Acceptance of Automated Investment Advisory: An Experimental Study of the Relevance of Trust Attributes of a Robo-Advisor

Tobias Schütz, Cindy Schröder and Carsten Rennhak

Summary: The influence of trust on the adherence to investment recommendations in the context of robo-advisors is under-researched. This relationship needs to be better understood because robo-advice lacks a critical element of trust: human interaction. Theory suggests that ability, integrity, and benevolence are key factors in building trust in human advisors. Using an experimental study design, our research examines the relationship between a robo-advisor's trust attributes and the acceptance of its investment advice. The results show that trust in a robo-advisor increases the propensity to follow its recommendations. While ability and integrity are significant, benevolence is not. The study contributes to the research on technology acceptance, trust, and the adoption of technology-based recommendations by improving the understanding of the relationship between trust and the acceptance of automated investment recommendations.

Keywords: Financial Services; Robo-Advisory; Technology Acceptance; Investment Advice; Trust; Ability, Integrity; Benevolence; Experimental Study

Akzeptanz automatisierter Anlageberatung: Eine experimentelle Studie zur Relevanz von Vertrauensattributen eines Robo-Advisors

Zusammenfassung: Der Einfluss von Vertrauen auf die Befolgung von Anlageempfehlungen eines Robo-Advisors ist noch nicht ausreichend erforscht. Da einem Robo-Advisor eine entscheidende Vertrauenskompetente – die zwischenmenschliche Interaktion – fehlt, ist die Bedeutung dieser Komponente näher zu beleuchten. Die Theorie besagt, dass Kompetenz, Integrität und Wohlwollen Schlüsselfaktoren für das Vertrauen in menschliche Berater sind. Mit Hilfe eines experimentellen Designs untersucht unsere Studie die Beziehung zwischen den Vertrauensattributen eines Robo-Advisors und der Akzeptanz seiner Anlageempfehlung. Die Ergebnisse zeigen, dass das Vertrauen in einen Robo-Advisor die Bereitschaft erhöht, seinen Empfehlungen zu folgen. Während Kompetenz und Integrität statistisch signifikant sind, trifft dies auf Wohlwollen nicht zu. Die Studie leistet einen Forschungsbeitrag zu den Themenfeldern Technologieakzeptanz, Vertrauen und Befolgung technologiebasierter Empfehlungen, indem sie das Verständnis der Beziehung zwischen Vertrauen und der Akzeptanz automatisierter Anlageempfehlungen verbessert.

Stichworte: Finanzdienstleistungen; Robo-Advisory; Technologieakzeptanz; Anlageempfehlung; Vertrauen; Kompetenz, Integrität; Wohlwollen; Experimentelle Studie

1. Introduction

The financial services industry has been significantly impacted by technological advances. Among other major changes in the industry, a whole new industry has emerged around FinTech, or financial technology. *FinTechs* are driving the digital transformation of the financial services industry, using information and communication technologies to optimize the accessibility, availability, and transferability of resources in service systems. This leads to new, technology-enabled value creation processes (Lusch & Nambisan, 2015; Breidbach & Maglio, 2016; Breidbach et al., 2020). Digital technology in the financial industry takes many forms including mobile apps, data management, analytics, and robo-advisory, a virtual financial advisor powered by artificial intelligence (AI).

Nevertheless, the financial services sector has been criticized for failing to implement comprehensive measures to improve customer orientation (Gold & Kursh, 2017). In Germany, this fact is reflected in a particularly low level of trust in financial services providers. Of the 28 markets surveyed in the Edelman Trust Barometer, only the Russian and the Spanish populations display less trust in financial service providers than Germans (Edelman, 2022). A central point of criticism is financial advice in the context of commission-based compensation models. These are seen as profit-driven and not always in the best interests of consumers (Hoffmann et al., 2012). Robo-advisor solutions make it possible to provide automated investment advice based on algorithms and AI (Gold & Kursh, 2017), and are therefore less likely to provide advice that is flawed by commissions. In traditional investment advice, client trust is a key element of the relationship (Jungermann & Fischer, 2005; Georgarakos & Pasini, 2011). This raises the question of whether the well-researched trust-building factors of human investment advice also apply to automated investment advice.

