INVESTMENT DECISIONS WITH ROBO-ADVISORS: THE ROLE OF ANTHROPOMORPHISM AND PERSONALIZED ANCHORS IN RECOMMENDATIONS

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INVESTMENT DECISIONS WITH ROBO-ADVISORS: THE ROLE OF ANTHROPOMORPHISM AND PERSONALIZED ANCHORS IN RECOMMENDATIONS

Research paper

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Abstract

The current wave of digitalization forces companies to adapt their offline activities to meet contemporary customer expectations and technological possibilities. One current challenge for the financial services sector is to shift its traditional, in-person advisory process into a digital, automated service (i.e., robo-advisory) to reduce costs as well as to reach a wider audience of prospective customers. By neglecting to increase and invest their savings, customers run the risk of making suboptimal economic decisions that may negatively affect their economic futures. Drawing on social response as well as anchor-adjustment theory, we investigate anthropomorphism (i.e., the attribution of human characteristics and goals to non-human agents) and personalized anchors in recommendations as IS design elements in the context of robo-advisory for investment decisions. Our results from an online experiment with 278 participants show that anthropomorphism (i.e., triggered by verbal and visual cues) and personalized anchors in recommendations lead to higher social presence which in turn lead to increased investment volumes. Additionally, we demonstrate that personalized anchors in recommendations directly increase investment volume. Thus, our results contribute by providing novel findings on how anthropomorphism and personalized anchors in recommendations can be used to improve economic decision-making.

Keywords: Robo-advisory, Nudging, Anthropomorphism, Anchor, Online recommender systems, Financial support systems
1 Introduction

Digitalization is a significant topic that is no longer dispensable. Caused by an increasing infusion of information systems (IS) into everyday activities and the rise of ubiquitous technologies, digitalization has an impact in various areas in economy and society, of which the financial services industry is no exception (Alt and Puschmann, 2016).

As a result, new financial services, such as “robo-advisory,” have emerged. Robo-advisors are IS that guide users through an automated investment advisory process by means of interactive and intelligent user support components (Sironi, 2016; Jung et al., 2018). Consequently, robo-advisory allows a larger audience to access and use a professional asset management at low costs, which before has been affordable by only wealthy investors who could pay costly human advisors (Jung et al., 2018). Indeed, A.T. Kearney estimates that assets under management by U.S. robo-advisors alone will grow to 2.2 trillion dollars by the end of 2020 (A.T. Kearney, 2015).

Because digital services replace the traditional human-to-human interaction between human advisors and their customers, one challenge that financial service companies face is the design of adequate robo-advisory services that are accepted by potential investors (Jung et al., 2017). Yet, little is known on how the design and mechanics of robo-advisory can improve economic decision making. Today’s customers might not save enough money for their future (Skinner, 2007), often being influenced by heuristics in their economic decision-making (Fleischmann et al., 2014), leading to biases against saving (Benartzi and Thaler, 2007). In offline contexts, several nudges have already demonstrated to improve the economic decision-making of customers regarding their saving and investment decisions (e.g., Cronqvist and Thaler, 2004; Thaler and Sunstein, 2008). However, online contexts such as robo-advisory may open the opportunity for new approaches to further improve economic decision-making.

Robo-advisory is a phenomenon that is still in its infancy in finance and IS, so that only few researchers have devoted their attention to this support system. Recent robo-advisory research draws on foundations from related fields, such as the development of portable advisory tools (Moewes et al., 2011; Heinrich et al., 2014) and the design of financial encounters (Dolata and Schwabe, 2016) to increase comprehension and success with regard to the configuration and profiling of users in form of user investment behaviour (Kilic et al., 2015; Musto et al., 2015) and the design of user interfaces to improve user experience (e.g., Nuesesch et al., 2014; Heyman and Artman, 2015). An important theory for forming a more natural bond between the user and the system may be found within anthropomorphism. Anthropomorphism leads humans to attribute human characteristics and intentions towards non-human agents (Epley et al., 2007), resulting in social behaviour even with non-human agents. Although anthropomorphism has been a topic of interest for scant research works in IS (e.g., Qiu and Benbasat, 2009; Qiu and Benbasat, 2010) and has even been researched in the context of robo-advisors by employing a simple name (Hodge et al., 2018), no study has yet explored the usage of anthropomorphism in the form of visual and verbal cues to increase investment volumes. Such visual and verbal cues have been proven to be decisive design elements in other fields like marketing and researchers have provided evidence that these cues can positively impact product likeability and product purchase intention (e.g., Holzwarth et al., 2006) and promise even more fruitful ventures in the future (Seymour et al., 2018). Based on such previous research findings, Pfeuffer et al. (2019) argue that the conventionally personal consultation talks between investor and investment advisor call for a more natural design of the human-computer interaction in robo-advisory. Therefore, it appears logical that employing an anthropomorphic conversational recommendation agent may lead to a higher efficiency of robo-advisory. Moreover, the emergence of robo-advisors as real-time recommender systems also raises questions with regard to how the provision of fast and personalized recommendations based on user input further shapes investors’ investment decisions. Thus, this paper aims to investigate the following research questions:

