decisions of the other participants in the experiment.

Each of the shares is of a certain type. The types differ in their probability of increasing (decreasing) in value at the beginning of the period. In the experiment there will be exactly one share of type "++", one share of type "+", one share of type "-", one share of type "--" and two shares of type "O". The number of shares of each type as well as the underlying probability distributions are shown in the following table. However, the exact allocation between shares and types is unknown.

Market Shares	Type	Probability of increase	Probability of decrease
1	++	60%	40%
1	+	55%	45%
2	O	50%	50%
1	-	45%	55%
1	--	40%	60%

Example

- Assume that the share A corresponds to the type "++"
- At the beginning of each period, the probability of an increase in the price of the share A is 60%
- At the beginning of each period, the probability of a price reduction of the share A is 40%
- If the price of the share A falls, it is reduced by 5%, if the price rises, it is increased by 6%

[Next, participants saw a video with text descriptions. The video showed and explained the surface of the experiment as well as how to buy/sell shares. They were tailored to each treatment group.]

Your Robo-Assistant

As you have seen in the video, you can chat with your robo-assistant Charles during the experiment. You can ask Charles basic questions about your portfolio or the price development of the shares. You can also ask for investment recommendations.

The following are sample questions that you can ask your robo-assistant

- "Which share has gained the most value? “
- "Which share has lost the most value? “
- "If share C increases in value, how much will it be worth in the following period? “
- "How many times did share F gain in value? “
- "How much is my portfolio worth? “
- "How many currency units would I receive if I sold all my shares? “
- "Who are you? “
- "What are your capabilities? “
- "Can you please give me some advice? “
- "What shares should I buy? “
- "What shares should I sell? “

Calculation of your variable payout amount

The experiment ends after period 13, all shares in your portfolio are automatically sold at the current price and the experimental currency units are added to your balance.

The variable amount of money you receive for this experiment is the result of:

Variable amount of money = your balance + value of the shares in your portfolio

Control questions *[correct answers in brackets]*

To ensure that you have understood the sequence of events in the experiment, please answer the following control questions. Your answers to the control questions have no influence on the amount of money you earn in this experiment.

- Does your trading activity influence the price development?

□ Yes

□ No [*correct answer*]

- Are the prices of the six shares determined independently?

□ Yes [correct answer]

□ No

- Suppose you buy a unit of the shares C, D and F in period 3 at the price of 96 and keep it in your portfolio until the end of the experiment. Does each of these units have the same probability of a price increase?

□ Yes

□ No [*correct answer*]

- By how much do prices rise when they rise?

□ 6 % [*correct answer*]

□ 5 %

- By how much do prices fall when they fall?

□ 6 %

□ 5 % [*correct answer*]

Summary of Control Questions

Before the experiment begins, in the following you will see the correct answers to the control questions as well as brief explanations:

Does your trading activity influence the price development?

NO. The prices are determined randomly. This means that prices are not influenced by your trading activity or the trading activity of other participants.

Are the prices of the six shares determined independently?

YES. Each investment has a specified probability of increasing or decreasing in value at the beginning of the period. These probabilities are independent of each other.

Suppose you buy a unit of the shares C, D and F in period 3 at the price of 96 and keep it in your portfolio until the end of the experiment. Does each of these units have the same probability of a price increase?

NO. There are a maximum of two shares for which the probability of a price increase is identical.

By how much do prices rise when they rise?

The price increases by 6% per period.

By how much do prices fall when they fall?

The price is reduced by 5% per period.

Web Appendix 3: User Interface

In the following, we present screenshots of the user interface during the experiment in all treatment groups for an exemplary price path. For comparison purposes, we assume that the investment decisions across the treatment groups do not vary. In period 3, the participant purchases 9 shares B and 9 shares C. In period 5, the participant requests an investment recommendation (except in the control group). In the same period, the participant sells all holdings in shares B and C and buy 16 shares A. The participant in the screenshots is assumed to be in period 7.