In recent years, researchers have increasingly focused on the acceptance of investment recommendations in the context of robo-advice (Hentzen et al., 2022). For example, Bhatia et al. (2020) use a qualitative approach to examine the extent to which behavioral biases of retail investors can be mitigated by robo-advisory in the Indian market. They find that the focus is on raising investor awareness through education and trust building. Zhang et al. (2021) examine the differences between high and low expertise human financial advisors and robo-advisors in relation to the components of consumer trust perception, performance expectancy, and attitude intention. They find that consumers prefer high-expertise human financial advisors but show no preference for hiring inexperienced human financial advisors over robo-advisors. Hildebrand & Bergner (2021) investigate whether conversational, natural language processing robo-advisors are perceived as more trustworthy and better at changing consumers' financial decisions than static robo-advisors. They find that respondents attribute significantly higher levels of affective trust to conversational robo-advisors. This effect increases when the advisor uses social cues, such as acknowledgements or emoticons. Attributions of benevolence towards the financial services firm also increase when a conversational robo-advisor is used.

In this study we examine all three factors of the trust construct introduced by Mayer et al. (1995) and validated by Serva et al. (2005) (i.e., ability, benevolence, and integrity) in the context of the acceptance of AI-based investment recommendations and, thus broadening the perspective to include both affective and cognitive elements of decision-making. The study was conducted in the German market, which has a highly over-banked market structure and has a lot of catching up to do in terms of digitization due to its pronounced sensitivity to customer data. The study also contributes to the extension of technology acceptance research. Other studies have already shown the importance of trust in the context of financial services (e.g., Madamba & Utkus, 2017; Chan et al. 2022). The technology acceptance models of Davis (1985) and Venkatesh & Davis (2000) have been extended to include the trust factor (e.g., Venkatesh et al., 2003). However, these approaches serve to predict acceptance in the terms of the willingness to use the new technologies. In the context of investment advice, however, consumers may show a willingness to use a technology without ultimately accepting and following its recommendation. Therefore, in this study, we start from the willingness to use the technology and focus on the actual use in terms of following the technology-based recommendation.

The study addresses two main research questions:

1. Are the trust factors of human investment advisors transferable to robo-advisors?
2. Does a higher level of trust in a robo-advisor lead to greater compliance with its investment recommendations?

In this study, we focus on an automated investment advice process in the B2C segment. The investor is guided through an automated investment process by an online questionnaire and underlying algorithms (Maedche et al., 2016). The aim of this study is to examine the acceptance of robo-advisor investment recommendations. This is crucial, as technologies that are accepted and perceived as trustworthy by consumers have an increasing influence on market success (Auge-Dickhut et al., 2014). Against this background, our study identifies the factors that convey trustworthiness and examines their impact on the acceptance of automated investment recommendations.

2. Trust as a Factor of Persuasion

This study draws upon prior research on communication and persuasion (e.g., Eisend & Tarrahi, 2022; Gennaioli et al., 2015; Hamilton & Winchel, 2019). Ideally, when seeking investment advice, the client shares private information with the advisor, who then provides a recommendation. The investor can then choose whether or not to follow the advice. However, studies have shown that investors do not always follow advisors' recommendations, and that trust plays a crucial role in acceptance (Georgarakos & Pasini, 2011; Stolper & Walter, 2017; Stolper, 2018). This is because investment advice is usually considered a credence good, meaning that clients lack objective ways to evaluate the quality of advice they receive (Emons, 2001). As a result, trust is crucial for making informed investment decisions.

There is typically a degree of information asymmetry between professional investment advisors and retail investors. Professional advisors have more or better information about investment decisions, creating challenges for clients to evaluate objectively the advice they receive (Bluethgen et al., 2008). In assessing investment advice, Jungermann (1999) proposes a distinction between option-related and person-related attributes. The former pertains to the quality of the recommended option from both the advisor and the client's perspectives, while the latter relates to the investor's perception of the advisor (e.g., perceived quality of advice, credibility) or the investor's self-confidence.