*RQ1: How does anthropomorphism in robo-advisors affect investors’ investment volumes?*

*RQ2: How do personalized recommendations in robo-advisors affect investors’ investment volumes?*
To answer our research questions, we employed an online experiment with 278 participants in a 3 (Anthropomorphism: Absent vs. Low vs. High) x 2 (Personalized Recommendation: Absent vs. Present) between-subject design and systematically analysed the first steps in a robo-advisory onboarding process and assessed the intended investment volumes. Consequently, we examined the impact of anthropomorphism, manipulated by verbal and visual design elements, as well as of personalized recommendations, operationalized through a user-input dependent numerical anchor in a recommendation by the robo-advisor. In doing so, we contribute to IS research and practice in several important ways. First, following the emergence and important growth of robo-advisory (A.T. Kearney, 2015; Jung et al., 2018) we address the theoretically and practically neglected effects of anthropomorphism and personalized recommendations as effective nudges in the newly emerging robo-advisory context. Second, we provide an explanation for these observations through the mediating effect of social presence, which is built upon the general bias towards social orientation of human being (Nass and Moon, 2000). Third, we depart from prior research by investigating how these influences improve economic decision-making like investment and savings behaviour. Lastly, we show the possibility of IS to provide real-time personalization in a financial context that would not be possible in a traditional offline setting. Thus, we not only shed theoretical light on our investigated effects, but also derive learnings for providers of financial services to increase investment volumes to improve economic welfare.

2 Theoretical Background

2.1 Robo-advisors and recommendations

Robo-advisors as financial support systems provide financial advice to potential investors based on algorithms that analyse financial information with less human intervention than ever before (Jung et al., 2017; Jung et al., 2018). As a result, robo-advisors challenge the traditional fund and wealth management industry (Phoon and Koh, 2017). Robo-advisors have several important applications, and depart from existing services (e.g., online investment platforms and online brokerage) with regard to customer assessment and customer portfolio management (e.g., Tertilt and Scholz, 2017; Jung et al., 2018): The traditional investor profiling that is normally conducted during offline human-to-human interviews is replaced by online questionnaires and self-reporting processes. Therefore, the user-provided answers (e.g., with regard to investment purpose or risk affinity) are used as inputs for algorithms and automated processes, instead of being processed by human advisors. Subsequently, the robo-advisor translates this information in real-time into an adequate portfolio of financial products, provides users with personalized recommendations as well as automatically manages the investment portfolio.

Previous research on automatically generated and personalized recommendations have primarily focused on exploring the effects in traditional online marketplaces, such as the trust in and adoption of such systems (e.g., Benbasat and Wang, 2005; Hess et al., 2009), the influence on customer’s choice (e.g., Senecal and Nantel, 2004; Benlian et al., 2012; Adam and Pecorelli, 2018), or satisfaction (e.g., Holzwarth et al., 2006; Jiang et al., 2010). Yet, besides one exception (Hodge et al., 2018), research lacks investigations of recommendations in connection with the non-traditional context of robo-advisory (Jung et al., 2018).

2.2 Anchoring-and-adjustment effect

A recommendation by a robo-advisor can include a piece of information that a user can use as an anchor for further decision-making. The anchoring-and-adjustment effect, or often simply called anchoring effect, is the disproportionate influence on decision-makers to make judgments that are biased toward an initially presented information (Epley and Gilovich, 2006). Heuristics reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations (Kahneman and Tversky, 1974). Accordingly, decisions are made using the given anchor regardless of whether the anchor is relevant and useful for the decision (Furnham and Boo, 2011). Kahneman and Tversky
(1974) provide one classical example to demonstrate the anchoring effect. They interviewed their study participants on the fraction of African nations in the United Nations. Based on a generated random number they asked in a first round whether the right answer is higher or lower than the random number. Afterwards, the participant should give a concrete answer to the question. The results showed that the answers of the participants were numbers close to the anchor they were given in the first round.

