# The Impact of Lay Beliefs about Artificial Intelligence on Behavioral Intentions towards Robo-advice

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**Abstract**

In this research, we investigate how consumer beliefs about artificial intelligence influence behavioral intentions towards robo-advice, a new type of self-service technology which automates professional advice giving. A qualitative study and an experiment show that beliefs about the relative level of artificial intelligence may have a strong impact on consumers' intentions to adopt a robo-advice service. In addition, our findings indicate that the impact of such beliefs is contingent on a robo-advisor's level of decision automation. Only consumers who feel that they are free to decide whether they want to follow advice or not regard a higher level of artificial intelligence as beneficial when receiving advice. These results may help to better understand consumer acceptance of robo-advice and other smart services.

*Keywords: robo-advice, smart technology, professional service*

*Conference Track: Services Marketing*

## 1. Introduction

In recent years, robo-advice has emerged as new type of self-service technology. Unlike support systems such as Internet banking which automate simple tasks such as transferring money, robo-advice automates professional advice giving, that is a complex service performance informed by specific knowledge (Baker and Dellaert, 2017; Seiders, Flynn, Berry, and Haws, 2015). Specifically, investment robo-advisors recommend and execute personalized investment plans with almost no human intervention. One may expect similar services to substitute human advice in other professional domains. An example would be a "robo-dermatologist" that uses digital images to recommend an optimal therapy.

To come up with advice similar or superior to human advice, robo-advice tools require relatively high levels of artificial intelligence (AI). In fact, services such as robo-advice have been labelled smart services (Wunderlich, Wangenheim, and Bitner, 2012). Scholars describe AI as machine intelligence mimicking human intelligence (HI) such as the ability of knowledge and reasoning, problem-solving, learning, perceiving, and acting (Russell and Norvig, 2009). Current robo-advisors, for example, analyze customer and financial data, systematically develop recommendations, and adapt advice based on changes in data. However, even though AI is an inherent feature of robo-advice and similar services (Huang and Rust, 2018), research has not yet examined how consumers perceive AI. Such perceptions may be of high relevance as the substitution of HI by AI is one of the most obvious characteristics of robo-advice and has been dealt with extensively by the popular press.

Against this background, the current study examines two important issues. First, we explore what beliefs consumers have about AI in a robo-advice context. In this regard, a qualitative study shows that consumers are concerned with how intelligent a robo-advisor is in comparison to a human advisor. Second, we conducted an experiment to investigate if and under which conditions beliefs about AI influence behavioral intentions. In this respect, our findings demonstrate that beliefs about AI may have a strong influence depending on the level of decision automation. In doing so, our research responds to recent calls to investigate consumer responses to smart services (e.g., Marinova, de Ruyter, Huang, Meuter, and Challagalla, 2016) and contributes to a better understanding of such services.

## 2. Conceptual Development and Hypotheses

### *2.1 Robo-advice and lay beliefs about artificial intelligence*

In a narrow sense, robo-advice is often regarded as an automated investment service. We use the term robo-advice more broadly to include similar services in other professional domains (e.g., robo-lawyers, robo-doctors) and define robo-advice as any automated service that provides professional advice based on a matching of consumers to personalized recommendations. Robo-advice is different from support systems previously studied in the self-service literature such as Internet banking. First, as mentioned above, robo-advice requires a higher level of AI than support systems (Huang and Rust, 2018). Second, while such self-services automate actions previously carried out by a frontline employee (e.g., a money transfer), robo-advisors automate recommendations previously made by a human advisor (e.g., recommendation of a specific investment) and sometimes even decisions previously made by a customer (e.g., decision to buy certain assets). In the following section, we first discuss consumer beliefs about AI. Next, we discuss the role of decision automation.

To understand how beliefs about AI influence behavioral intentions towards robo-advice, one may draw on research about implicit theories. According to this literature, individuals hold lay theories of intelligence which differ from explicit theories of intelligence (Sternberg, 1985). Specifically, it has been found that people view analytical abilities such as mathematical skills and logical reasoning as the essence of intelligence (Furnham, 2001). Research has also shown that individuals have different beliefs regarding the malleability of intelligence. While some people have the theory that intelligence is fixed, others believe that intelligence can be improved by training and effort (Dweck, Chi-yue, and Ying-yi, 1995). Importantly, such lay theories may affect expectations of oneself and others, which may, in turn, lead to behavioral consequences (e.g., Blackwell, Trzesniewski, and Dweck, 2007).