Because clients have limited ability to evaluate advice objectively, trust in the advisor is a critical factor in investment decision-making. Studies have shown that trust systematically influences decision-making behavior (Kollock, 1994; Morgan, 2002), and clients are more likely to delegate the investment decision to the advisor when they trust them (Calcagno et al., 2017).

Mayer, Davis, and Schoorman (1995) present a comprehensive and interdisciplinary model of trust, which marks a significant turning-point in the academic literature on trust, as noted by Ball (2009). The authors shift the focus of trust from being an individual trait to being a relational construct. Their model posits that trustworthiness is determined by the trustee's *ability*, *benevolence*, and *integrity*, as perceived by the trustor. Furthermore, the propensity to trust can modify the impact of the individual factors of perceived trustworthiness. Trust propensity reflects generalized trust and varies among individuals with different personality types, demographics, and experiences. The authors later expanded on their model by incorporating new developments in the field of organizational trust, leading to a more comprehensive understanding of the role of emotions and contextual factors in trust. They emphasize the significance of trust repair processes and provide insights into how trust can be restored after being violated (Schoorman et al., 2007). Although numerous studies have been published on trust since, many of them, such as Isaeva et al. (2020) or Oliveira et al. (2017), continue to reference the three dimensions of *ability*, *benevolence*, and *integrity* initially introduced by Mayer et al. (1995) in their trust models.

The *ability* dimension describes the investor's (trustor's) perception of the advisor's (trustee's) qualifications and skills needed to provide advice (Mayer et al., 1995). Colquitt et al. (2009) refer to this dimension as competence. An advisor's competence can be perceived subjectively and/or verified objectively, e.g., through diplomas or other certifications (Metzger et al., 2003). Guillemette & Jurgenson (2017) examine the influence of certified financial professionals on the investment decisions of retail investors. Their results suggest that advice from a certified expert changes the choice behavior of low-income retail investors and increases their trust in the advisor. Steinmann (2013) also finds that the perceived ability and benevolence have a significant impact on trust.

Benevolence describes the extent to which the advisor acts in the client's best interest, as perceived by the client. The advisor's individual motives, such as commissions or firm objectives, can influence benevolence (Mayer et al., 1995). Jodlbauer & Jonas (2011) examine the effect of the advisors' perceived self-interests on the acceptance of their recommendations. They conclude that profit-seeking advisors are perceived as having greater self-interest and are rated as being less trustworthy. Hackethal et al. (2010) analyze the investment decisions of retail clients of a German broker. They show that clients are more likely to follow advice when they are less aware of any underlying conflicts of interest. Grillo & Pizzutti (2021) state that the identification of the communicator as an agent with ulterior motives tends to reduce trust in the communicator.

The dimension of *integrity* encompasses the adherence to principles that are deemed acceptable to customers. This involves perceived honesty, as well as moral behavior such as fulfilling promises and meeting standards, as outlined by Mayer et al. (1995). Advisors are regarded as having integrity when they demonstrate ethical conduct, adhere to guidelines, and avoid taking advantage of advisory situations, as noted by Moorman et al. (1993).

Oliveira et al. (2017) utilize a model of *integrity* that includes attributes such as honesty, sincerity, truthfulness, authenticity, and the fulfillment of commitments.

3. Derivation of Research Hypotheses

Even though the original trust models refer to the interaction between humans, the transferability of interpersonal relationships to human-machine interaction has been demonstrated several times. For instance, Nass et al. (1996) observe that individuals tend to assign social roles to TV sets and engage with computers in a similar manner as they do with people. The Computers Are Social Actors (CASA) paradigm, discussed by e.g. Gambino et al. (2020), further posits that humans tend to perceive and treat computers as social beings.

A comparative study conducted by Jian et al. (2000) finds that participants use traits such as integrity and honesty to describe trust, regardless of whether the object of trust was human or automated. Cassell & Bickmore (2000) confirm these findings for systems with both simple text interfaces and interactive virtual agents. The models developed by Tan & Thoen (2000), Chi et al. (2021) suggest that trust in human-machine interactions should be conceptualized to include the propensity to trust the robot, the trustworthy robot function and design, and the trustworthy service task and context.