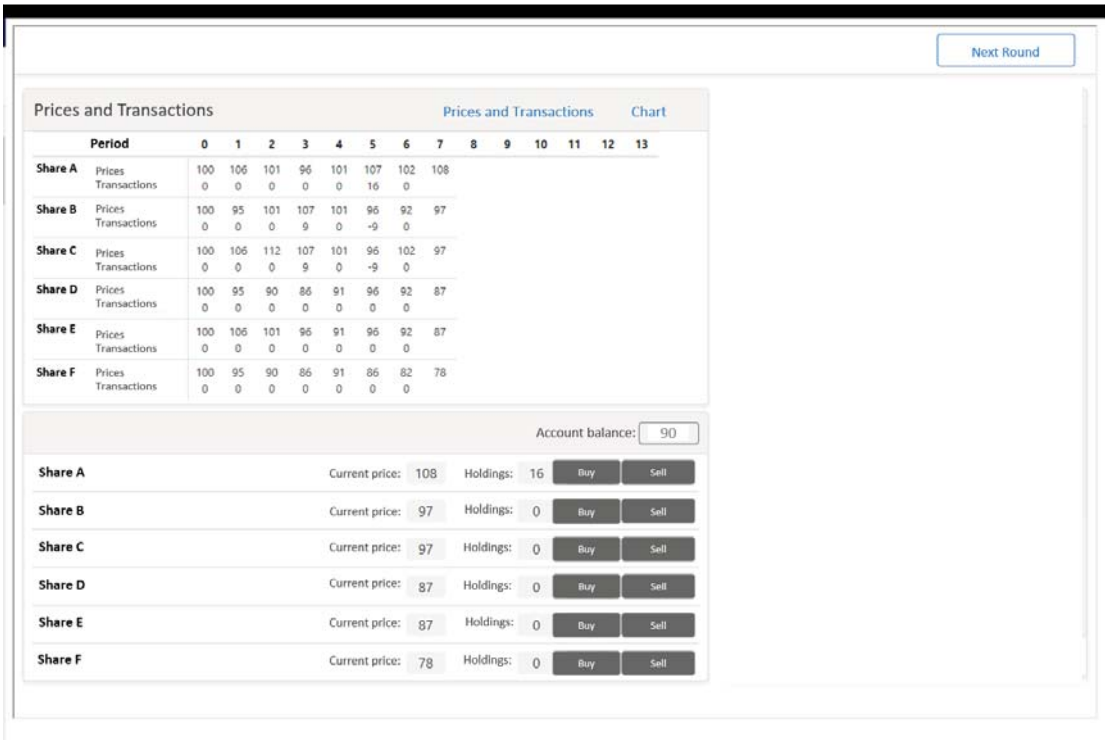

Figure A1: User interface in the control group.