This experiment shows that the anchor is used as a starting point for a decision, which is adjusted until it matches the anchor (Janiszewski and Uy, 2008). After nearly 40 years’ worth of research on the effect, the anchoring effect can be considered one of the most robust psychological processes that influences human decision-making (Furnham and Boo, 2011). The anchoring effect is usually interpreted as a sign of human irrationality, but recently studies suggested that the anchoring effect results from people’s rational use of their finite time and limited cognitive resources (Lieder et al., 2018).

The effect has been demonstrated in various domains such as real estate valuation (by experts and amateurs) (Northcraft and Neale, 1987), purchasing of consumer products (Wansink et al., 1998), or savings (Cronqvist and Thaler, 2004). Especially in the area of financial decision-making, anchors seem to play an important role because humans typically do not (want to) spend much time on decision-making in this area (Benartzi and Thaler, 2007). One large impediment to the anchoring effects in savings is liquidity constraints of each customer: Extreme anchor values can have no effect if customers do not have the liquidity to save such or similar volumes (Loibl et al., 2016). Vice-versa, Braeuer et al. (2017) indicated that small anchors in robo-advisory have little or no effect on customers who aim to invest large volumes.

2.3 Anthropomorphism, avatars and social presence

A current trend in designing IS and specifically robo-advisory (Hodge et al., 2018) comprises the employment of anthropomorphic cues. Anthropomorphism describes the attribution of humanlike characteristics, behaviour, and emotions to nonhuman agents (Epley et al., 2007). It can be understood as a human heuristic to alleviate the understanding of unknown agents by applying anthropocentric knowledge (Griffin and Tversky, 1992; Epley, 2004). Accordingly, Pfeuffer et al. (2019) define anthropomorphic IS as “IS in which the technical and informational artefacts possess cues that tend to lead humans to attribute human-like physical or non-physical features, behaviour, emotions, characteristics and attributes to the IS.” Thus, the thoughtful design of anthropomorphic cues can lead to an increased recognition of anthropomorphic features by humans, likeability, ease of use, and efficacy of an IS (Burgoon et al., 2000; Epley et al., 2007).

Because anthropomorphism as an innate tendency that influences the decisions and judgements of humans to a large extent, various research fields have been exploring its capabilities and effects in product design and on human behaviour (e.g., Nass et al., 1999; Aggarwal and McGill, 2007; Wang, 2017). Studies drawing on social response theory (Nass and Moon, 2000) provide strong evidence that in various situations, humans tend to apply social rules and heuristics to anthropomorphically designed computers. While mental features such as the ability to chat may increase the perception of intelligence in a non-human technological agent, the main goal of visual features, such as appearance or embodiment, is to improve the social connection by implementing motoric and static human features (Eysel et al., 2010). As such, static and motoric human-like embodiments through avatars (e.g., Holzwarth et al., 2006) have been observed in previous research as an important factor in influencing trust and forming social bonds with virtual agents (e.g., Goetz et al., 2003; Qiu and Benbasat, 2009; Broadbent et al., 2013).

Since IS research is partly concerned with the amalgamation of existing theory with novel aspects of technology, the effects of such anthropomorphic design-elements on the perception of human-likeness must be made measurable and theoretically explainable. Previous efforts in IS research have employed and tested the construct of social presence as a measure of the perception of human-likeness in an interaction partner (Gefen and Straub, 2003; Qiu and Benbasat, 2009). Social presence theory originally describes the awareness of another human partner within a social interaction (Short et al., 1976). The
idea to apply the theory of social presence in the form of a psychometric construct to the context of IS arose from the suggestions that theories from (social) psychology may in principle also be applicable to human-computer interaction (Nass et al., 1994). Indeed, previous research in IS has shown that social presence is well applicable as a means of measurement of the perception of a human touch within various IS contexts (Holzwarth et al., 2006; Qiu and Benbasat, 2009). In fact, it appeared that through the construct of social presence, effects of anthropomorphic cues on likeability, trusting beliefs, perceived enjoyment and other important determinants of systems success could be explained (Gefen and Straub, 2003; Tourangeau et al., 2003; Cyr et al., 2007).