A plausible hypothesis is that a higher level of trust in a robo-advisor, as assessed by perceived *ability*, *integrity*, and *benevolence*, will lead to greater compliance with its investment recommendations, similar to a human advisor. However, as trust evolves from initial impressions to prior experience, the impact may vary (McKnight et al., 2002). Chang et al. (2010) demonstrate that trustworthiness is influenced by first impressions and direct experience. Therefore, it is crucial to distinguish between the initial and repeated interactions. The former is solely determined by the robo-advisor's initial presentation, while the latter may be influenced by the perceived quality of past investment recommendations. Hypothesis 1 can therefore be formulated as follows:

H1: Investor compliance with a robo-advisor's recommendation is higher if the robot is initially perceived as more trustworthy.

When investors receive information about the financial performance of a robo-advisor's recommendation in comparison to other alternatives, it can be inferred that they will integrate this knowledge into their future decisions. Amelia et al. (2022) investigate customer acceptance of robots in the financial services industry based on their interaction experiences. The study suggests that acceptance is influenced by multiple factors, including task heterogeneity, perceived quality of interaction, and interaction results. Hence, the perception of recommendation quality can positively or negatively impact the acceptance of subsequent recommendations.

However, the initial trustworthiness attributed to the robo-advisor is still expected to influence acceptance. Delgado et al. (2005) provide evidence indicating that initial impressions of perceived trustworthiness impact the evaluation of repeated interactions. We anticipate this effect to persist, regardless of whether the experience with the advisor's recommendations is positive or negative. Hypotheses 2a and 2b can therefore be formulated as follows:

H2a: After a positive confirmation of the robo-advisors investment advice, compliance with the robo-advisor's recommendation is higher if the robot is initially perceived as more trustworthy.

H2b: After a negative confirmation of the robo-advisors investment advice, compliance with the robo-advisor's recommendation is higher if the robot is initially perceived as more trustworthy.

4 Method

4.1 Experimental Design

To test the hypotheses, we conducted an online experiment in the form of an investment game[1] played over 4 periods with a sample of 72 young professionals and masters students with an average age of 23 years[2]. The experimental group consisted of 33 participants and the control group of 39 participants. 42 of the respondents identified as male, 30 as female. 33 held stocks or mutual funds. 9 had professional exposure to financial investments, 7 had prior experience with robo-advisory.

Participants were presented with a fictitious scenario in which they had to maximize an initial capital of €10,000 over a period of 5 months by building and adjusting a portfolio. They were given the choice of investing in the shares of 3 companies randomly selected from the MDAX, 2 Exchange Traded Funds (ETFs) and an interest- and risk-free demand deposit.

In the experiment, a game period corresponded to one month in real time. At the beginning of each period the participants received fictitious press reports containing economic news and a table of indicators describing the development of the economic situation[3]. The press reports dealt with different aspects in each game period. The tabular presentation of the indicators covered the past 6 months on a rolling basis and was modified in each period by the developments of the previous game period. The presentation of specific investment options was identical in all periods and for all investment options. Asset price tables and graphs of performance over the last 12 months were adjusted for each period. In addition, information on sector performance and the outlook for the subsequent periods was modified for each period.

Furthermore, the participants were provided with personalized recommendations from a robo-advisor, which suggested a single investment option for each period. The participants were informed that the advisor utilizes artificial intelligence to evaluate extensive data and generate automated investment recommendations. Additionally, they were requested to assume that they had already furnished their personal details, including their risk tolerance and investment objectives, through an online questionnaire.

The information about the investment options was presented in such a way that no option was seen as dominant. Participants were free to base their decision on the robo-advisor's recommendation and / or on the other sources provided. Participants built their portfolios by allocating the total amount available across different investment options.