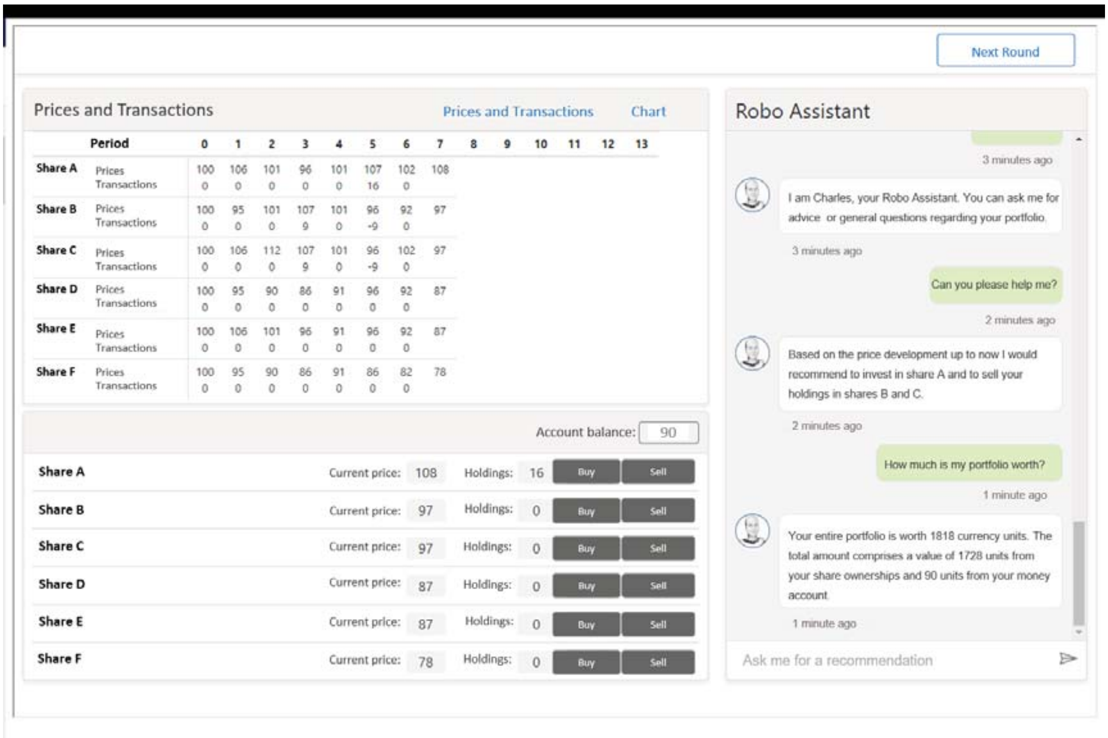

Figure A2: User interface in the robo-advisor group.

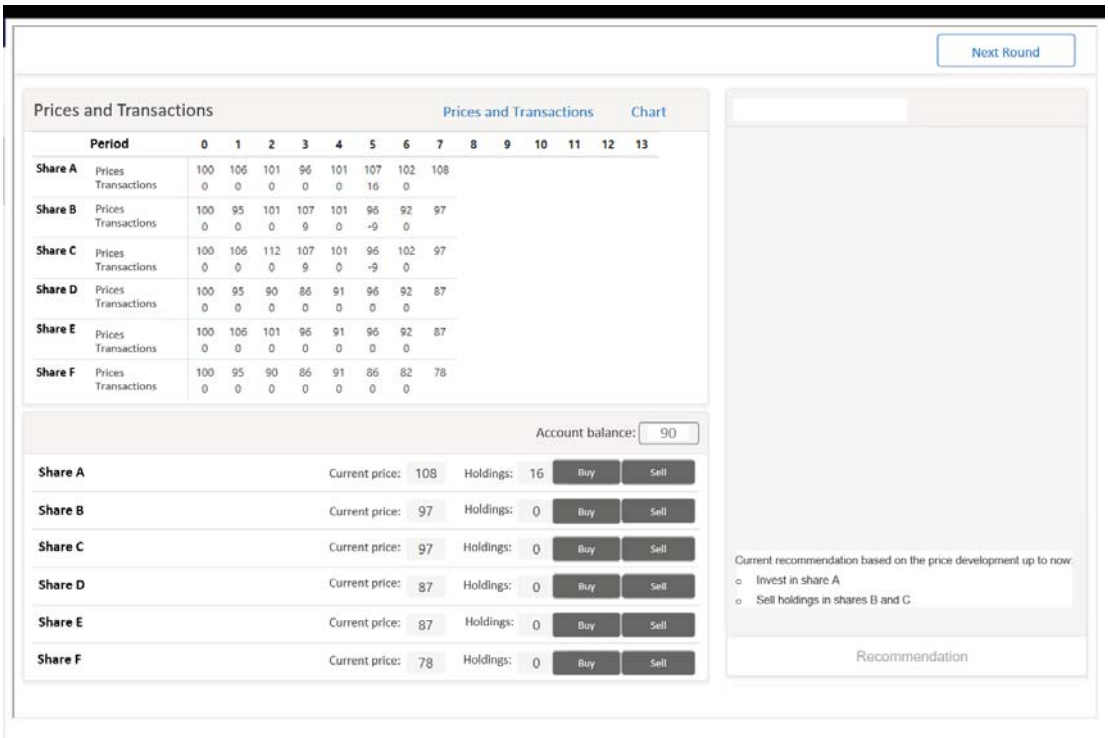

Figure A3: User interface in the recommendation algorithm group.

Web Appendix 4: Supplementary Qualitative Analysis (Study 2)