3  Research Framework and Hypothesis Development

Based on what has been presented so far, a research model was developed that explicates how a robo-advisory’s personalized anchor and anthropomorphism increase investment volume directly or by enhancing social presence. Figure 1 illustrates our conceptual research framework. Subsequently, we present the derivations for each of our hypotheses.

Figure 1  Research framework

3.1  The effect of personalized recommendations on investment volume

The previous section mentioned that the anchoring effect is a well-known effect that exists in many domains. However, in an investment or savings context, results from studies that manipulate anchors are mixed. Loibl et al. (2016) provided evidence that the same quantitative anchor for all investors had no effect on investors, who were restrained to reach the anchor by their personal liquidity constraints. Simultaneously, low anchors in an investment context revealed to have little or no effect on investors with large investment volumes (Braeuer et al., 2017).

Moreover, there is a shift from traditional offline banking services to online services like robo-advisory which increases the occurrence of decision-making environments in an investment context. Generally, customers tend to underinvest, which may be grounded in the hyperbolic discounting bias (Laibson, 1997). In effect, this bias leads customers to value their present liquidity higher than possible gains in the future, thus discounting their future financial welfare. In the context of robo-advisory, the presence of this bias may influence customers to underinvest, which hinders the possibility of otherwise greater future savings through higher investments for these customers. Addressing this issue within robo-advisory is inevitable, since not only financial service providers may profit from higher investments, but foremost customers may experience greater economic welfare. Based upon the anchoring effect, we aim to demonstrate that an anchor can be placed successfully for all robo-advisory users in such an environment to influence their economic decision-making. The anchor should effectively influence the propensity of customers to invest a higher amount relative to his or her liquidity.
constraints, thus being personalized and countering under-saving effects. Therefore, we state our first hypothesis:

$H1$: A personalized anchor in a recommendation increases a user’s investment volume.

3.2 The effect of personalized recommendations on social presence

Recommendations can help in the decision-making process, especially if given by an expert agent (Dalal and Bonaccio, 2010). Through an explicit recommendation for example, the decision of a person can be led into a special direction. Also, a specified recommendation against an option may make the decider to not consider this option anymore. Furthermore, a recommendation without an explicit advice can be made through additional information that was given to one of the options, making certain options more attractive to the decider (Dalal and Bonaccio, 2010). Moreover, recommendations do not only have the function to guide a person in a certain direction but also serve as social support. The existence of a recommendation gives individuals the feeling that they are not alone with making a critical decision, hence creating social presence. This could be achieved through showing compassion and understanding of the feelings associated with the decision (e.g., Horowitz et al., 2001; Dalal and Bonaccio, 2010). Based on these findings, we choose to provide some users with a personalized recommendation, which includes a personalized anchor that is dependent on the user’s input. Finally, we derive the following hypothesis regarding the recommendation including personalized anchor:

$H2$: A personalized anchor in a recommendation increases the social presence of a robo-advisor.

3.3 The effect of anthropomorphism on social presence

A robo-advisor is an IS designed to provide financial advice and can reduce the costs of contemporary human advice services. Therefore, it is important to design a trustworthy, serious, and social atmosphere for the customer when interacting with the robo-advisor (Jung et al., 2017). Anthropomorphic design cues in human-computer interfaces could create this required atmosphere. Holzwarth et al. (2006), for example, showed in several experiments that using an avatar in online shopping positively influences a customer’s attitude towards the product as well as purchase intentions. Additionally, the social presence elicited by an anthropomorphic avatar appears to increase customer satisfaction with the retailer (Holzwarth et al., 2006), trust in the presented information on the website, and pleasure to visit and use the website (Etemad-Sajadi, 2016). Qiu and Benbasat (2009) present more specific research findings on decision aiding systems, especially on recommender systems and anthropomorphic design. Their study, for example, revealed that while an anthropomorphic avatar for a recommendation agent had a direct influence on social presence. Thus, we derive the following hypothesis:

$H3$: Anthropomorphism increases the social presence of a robo-advisor.