1 The experiment was hosted on the Labvanced platform (www.labvanced.com).
2 The sample is a convenience sample. Among the 50 % most successful participants a shopping voucher was raffled off. Success was determined by the terminal value of the portfolio.
3 ifo Business Climate Index, Euro / USD exchange rate, oil price in USD / barrel and MDAX.

There were no transaction costs and investments in the interest-free savings account were capped at 50 % to prevent unrealistically risk-averse behavior.

At the start of each new period, any adjustments to the portfolio resulting from changes in asset prices were automatically calculated and displayed online. Participants were also presented with an overview of the performance of each investment option, with the option recommended by the robo-advisor highlighted in color. Following the second portfolio formation, all investment options experienced positive performances. While the robo-advisor's recommendation was relatively good, it was not the most profitable option available. After the participants' decision in period 3, all performances were negative with the robo-advisor's recommendation being the worst. Unexpectedly for the participants, the experiment ended after four rather than the announced five periods to avoid unrealistic high-risk strategies in the last period to compensate for previous losses (e.g., Schütz, 2005).

An overview of the procedure of the experiment can be found in figure 1.

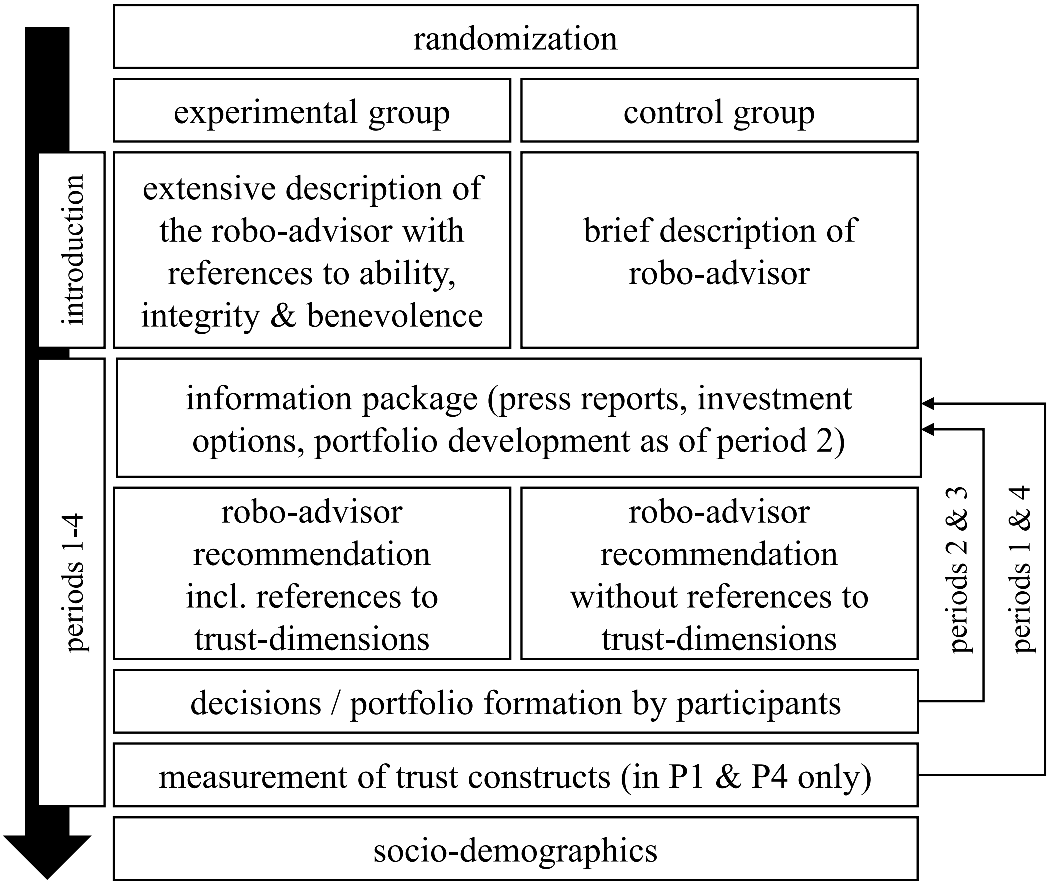

Figure 1: Procedure of experiment

The experiment's purpose was not revealed to the participants. Group formation was randomized. To manipulate the experimental group's level of trust in the robo-advisor they were given additional information. Specifically, the following information was presented to influence the perception of:

Ability (qualifications and skills needed to provide advice)

- *The robo-advisor you are using was featured in a study conducted by the prominent business magazine 'Capital' and ranked among the top 10 robo-advisors in Germany.*
- *Through research, you discovered that the robo-advisor was developed by financial economics experts from a well-respected university.*

Benevolence (extent to which the advisor acts in the client's best interest)

- *Your robo-advisor is not tied to any particular financial product provider.*
- *This means that the provider does not receive sales commissions for promoting specific investment options.*

Integrity (adherence to principles that are deemed acceptable to the client)

- *The robo-advisor is subject to multiple regulatory frameworks.*
- *Your data is kept in a secure, private cloud environment in Germany and is encrypted with AWS EBS encryption.*

The treatment was first administered during the introduction phase (see Fig. 1) and repeated in each period in connection with the presentation of the investment recommendation. To ensure that the treatments were as realistic as possible, extensive research was conducted on robo-advisors available in Germany. The research focused specifically on the presentation of information that could be interpreted as trust-building attributes. The control group received the investment advice without any further information. All other conditions were the same.

4.2 Operationalization

Acceptance of the recommendation was operationalized by the proportional amount that the participants invested in the investment option recommended by the robo-advisor.

As a grouping of three first-order constructs, trustworthiness is differentiated into the dimensions of *ability*, *benevolence* and *integrity*. Items validated by Serva et al. (2005) were used to assess the dimensions and were adapted for the context of this study. All items began with the words *"I believe..."* because the initial measurement was based on first impressions.

Ability	
1	I believe my robo-advisor is competent in making recommendations that will increase my wealth.
2	I believe that my robo-advisor performs its role of providing investment recommendations successfully.
3	Overall, I believe my robo-advisor is a capable and proficient online wealth manager.
4	In general, I believe my robo-advisor is very knowledgeable about financial investments.
Benevolence	
1	I believe my robo-advisor is making recommendations in my best interest.

2	I believe that my robo-advisor wants to help me and is doing its best to make appropriate recommendations.
3	I believe my robo-advisor's intentions are designed to increase my return on investment.
4	I believe that my robo-advisor's recommendations are honest and appropriate.
Integrity	
1	I believe that my robo-advisor is truthful and unbiased when making recommendations.
2	I believe that my robo-advisor is doing its job in compliance with its obligations, such as regulatory requirements.
3	I believe that my robo-advisor's recommendations are honest and genuine.

Table 1: Items by trust factor

Participants rated these items using a 7-point symmetrical Likert scale. The first measure was administered after the participants had made their investment decisions in the first period and served as a manipulation control for the trust construct. For this purpose, the participants rated the robo-advisor based on their first impressions. A second trustworthiness measure was administered after participants had made their investment decisions in the final period.

4.3 Results

The experiment initially included 91 subjects. A plausibility check was performed prior to data processing, resulting in the elimination of 1 participant. 18 participants were excluded due to incomplete questionnaires. Chi-square tests were performed to rule out systematic attrition, and no systematic effects were detected. After elimination, a total of 72 participants remained, with 33 participants in the experimental group and 39 participants in the control group.

Exploratory principal component analysis with varimax rotation was used to determine the initial values for the three factors of perceived trustworthiness. It turned out that the data pattern was very similar to that suggested by the literature[4]. We extracted 3 factors with eigenvalues >1 and a total variance explained of 0,710. Communalities ranged from 0,582 to 0,824. According to the preliminary content-related considerations, the three factors can be interpreted as *ability*, *benevolence*, and *integrity*. The internal consistency of the scales can be classified as *good* for integrity (Cronbach's α: 0,710) and *very good* for *ability* and *benevolence* (Cronbach's α: 0,860 and 0,854).