In this section, we examine participants' text-based responses to the applied investment strategy. We collected 215 open-end-type written answers regarding participants' investment strategy. We performed a qualitative analysis following standard procedures (Gioia et al. 2013). First, we identified relevant categories. Then, the data was coded by two "uninformed" coders. In case of a mismatch, the data was revisited by the co-authors and consensual decision rules were applied regarding the interpretation of the data. Since we are primarily interested in the influence of the digital advisor, we base our analysis on the subset of observations that includes a reference to either the advisor or the investment advice in general. These observations amount to 81 out of the 215 observations. We identified two relevant categories. The first one refers to the extent to which the advisor is anthropomorphized, i.e. assigned humanlike traits such as benevolence, malevolence, or social companionship (Epley et al. 2007). Accordingly, the variable *anthropomorphization* was coded as a dummy variable taking the value of one if the advisor was assigned humanlike traits and zero otherwise. The second identified category refers to whether the advisor positively influences investors' strategy, i.e. if there is to some degree a convergence towards the expected profit maximizing strategy applied by the algorithm. Accordingly, the variable *influence* was coded as a dummy variable, i.e. taking the value of one if the advisor exerted positive influence and zero otherwise (see also Table A1 for exemplary quotes and codifications across the identified categories).

Strategy description (exemplary quote)[2]	Anthropomor-phization	Influence	Treatment group
„No strategy considered beforehand. Orientation towards the bot's advice and focus on the rising curve. "	0	1	Recommendation algorithm
„The robo-advisor was something else. It's crazy how you feel more 'in good hands' even though you don't know if he means well with you. But his 'presence' alone made me feel safe, even if I didn't follow his advice."	1	0	Robo-advisor
„At first I wanted to invest equally across the assets D, E and F, because all three had positive developments. However, the bot's advice changed my mind because I thought that he was smarter than me. "	1	1	Robo-advisor
„I asked Charles for advice once, and I followed the advice and bought some shares F. However, I should trust myself more, since the robot could only take past price developments into consideration, just as me. If I act reasonable, I don't need the advice from the robot, since I can reach the same conclusions myself. "	1	1	Robo-advisor
„At the beginning I paid attention to the advice, but then I noticed that the advisor only recommended assets with increasing prices. I looked more at the graphical representations and decided for myself how likely it is that a price will rise again. "	0	0	Recommendation algorithm

Table A1: Exemplary quotes and assigned codes from qualitative analysis

Figure A4 shows the resulting categories across groups. From the bar chart on the left side, we note that participants indeed anthropomorphized the robo-advisor to a larger extent compared to the recommendation algorithm ($\chi^2(1, n = 81) = 30.80, p < 0.001$). Moreover, the bar chart on the right side indicates that the recommendation algorithm exerted a bigger influence on investors' strategy compared to the robo-advisor ($\chi^2(1, n = 81) = 2.99, p = 0.084$). In other words, participants in the robo-advisor group hold on to their own strategy to a greater extent and are more reluctant to investment advice. Indeed, we find that participants who are coded with influence = 1 requested more often advice compared to participants with influence = 0 ($\chi^2(17, n = 81) = 32.565, p = 0.013$).

[2] Quotes were translated by one of the co-authors.

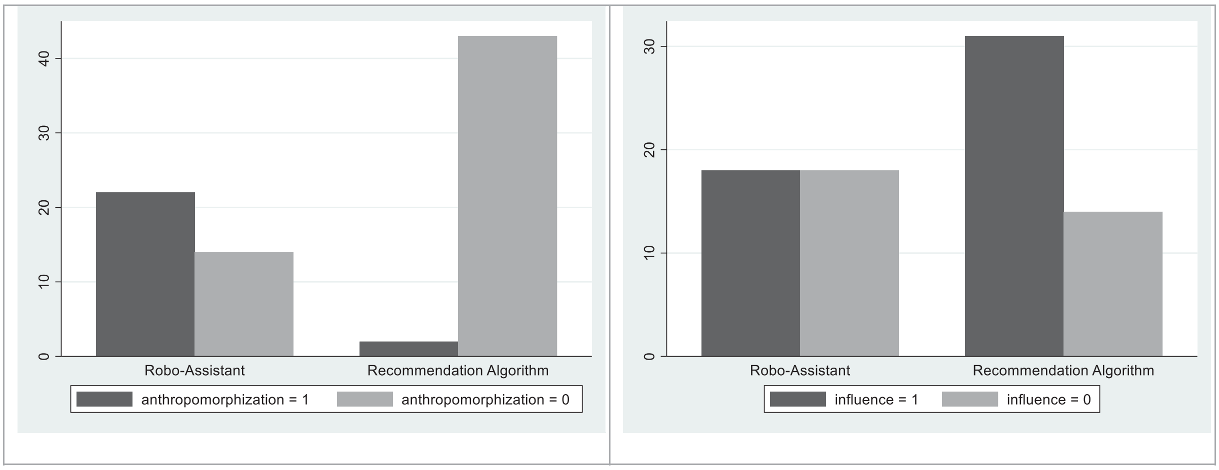

Figure A4: Results from qualitative analysis

We summarize our findings in two results.