Because humans tend to anthropomorphize inanimate objects, one may assume that consumers have implicit theories about the intelligence of a robo-advisor. Specifically, as robo-advisors possess analytical abilities and as individuals tend to equate analytical abilities with intelligence, one may expect that consumers regard robo-advisors to be intelligent (Furnham, 2001; Huang and Rust, 2018). Consumers who believe that AI can adapt also seem likely to believe that robo-advisors can improve their intelligence. However, such beliefs may only represent a relative advantage when consumers perceive AI to be higher than HI. That is, a higher level of AI may increase the accuracy of advice-based decisions from a consumer's perspective. Research on advice shows that consumers seek to maximize decision accuracy and that accuracy of a decision is higher when advisors have high intelligence (LePine, Hollenbeck, Ilgen, and Hedlund, 1997). Hence, consumers who perceive AI to be higher than HI may have stronger behavioral intentions towards robo-advice.

*2.2 The moderating role of decision automation*

One factor which may moderate the impact of implicit theories of AI on behavioral intentions towards robo-advice is decision automation. As mentioned above, robo-advisors may automate decisions previously made by customers. For example, investment robo-advisors have so-called "rebalancing functions". That is, they buy and sell assets automatically to maintain a desired portfolio strategy. Such functions may strongly affect perceived decision autonomy. Research on motivation suggests that autonomy is a central human need and that individuals want to experience that they are the originators of their actions (e.g., Deci and Ryan, 1991). In a related vein, advice research argues that maintaining decision autonomy is a key motive in an advice context (Dalal and Bonaccio, 2010). In fact, decision-makers often decide not to follow advice and to rely on their own opinion. Robo-advisors with a high degree of decision automation deprive consumers of this option. In contrast, robo-advisors with a low degree of decision automation (e.g., asking customers whether they want to follow advice or not) seem less limiting for decision autonomy.

Importantly, we propose that there is an interdependence of decision automation and beliefs about AI. Specifically, the positive effect of consumers believing that AI is higher than HI on behavioral intentions may only occur when decision automation is low. First, research suggests that individuals estimate and balance the potential benefits and costs of advice (Schrah, Dalal, and Sniezek, 2006). Whereas a high level of AI may be regarded as a benefit because it makes decisions more accurate, a high degree of decision automation may be seen as a cost because consumers fear that they lose decision autonomy (Dalal and Bonaccio, 2010). When a robo-advisor has low decision automation such costs seem minimal and accuracy benefits may outweigh potential disadvantages. Second, research indicates that high AI *per se* may be regarded as a threat to human autonomy. Specifically, consumers may fear that AI subliminally manipulates them into outcomes they do not want (Marinova *et al.*, 2016). A low level of decision automation may mitigate such feelings. More precisely, low decision automation may be a mechanism which signals consumers that they still have control over an outcome and that they can stop the implementation of a recommendation if they do not want it (Wunderlich *et al.*, 2012). Thus,

*H1:* Consumers believing that AI is higher than HI will express greater behavioral intentions than consumers believing that AI is lower than HI when a robo-advisor with *low* decision automation is implemented.

In contrast, high decision automation may outweigh accuracy benefits as consumers who interact with a self-deciding robo-advisor may feel that it is very difficult to derive at autonomous decisions. Such types of robo-advisors may reinforce rather than mitigate fears that AI is outsmarting humans. Thus,

*H2:* Consumers believing that AI is higher than HI will *not* express greater behavioral intentions than consumers believing that AI is lower than HI when a robo-advisor with *high* decision automation is implemented.

## 3. Study 1

### *3.1 Participants and procedure*

Our first study used four focus groups with consumers to explore how respondents perceive AI in a robo-advice context and to find out whether our hypotheses were consistent with consumer considerations. Because individuals with and without experience with robo-advice may have different beliefs about AI, two focus groups were held with bank customers using robo-advice and two focus groups were held with bank customers not using robo-advice. Participants varying in age and occupation were recruited with the help of two Swiss banks and a market research company. In total, 29 individuals participated in the focus group (48% robo-advice users, age between 19 and 86, 24% female, 86% working adults with professions ranging from craftsman to business consultant). Our aim was that the mutual discussion of AI stimulated feelings and thoughts of participants.

As recommended, a discussion guide was developed for both types of focus groups (Morgan, 1998). All participants were asked to express what comes to their mind when they think about AI and to discuss what artificial (human) intelligence is better able to do than human (artificial) intelligence. In the robo-advice group, participants were asked to describe advantages and disadvantages of advice based on artificial intelligence in comparison to human advice. In groups consisting of non-robo customers, an example of an investment robo-advice tool was shown, and participants were asked to discuss reasons why customers may or may not prefer advice based on AI. Focus groups lasted between 60 and 90 minutes. All groups were recorded and transcribed, which resulted in 144 pages of verbatim transcripts. To code and analyze the transcripts, we followed the principles of thematic analyses which involve constant re-reading of the data (e.g., Fereday and Muir-Cochrane, 2006).