We conducted an analysis to determine if our manipulation of the participants' perception of trustworthiness was effective. Specifically, we examined whether there was a significant difference in trustworthiness ratings between the experimental group (who received the treatment) and the control group. The results showed that, on average, participants in the experimental group rated all three factors higher than those in the control group. However, the differences were only statistically significant for the *ability* and *integrity* factors, as shown in Table 2. The results indicate that the manipulation

4 The item "I believe that my robo-advisor's recommendations are honest and appropriate" showed the highest loading on the *benevolence* factor, whereas Serva et al. (2005) considered it to be part of *integrity*. All other items were assigned according to Serva et al. (2005).

was successful in influencing the participants' perceptions of the *ability* and *integrity* dimensions, with a medium effect size for *integrity* (Cohen’s d >0,5) and a large effect size for *ability* (Cohen’s d >0,8).

	Levene’s test		t-test for equality of means							
Factor	F	Sig.	T	df	Sig. (one-tailed)	Mean difference	Standard error	95 % confid.-interv. for difference		Cohen’s d
								Lower	Upper	
Ability	0,963	0,330	4,232	70	0,000	0,899	0,212	0,475	1,323	1,001
Benevolence	0,180	0,673	0,365	70	0,358	0,086	0,237	-0,387	0,561	0,086
Integrity	0,449	0,505	2,600	70	0,006	0,591	0,227	0,137	1,045	0,615

Table 2: T-test for initial trust factor value differences

To test H1, we analyzed whether the mean values of the relative acceptance of the investment recommendation (percentage of investment in the recommended option) differed between the groups. In the initial relationship, participants who had received information about the robo-advisor’s trust-building characteristics, invested an average of 39,0 % of their funds in the robo-advisor’s recommendation. At 28,6 %, the control-group members were significantly less likely to select the advisor's recommendation. The observed effect is of medium size (p-value 0,017, Cohen’s d 0,514, see Table 3). Thus, there is empirical support for H1.

	Levene’s test		t-test for equality of means							
Hypothesis	F	Sig.	T	df	Sig. (one-tailed)	Mean Difference	Standard error	95 % confid.-interv. for difference		Cohen’s d
								Lower	**Upper**	
H1	0,304	0,583	2,174	70	0,017	0,104	0,048	0,009	0,200	0,514
H2a	1,280	0,262	2,174	70	0,018	0,096	0,045	0,007	0,185	0,508
H2b	1,843	0,179	2,174	70	0,067	0,082	0,054	-0,026	1,190	0,359

Table 3: Group differences in following robo-advisor’s recommendation

H2a refers to the acceptance of an investment recommendation after the subjects had received information about the performance of the investment options. They learned that, in periods 2 and 3, investing in the respectively recommended option led to an increase in wealth. The research hypothesis is empirically supported if, even after receiving repeated information that following the robo-advisors advice leads to positive results, members of the control group still invest a significantly lower proportion of their portfolio in the recommended option. While the recommended option accounted for an average of 30,8 % of the portfolios of the experimental group, members of the control group invested an average of 21,2 %. The independent samples t-test is significant with a medium effect size (p-value 0,018, Cohen’s d 0,508, see Table 3) and H2a is supported.

H2b refers to the acceptance of robo-advice after the subjects had learned that the previous recommendation had performed negatively. The subjects that chose this investment lost money. To test H2b, the difference in the mean values of the investment amounts in the fourth period was analyzed. In period 4, subjects in the experimental group invested an average of 26,2 % in the asset recommended by the advisor. Compared to the acceptance rates in the other periods, this was the lowest average investment rate of the experimental group. The control group invested 18.0 %. This is also the lowest average investment rate for the control group. Therefore, we can assume that the negative experience associated with the robo-advisor's recommendation led to an immediate decrease in the participants' willingness to follow the recommendation to the extent previously shown. Although the experimental group still invested more than the control group, this difference is not significant in period 4 (p-value 0,067, Cohen's d 0,359, see Table 3).