Result A1: Anthropomorphic design elements increase investors' propensity to describe the robo-advisor with both positive and negative humanlike traits (e.g., intention, intelligence).

Result A2: Anthropomorphic design elements decrease investors' propensity to imply an adaptation of their investment strategy toward the expected profit maximizing strategy.

Web Appendix 5: The Robo-Advisor Application

Figure A5 illustrates the communication between users and the implemented robo-advisor from a conceptual perspective. The robo-advisor compromises six components: (i) the program logic, (ii) the game data, (iii) the Azure Bot Service, (vi) the Meta-LUIS, (v) the question and answer (QnA) Maker, as well as (vi) the Main-LUIS. The program logic and the game data components are part of the web-based application and include the trading game logic, dialog manager, storage of all game data and the integration of the robo-advisor chatbot which comprises the four remaining components. Azure Bot Service receives messages from the program logic, processes them and sends the response back to the program logic. Meta-LUIS is a component instantiating Microsoft's language understanding intelligence service (LUIS) and decides if the incoming user message is processed by one of our two natural language processing components: QnA Maker or Main-LUIS. Specifically, every incoming message is processed by both components and the return results include an additional confidence score. Based on this confidence score, Meta-LUIS decides which of the two results is sent back to the Azure Bot Service.

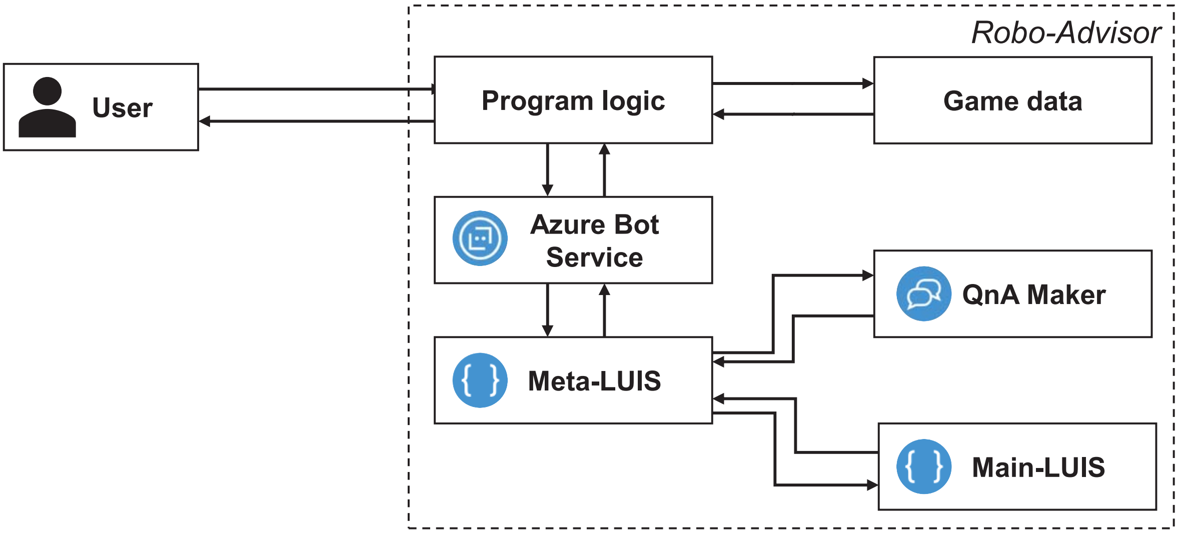

Figure A5: Conceptual Overview

The QnA Maker[3] provides an easy-to-use service to provide answers to common questions, similar to Q&A websites. The general process is as follows: First, exemplary questions or phrases with their respective answers (e.g., phrase: "Thanks", answer: "You are welcome") are provided. Second, the service runs a machine learning algorithm to train the model based on the input in the first step. Lastly, interactions with users based on natural language are facilitated by the model. The trained model is able to identify alternative phrasings and return an appropriate answer based on confidence scores.