3.4 The effect of social presence on investment volume

As robo-advisory is a relatively new phenomenon (Jung et al., 2018), we use insights from neighbouring domains to derive our next hypotheses. Essentially, financial investment decisions via a robo-advisor base on the relationship between the investor and the advisor who offers financial products. In this respect, the investor-advisor relationship bares similarities to the investor-founder relationship that is developed in the crowdfunding domain (Agrawal et al., 2010). Within the crowdfunding domain, the aspect of social presence has gained some attention (Zhang and Benyoucef, 2016; Raab et al., 2017). Findings from this domain suggest that social presence is of importance to build a strong investor-founder relationship (Lu et al., 2016) and that social presence positively influences the success of a crowdfunded initiative in terms of pledged money. Based on these results from the crowdfunding domain and the results regarding the effects of anthropomorphism and recommendations on social presence as mentioned above, we hypothesize that social presence affects a user’s investment volume.

$H4$: Social presence of a robo-advisor increases a user’s investment volume.
4 Experimental Design

To test our hypotheses, we conducted an online experiment with a 3x2 full factorial design. We simulated an online investment decision with the aid of a robo-advisor, using all six possible combinations of the two independent variables: (1) the degree of anthropomorphism (no, low, or high) and (2) the presence or absence of a personalized anchor in a recommendation.

4.1 Manipulation of anthropomorphism

To examine the influence of anthropomorphism, we designed three robo-advisors with different degrees of anthropomorphism. We used various verbal cues to operationalize the degree of anthropomorphism: Both the low and high anthropomorphism conditions welcomed and took leave of the participants, but only in the high anthropomorphism condition did the robo-advisor introduce itself and used personal pronouns (e.g., “I” and “me”) to signal a personality and identity (Pickard et al., 2014). Additionally, we employed some visual cues that are displayed in Table 1.

<table>
<thead>
<tr>
<th>Degree of Anthropomorphism</th>
<th>None</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Picture</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Name</td>
<td>-</td>
<td>“Robo-Advisor”</td>
<td>“Robin”</td>
</tr>
<tr>
<td>Speech Bubble</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Table 1 Operationalization of anthropomorphism based on visual cues

The first operationalization (i.e., no anthropomorphism) lacked any anthropomorphic design elements. For this treatment, we designed the robo-advisory as very anonymous without any visual or verbal cues (e.g., no picture or speech bubble).

The second operationalization (i.e., low anthropomorphism) employed a few anthropomorphic design elements. The robo-advisor displayed a picture in form of a pictogram and a non-human, function-oriented name (“Robo-Advisor”). Moreover, we designed the interaction as a dialogue between the pictogram and the user by using speech bubbles, signalling rudimentary cues of an actual conversation.

The third and last operationalization used an avatar with a human embodiment adopted from Wünderlich and Paluch (2017) to ascertain tested humanlike appearance cues for the design of the avatar. We, however, gave up other anthropomorphic elements like a voice output or any animations because previous studies have demonstrated that their effects depend on the context and the expectations the user has with regard to the services placed on the website (McBreen and Jack, 2001; Powers et al., 2003). Moreover, the robo-advisor used first-person singular pronouns as well as displayed a gender-neutral name (i.e., “Robin”) (e.g., Nass et al., 1997; Hodge et al., 2018) and introduced itself to the customer at the beginning of the robo-advisory interaction.
4.2 Manipulation of personalized anchors in recommendation

To operationalize and calculate a suitable and realistic personalized anchor we designed a recommendation based on contemporary robo-advisors in practice as references.

In the first step, our system calculates the personal maximum possible investment volume of the participant. The personal maximum available investment volume is based on a user’s entries with regard to current savings and income per month. Based on contemporary practices, we argued that a full month income should always be liquid and readily available for unexpected emergencies (Havlat, 2018). In contrast, many participants may prefer a higher liquidity instead of investing their savings. Yet, insisting on a higher liquidity than necessary is suboptimal, since the participant may lose out on the possibility of increased economic welfare. Consequently, the personal maximum possible investment volume is calculated per participant as following:

\[
\text{Personal Maximum Investment Volume} = \text{Savings} - 1 \times \text{Full Month Income}
\]

Subsequently, our system calculates the personalized anchor in real time. We used 90 percent of the personal maximum investment volume as our anchor value:

\[
\text{Personalized Anchor} = \text{Personal Maximum Investment Volume} \times 0.9.
\]