### *3.2 Findings*

*Beliefs about AI.* The findings suggest that AI is predominantly viewed as analytical-mathematical intelligence. Participants in all focus groups agreed with this assessment:

> Artificial intelligence can process mountains of numbers that a human being can never handle. The intelligence lies above all in the mathematical field (Robo-advice customer, male, 35).
>
> I think when it comes to computational things, where you can figure something out - there is a robot certainly the first. It looks different when it comes to talking. A robot has no feelings (Customer, male, 19).

In addition, it was argued that AI that was able to self-learn can be considered as a form of high intelligence. The rationale for this belief was that such AI could improve without human help, while AI which is not able to self-learn depended on humans to improve. However, participants disagreed whether the AI of current robo-advisors was able to self-learn or not.

> High intelligence is an intelligence that can evolve itself and that acquires skills to develop and renew its own program (Robo-advice customer, male, 36).
>
> I believe that AI can only be as smart as the intelligence of the people who programmed it (Customer, female, 42).
>
> I think my robo-advisor is not very intelligent because he works rule-based. The rules are predetermined, and he acts based on these rules. Self-learning, learning to independently adapt the rules, that's artificial intelligence for me and I do not see that in this specific example (Robo-advice customer, male, 37).

*Beliefs about AI and behavioral intentions towards robo-advice.* Robo-advice users argued that they use robo-advice because they believed that robo-advice was more accurate than human advice. This was linked to greater analytical skills (e.g., storing data, processing information). In contrast, human advice was considered to more likely suffer from bias.

> Robo-advice is better than personal advice when it comes to making quantitative decisions based on data (Robo-advice customer, male, 35).
>
> I always compare robo-advice with medical diagnoses. With artificial intelligence you can make much better medical diagnoses. Do you know Watson? A machine such as Watson can store all human illnesses and can precisely analyze them for possible diagnoses (Robo-advice customer, male, 33).
>
> I like robo-advice very much because there is no personal bias of an advisor. (Robo-advice customer, female, 60).

In focus groups with non-robo customers, discussion emphasized shortcomings of robo-advice such as a lack of intuition and empathy. Participants also feared to lose the autonomy to decide how to invest their money. Some participants of the robo-advice groups also expressed this concern.

> Robo-advice is nice and practical. But somehow it is also a loss of control. You really give up control. I wonder if it is still a free decision at the end. (Customer, female, 28).
>
> When I think about the automatic processes that run in the background, I sometimes have a queasy feeling. When something is automatically bought or sold, I feel like I lose control (Robo-advice customer, male, 49).

In sum, the findings of study 1 clearly show the importance of AI beliefs. That is, study 1 shows that consumers associate AI with greater accuracy of robo-advice than human advice. Consumers also believe that the ability to self-learn differentiates low and high AI. Results also suggest that consumers fear to give up autonomy when using robo-advice.

## 4. Study 2

### *4.1 Design, participants, and procedure*

The purpose of study 2 was to test H1 and H2. The study used a 2 × 2 design with implicit theory (AI higher, lower than HI) and decision automation (low, high) as between-subject conditions. A total of 122 individuals taking part in executive classes at a Swiss university participated in the study (24% female, average age: 36.3 years). Similar to previous studies, participants read a prime intended to temporarily manipulate implicit theories (e.g., Hong, Chiu, Dweck, Lin, and Wan, 1999). That is, participants read a short interview with a professor purportedly extracted from a newspaper. Based on the insights from the focus groups, the professor either argued that AI was *higher* than HI because AI was able to self-learn or that AI was *lower* than HI because AI was not able to improve without human programming. Next, participants were presented with a screenshot from a fictitious robo-advisor called Robowealth. While most information was the same, the level of decision automation was described differently. In the low automation condition, it was stated that Robowealth made recommendations to sell and buy assets, but users could decide whether they wanted to follow advice or not. In the high automation condition, participants were informed that Robowealth bought and sold assets automatically without consultation of customers. After reading the information, participants responded to the dependent measures, the manipulations checks, and various control measures. Finally, they were debriefed.

### *4.2 Measures*

Behavioral intentions were measured with two items adapted from Herhausen, Binder, Schoegel, and Herrmann (2015) reflecting intentions to invest money through robo-advice ("What amount of money would you invest through Robowealth?"; "What percentage of your money would you invest through Robowealth?"). We included several control measures from previous research on technology adoption such as self-efficacy (two items; $r = .80$), need for interaction (three items, $\alpha = .83$), and inertia (single item) (e.g., Meuter, Bitner, Ostrom, and Brown, 2005). In addition, we controlled for participants' income and the degree of perceived realism of Robowealth. All items used seven-point scales.