[3] https://www.qnamaker.ai/

Table A2 shows the question-and-answer pairs in the QnA Maker component for our robo-advisor, i.e. the training data for the model. In our instantiation of the robo-advisor we relied on the QnA maker for responding to small talk questions. Here, user messages correspond to participants' inputs (first column). After the input is processed, the robo-advisor responded with the corresponding reply (second column).

User messages	**Answer**
Thanks	You are welcome
Hey	Hello
How are you doing?	I am doing very well. Thanks for asking!
What are you?	I am Charles, your Robo Assistant. You can ask me for advice or questions regarding your portfolio.
How old are you?	I was first created in the summer of 2019 in the code of a programmer and since then I have been developing continuously.
Who programmed you?	Very dedicated researchers have programmed me. I am constantly being developed and am learning more and more.
Note: All questions and answers were trained in German and translated for this article.	

Table A2. Exemplary questions and answer pairs of our robo-advisor (QnA Maker component)

The Main-LUIS is a natural language processing component offered by Microsoft that is able to recognize previously trained entities and intents in text-messages. An entity is a defined variable in LUIS, which acts as a placeholder and can take one of a set of specified values (e.g., the entity "Share" can take the values "A", "B", "C", "D", "E", or "F"). If a user message contains a reference to an entity, LUIS is capable of recognizing the entity during the linguistic processing of the message and marks it accordingly. An intent indicates the meaning or the goal of a message. Intents are recognized by LUIS based on the trained model. Table A3 and Table A4 display the entities and intents configured in LUIS for our robo-advisor accordingly. We use the Main-LUIS component to process user messages that refer to the trading game and are not considered small talk. To train the model in Main-LUIS, we provided multiple exemplary sentences for each intent and labeled all possible entity values. Table A5 provides exemplary user messages, the recognized entities, their values and the intent of this message as well as an exemplary reply by the robo-advisor (based on the identified intent and the dialog manager implemented in the program logic component).

Entity	**Values**
Share	A, B, C, D, E, F
Category	++, +, 0, -, --

Table A3. Entities configured for the robo-advisor (Main-LUIS component)

Intent	Explanation
share_gained_max	Identify the share with the largest amount of increases
share_loss_max	Identify the share with the largest amount of decreases
share_potential_loss	The potential loss amount of a specific share after a hypothetical decrease
share_potential_win	The potential gain amount of a specific share after a hypothetical increase
share_specific_won	Identifies whether a specific share price increased (relative to the previous round)
share_specfic_loss	Identifies whether a specific share price decreased (relative to the previous round)
share_category	Identifies the categories of all shares
share_specific_category	Identifies the category of a specific share
give_advice	Investment recommendation for the current investment round
what_can_you	List of capabilities of the robo-advisor
value_portfolio	Current value of the portfolio
Note: All questions and answers were trained in German and translated for this article.	

Table A4. Intents configured for the robo-advisor (Main-LUIS component)

User message	Entities	Intent	Reply by robo-advisor
Which share has won the most?		share_gained_max	Share B, share D and share F have gained the most value so far.
How does the price of share C develop if it increases?	Share {value = c}	share_potential_win	If the value of share C increases, it will be worth 96 currency units in the following period.
How often has share A lost so far?	Share {value = A}	share_specfic_loss	Share A has lost 3 times in value so far.
Which share should I buy?		give_advise	Based on the price development up to now I would recommend to invest in share A and to sell your holdings in shares B and C.
How much money are my shares worth?		value_portfolio	Your entire portfolio is worth 1818 currency units. The total amount comprises a value of 1728 units from your share ownerships and 90 units from your money account.

Table A5. Exemplary user messages and replies (Main-LUIS component)

The operationalization of the *recommendation algorithm* is as follows. From an implementation point of view, both the user interface and the underlying processing of user inputs follow the same logic as in the operationalization of the robo-advisor. The following modifications were implemented. First, the input field of the chat interface was made invisible. Instead, a button labeled “Recommendation” was shown. This limited users' interactions with the system, since they were only able to click on the button which triggered the system to send the message "Which share should I buy?" to the Azure Bot Service. This message is processed as in the robo-advisor application. The resulting reply is then displayed in the user interface above the button (the location of the reply was thus comparable to the robo-advisor application). Second, the language style in the reply was slightly modified to convey a less personalized and more neutral tone (e.g., "Invest in share A" instead of "I recommend you to invest in share A").

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