The personalized anchor was rounded off to hundreds to avoid concurrent adjustment effects due to the different precision of different anchors, as more precise anchors lead to less adjustment (Janiszewski and Uy, 2008). Personalized anchors were combined with an investment recommendation (i.e., “The robo-advisor recommends you to invest...” or “I recommend you to invest...”). The control group did not receive a recommendation and, thus, no personalized anchor. All groups subsequently made an entry about the volume they would invest.
4.3 Dependent variables, control variables and manipulation checks

We focus on Social Presence and Investment Volume as dependent variables. The items to measure the dependent variable Social Presence were adapted from Gefen and Straub (2003) (e.g., “There is a sense of human warmth in the website”). They were presented on a 7-point Likert-type scale ranging from strongly disagree to strongly agree. We measured the second dependent variable Investment Volume by the numerical answer the user provided for the question: “How much would you consider investing?”. Users entered absolute values (e.g., 500€) which were then normalized for each user by its personal maximum investment volume for analysis of results later on.

In addition, we also tested various demographics (i.e., Age, Gender, and Previous Experience with Robo-Advisory) and control variables that have been identified as the most influential drivers in extant literature: The items for Personal Innovativeness were adapted from Agarwal and Prasad (1998) (e.g., “I like to experiment with new information technologies”), Trusting Disposition (e.g., “I generally trust other people”) and Product Knowledge (e.g., “How much do you know about robo-advisory services?”) from Qiu and Benbasat (2010), Institution-Based Trust from Hess et al. (2009) (e.g., “I am comfortable making decisions using decision-making software”), Plan for Money Long-Term from Netemeyer et al. (2018) (e.g., “I set financial goals for the next 1-2 years for what I want to achieve with my money”), Product Involvement from Zaichkowsky (1985) (e.g., “I am interested in robo-advisory services like the one provided by Robo Bank”) and Willingness to Take Investment Risks from Netemeyer et al. (2018) (e.g., “When thinking of your financial investments, how likely are you to take risks?”). Additionally, we asked some multiple-choice questions to test the Financial Literacy of the participants (Netemeyer et al., 2018) (e.g., “When an investor spreads his money among different assets, I believe that the risk of losing a lot of money will: increase/decrease/stay the same/don’t know”). As manipulation checks, the participants stated whether there was an assistant who helped in making an investment decision and whether the robo-advisor recommended a possible investment volume.

4.4 Experimental procedure

We segmented the experiment in six steps, in which all participants received the same questions (Figure 4): (1) The first part started with a random assignment of the participants as well as with a short introduction of the experiment’s rule set, followed by (2) a simple explanation of the use and functions of contemporary robo-advisors. (3) Participants received the information that they would be interested in investing money and that they would consider investing it in a robo-advisor. Afterwards, participants saw the ad of the fictional company ‘Robo Bank’, and received the instructions to start the advisory service. (4) Comparable to the traditional human advisory process (Jung et al., 2018), the next step represented the configuration phase, where the information asymmetry between the user and the robo-advisor was reduced: Here, similar to contemporary robo-advisors, the robo-advisor introduced itself and asked the user some questions about his or her demographics as well as financial situation and preferences. (5) Subsequently, in the matching & customization phase, the user chose the investment volume. In the personalized recommendation conditions, the robo-advisor would place a personalized anchor in form of a recommendation about the investment volume based on the user’s former entries. In the other conditions, the robo-advisor would just ask the user for the desired investment volume without any indication how much he or she should invest. (6) The final part of the experiment was a survey about the participants’ advisory experience over multiple pages, ending in a short debriefing.
5 Analysis and Results

5.1 Sample description, controls and manipulation checks

We recruited a total of 557 participants through the crowdsourcing marketplace Amazon Mechanical Turk, a suitable platform to get in touch with Internet-savvy users, who are potential users of robo-advisors. Moreover, we restricted participation to users who are U.S. residents with at least 95 percent approval rate (Goodman and Paolacci, 2017). 145 participants were excluded due to failing manipulation checks as they did not recognize the presence of an avatar and/or a recommendation. Out of the remaining 412, we further screened for participants to ensure eligibility of our participants for robo-advisory services and ascertain the validity of our data: We excluded those who (1) intended to invest more than their actual savings, (2) declared an unusual high monthly income of more than $5,000, and/or (3) were not eligible for robo-advisory services as they declared to have higher monthly costs than income. After all these checks, the final data set consisted of 278 participants.