### *4.3 Results*

*Manipulation checks.* The success of the implicit theory manipulation was tested with one item ("Artificial intelligence is better able to solve complex problems than human intelligence"). As expected, individuals in the higher AI condition supported this statement more strongly than individuals in the lower AI condition ($M_{\text{high\_AI}}$ = 4.78, $M_{\text{low\_AI}}$ = 3.63; $F$(1, 118) = 16.58, $p$ < .001). Moreover, participants in the high automation condition perceived decision automation to be higher ($M$ = 5.58) and perceived to give up more decision autonomy when using robo-advice ($M$ = 4.80) than participants in the low automation condition (decision automation: $M$ = 4.75, $F$(1, 118) = 11.13, $p$ < .01; loss of decision autonomy: $M$ = 3.42, $F$(1, 117) = 21.78, $p$ < .001).

*Control variables.* Inertia and realism emerged as significant covariates and were thus included in the analyses. In general, participants considered the presented robo-advisor very realistic ($M_{\text{diff\_from\_4}}$ = 4.69; $t$(117) = 4.60, $p$ < .001).

*Hypotheses testing.* Two 2 × 2 ANCOVAs revealed that the main effects for implicit theory (amount to invest: $F$(1,104) = 1.39, $p$ = .24; percentage to invest: $F$(1,105) = 0.82, $p$ = .37) and decision automation were not significant (amount to invest: $F$(1,104) =.05, $p$ = .82; percentage to invest: $F$(1,105) = 1.87, $p$ = .17). However, the interaction effect was significant for both dependent variables (amount to invest: $F$(1,104) = 3.90, $p$ = .05; percentage to invest: $F$(1,105) = 4.45, $p$ = .04). When a low automation robo-advisor was implemented, participants intended to invest more money and a greater percentage of their money through robo-advice when they believed that AI was higher than HI (amount to invest: $M_{\text{high\_AI}}$ = 6,404 Swiss Francs, $M_{\text{low\_AI}}$ = 2,769 Swiss Francs, $F$(1,104) = 4.75, $p$ = .03; percentage to invest: $M_{\text{high\_AI}}$ = 8.07, $M_{\text{low\_AI}}$ = 3.67; $F$(1,105) = 4.27, $p$ = .04). In contrast, when a high automation robo-advisor was implemented, participants did not express greater intentions to invest through robo-advice in the higher AI condition (amount to invest: $M_{\text{high\_AI}}$ = 3,850 Swiss Francs, $M_{\text{low\_AI}}$ = 4,045 Swiss Francs, $F$(1,104) = 0.33, $p$ = .57; percentage to invest: $M_{\text{high\_AI}}$ = 3.72, $M_{\text{low\_AI}}$ = 3.42; $F$(1,105) = 0.77, $p$ = .38). These results support H1 and H2.

## 4. Discussion

Our research is one of the first to investigate behavioral intentions towards robo-advice. While previously identified determinants of technology acceptance (e.g., Meuter *et al.*, 2005) may still be of relevance in a robo-advice context, our research indicates that acceptance of robo-advice also depends on lay theories about AI. Specifically, our study shows that consumers' belief that AI is higher than HI may positively influence behavioral intentions towards robo-advice. Hence, our results extend previous research by identifying a new determinant of self-service acceptance. This determinant may be especially helpful to understand consumer acceptance of smart services such as robo-advice.

Second, our study addresses how service providers must design robo-advisors to mitigate consumer concerns (Marinova *et al.*, 2016). In this respect, we found that consumers fear to lose decision autonomy when interacting with a robo-advisor. Our results show that low decision automation is a mechanism which can reduce such feelings. When a robo-advisor with low decision automation is implemented, consumers fear less strongly to lose autonomy and may therefore react more positively to higher AI than lower AI. This finding extends research by specifying the optimal levels of perceived AI and decision automation.

Finally, our research may contribute to research on lay beliefs about intelligence. Our results indicate that individuals not only have implicit theories about HI but also about AI. Specifically, we find that high AI is associated with the ability to self-learn without human help, whereas low AI is regarded to improve with human help only. This represents a notable difference to lay theories about HI (e.g., Dweck *et al.*, 1995). Future research may want to investigate if such beliefs also influence the acceptance of self-service technologies that require other types of intelligence. For example, it may be interesting to investigate self-services based on affective computing which mimic emotional intelligence (Huang and Rust, 2018). In doing so, a more holistic picture of lay beliefs about AI may emerge.

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