We conducted several one-way analyses of variance (ANOVAs) to confirm the random assignment to the different experimental conditions and to check our control variables. There were no significant differences in demographics in terms of Gender (F=0.281, p>0.1), Age (F=0.799, p>0.1) or Previous Experience with Robo-Advisory (F=1.121, p>0.1) between the six experimental groups and no significant differences regarding Personal Innovativeness, Trusting Disposition, Product Knowledge, Institution-based Trust, Plan for Money Long-Term, Product Involvement, Financial Literacy or Willingness to Take Investment Risks (all p>0.1), indicating that these (control) variables did not confound our dependent variables.

5.2 Reliability and validity

Table 3 shows that both, the construct’s Cronbach’s alpha (0.956) and composite reliability 0.955), were above the recommended level of 0.70 and show a high internal consistency (Nunnally and Bernstein, 1994). We measured Investment Volume directly via the numerical answer of the users and, thus, the construct has the highest reliability. We tested convergent validity based on the values of the loadings and the average variance extracted (AVE). The results show that the loadings of all items were higher than 0.70. AVE was 0.811 and above the recommended level of 0.50, suggesting that on...
average, the construct explains more than half of the variance of its indicators (Hair et al., 2014). These results confirm the convergent validity of the measures.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Number of items</th>
<th>Loadings range</th>
<th>Composite reliability</th>
<th>Cronbach’s alpha</th>
<th>AVE</th>
</tr>
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<tbody>
<tr>
<td>Social Presence</td>
<td>5</td>
<td>0.866-0.940</td>
<td>0.955</td>
<td>0.956</td>
<td>0.811</td>
</tr>
</tbody>
</table>

*Table 3 Reliability and convergent validity of our principal constructs*

We used the heterotrait-monotrait ratio of correlations (HTMT) for assessing discriminant validity as there is evidence of its superior performance to Fornell-Larcker test (Henseler et al., 2015). The maximum value of HTMT was 0.397, below the maximum value of 0.9 suggested by Teo et al. (2008), indicating that the constructs differ from each other and discriminant validity is supported. We also tested for multicollinearity by calculating the maximum variance inflation factor (VIF) which was equal to 1.013. Mason and Perreault (1991) indicate that a VIF of 10 or higher is an evidence for multicollinearity, which is not the case in our data, indicating the absence of multicollinearity.

### 5.3 Hypotheses testing

We used a partial least squares approach, with the SmartPLS 3 software as widely accepted tool (e.g., Mero, 2018). PLS suits this research as the primary focus is on the path relationships and variance explained of the constructs rather than on the model fit per se (Sarstedt et al., 2014). A path-weighting scheme was used to estimate the path coefficients. A two-tailed bootstrapping with 5,000 subsamples determined the significance levels, reliability, and validity. The model fit determined by SRMR (Henseler et al., 2016) was 0.066, below the cut-off value of 0.08 indicating a good model fit (Hu and Bentler, 1999). Figure 4 indicates path coefficients and significance levels.

*Figure 4 Research model including path coefficients results*

Overall, the results support our theoretical model and hypotheses. The personalized anchor in a recommendation had a positive direct effect on Investment Volume (relative to personal maximum investment volume) with $\beta=0.381$ and $p<0.001$, thus supporting H1 and meaning that the presence of a personalized anchor in a recommendation increased the investment volume independently of the personal maximum investment volume available. The recommendations including personalized anchors had also an effect on Social Presence ($\beta=0.114$ with $p<0.05$) which supports H2. Moreover, as ex-

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1 Additional ANOVAs and planned contrast analyses were conducted that support the results of the PLS analysis.
pected, a higher degree of anthropomorphism led to a higher degree of Social Presence ($\beta=0.131$, $p<0.05$), supporting our hypothesis H3. Increasing Social Presence further resulted in a higher Investment Volume (relative to personal maximum investment volume), supporting H4 with $\beta=0.146$ and $p<0.01$. The anchoring effect was also clearly demonstrated in Figure 5 showing the average investment volumes (relative to the personal maximum investment volume) across the different groups. On the horizontal axis, the figure displays the six different experiment groups (see also Table 2). On the vertical axis, the average investment volume selected by the participants is shown. All groups with a personalized anchor in a recommendation are hatched. For the different conditions of anthropomorphism, the figure illustrates that once the robo-advisor placed a personalized anchor in a recommendation, the average investment volume nearly doubled.

![Figure 5](image.png)

**Figure 5** Average investment volume as percentage of the personal maximum investment volume over the six experimental groups shows important influence of the personalized anchor in a recommendation

### 6 Discussion

The effective design of interfaces between users and IS has become an increasingly relevant topic for both researchers and practitioners, as the ongoing technological advancements force companies to rethink contemporary services. This piece of research aimed to show possibilities of effectively designing financial support systems - such as robo-advisors - to increase not only user acceptance and investment volume, but also the propensity to invest. Thus, robo-advisors may help in countering systematic under-savings that reduces economic welfare. Precisely, we examined the effects of advisors with varying degree of anthropomorphism in combination with a personalized anchor placed in a recommendation, whereby the anchor was calculated based on information the user provided.

The most important finding of our study demonstrates that an increasing degree of anthropomorphism in robo-advisors leads to higher perceptions of social presence, which in turn leads to higher investment volumes as well as higher usage intentions. Moreover, our research reveals that personalized anchors in recommendations not only positively influence the perception of social presence, but also have a direct positive effect on investment volumes.
6.1 Implications for research and practice

Our paper contributes to research by providing a novel perspective on the nascent area of designing financial support systems, but has unprecedented impetus for financial service providers as well. Following the call to further explore nudging, especially personalization in recommender systems (e.g., Goes, 2013; Weinmann et al., 2016), and to explore the novel robo-advisory phenomenon (Jung et al., 2018), we address the theoretically and practically neglected effects of anthropomorphism and personalized anchors in recommendations as effective nudges in the robo-advisory context (Jung et al., 2018). First and foremost, we provide first empirical evidence that a personalized anchor in a recommendation carried out by a robo-advisor directly increases the investment volume of users. Furthermore, we demonstrate how anthropomorphic design cues in conjunction with personalized recommendations can additionally increase the investment volumes through the mediation effect of social presence. Most importantly, we depart from prior research by examining how these anthropomorphic design elements impact economic decision-making. These findings may provide a foundation for further research in the directions of robo-advisory, service personalization or impact of human-like IS on economic behaviour.

From a managerial point of view, our research has relevant implications for financial service providers as well. Building a familiar, socially-oriented atmosphere through anthropomorphic design elements in form of verbal and visual cues as well as the pronunciation of a personalized anchor may be simple mechanisms for robo-advisors because it can increase the investment the user would make. We showed how robo-advisory can profit from IS by calculating personalized anchors in real-time. These anchors served as cues that effectively mitigate possible underinvestment and therefore influenced users to make more future-oriented economic decisions. Thus, we not only shed theoretical light on our investigated manipulations and derived learnings for providers of financial services to increase investment volumes, but also discovered IS design elements with a possible impact on the future welfare of today’s society.

6.2 Limitations, directions for future research and conclusion

Despite the aforementioned contributions of this research, the conducted studies should be treated as an initial examination into the research field of financial support systems. Therefore, we want to point out some noteworthy limitations and directions for future research. First, our experiment was designed as an online survey, so that the results do not represent actual robo-advisory with a binding investment decision. It would be interesting to test our hypotheses in a field study with a real robo-advisor to further explore external validity. Second, we also examined only social presence as a potential mediator. Here, further mediators and moderators which are also relevant in the research of the effect of computational agents like trusting beliefs and perceived enjoyment could be examined. Also, other dependent variables, such as user satisfaction or financial well-being, could be explored. Third, further research could investigate the degree of anthropomorphism that is accepted by the customer. In our experiment, for example, the chosen avatar was a gender-neutral static picture with a humanlike looking but without any motions. Some possible research directions would be the influence of an animated avatar, the effect of a voice output, or the influence of an avatar with a clear gender. However, the designers should be careful: The use of anthropomorphism must be coordinated with the context and the number of anthropomorphic elements should be well-thought-out (e.g., Seymour et al., 2018). In case that the anthropomorphic design of the system deviates from the expectations of the users, it may create a feeling of eeriness and may lead to a decrease of trust in the system (i.e., “uncanny valley”) (Mori, 1970).

Overall, our study is an initial step towards better understanding how the design of interfaces may improve economic decision-making in the context of financial support systems. Specifically, we shed light on the effects of anthropomorphism and personalized anchors in recommendations in the design of robo-advisors. We hope that our study provides impetus for future research on digital nudges as well as actionable recommendations for designing IS.
References


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*Mental Rotation and Recommendations in Robo-Advisory*

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