This suggests that the positive effect of communicating trust-building characteristics disappears or is mitigated when following the advice has led to unfavorable investment decisions. Negative experiences may at least in part compensate for the trust-building efforts. On the other hand, it is possible that the trust-building information introduced in the familiarization phase was forgotten or diluted over the 4 periods as it was only briefly mentioned in each round. If this were the case, however, the trust factor constructs should not differ systematically between the experimental and the control groups after period 5. To rule this out, a second measurement of the items reflecting the 3 factors of trust was conducted after the last investment decision in period 4 and a principal components analysis with varimax rotation was performed. The factors extracted (total variance explained 0,806) were structurally identical to those previously identified. Also, the comparison of the experimental and the control groups yielded results very similar to those of period 1. Participants in the experimental group rated all 3 factors higher. However, the differences were significant only for *ability* and *integrity*, and again not for *benevolence* (see table 4).

	Levene's test		t-test for equality of means							
Factor	F	Sig.	T	df	Sig. (one-tailed)	Mean difference	Standard error	95 % confid.-interv. for the difference		Cohen's d
								Lower	Upper	
Ability	1,229	0,271	3,374	70	0,000	0,745	0,221	0,305	1,186	0,798
Benevolence	1,366	0,246	1,153	70	0,126	0,272	0,236	-0,199	0,743	0,273
Integrity	0,718	0,400	2,612	70	0,006	0,594	0,227	0,140	1,047	0,618

Table 4: T-test for final trust factor value differences

Thus, we can conclude that the assimilation of both groups' investment decisions in the final period was not caused by a convergence of the perceived trust in the robo-advisor itself. Rather, it seems that trust is less important for following an investment recommendation when it is preceded by a negative experience with the previous recommendation.

5. Discussion

The banking industry has been transformed by technological advancements, leading to the emergence of new challenges. The acceptance and perceived trustworthiness of technologies by consumers have become increasingly important for achieving market success, as highlighted by Auge-Dickhut et al. (2014). Against this backdrop, our study aimed to identify the factors that contribute to trustworthiness and to investigate their impact on the acceptance of AI-based investment recommendations.

To achieve this goal, we first conceptualized trust and drew upon existing empirical research on trust in investment advisory services. We identified *ability*, *benevolence*, and *integrity* as critical dimensions of perceived trustworthiness. These attributes of trust in an investment advisor can significantly impact the acceptance of investment recommendations by individuals.

5.1 Theoretical contribution

Research on trust and technology suggests that people view technology as a trusted object and assign specific attributes to it. In the context of robo-advisors, we can apply models from persuasion research to understand consumer behavior. Once individuals have adopted heuristic processing strategies and begin focusing on factors such as awards, their acceptance of robo-advice may be more influenced by intuitively assessable features rather than substantive arguments. Therefore, perceived robo-advisor characteristics, such as ability, integrity, and benevolence, are likely to play a crucial role in initial trust-building and increasing acceptance of automated investment recommendations. Notably, these components of trust between humans and technology are not significantly different from trust between humans. Consistent with Hancock et al. (2011), we come to the conclusion that a favorable perception of a robo-advisor's characteristics contributes to the development of trust in a robo-advisor in the same way as it does in a human advisor.

Analysis of the factor differences using the effect size (Cohen's d) showed, that the experimental and the control group differed most distinctly on perceived *ability* of the robo-advisor. While the *integrity* treatment produced significant group differences, the effect size was only medium. We found that the treatment caused no significant difference in the perceived *benevolence* of the robo-advisor between the experimental groups. However, since we were able to show that the members of the experimental group were significantly more likely to follow the recommendations of the robo-advisor, it can be assumed that ability and integrity alone already exercise a substantial influence on the investors' decision behavior. This also suggests that the cognitive trust factor (ability) has a greater impact on the investment decision than the affective factors (integrity and benevolence). Schlosser et al. (2006) come to a similar conclusion in their study of online shopping behavior.

To contextualize our work and differentiate it from previous research discussed in the introduction, we can summarize as follows: Earlier studies have shown that people perceive technology as a trusted object and attribute certain characteristics to it. Our study extends these findings to the context of trust and robo-advisors and suggests that consumers' acceptance of robo-advice is influenced by trust dimensions traditionally associated with humans. However, our research did not find a significant difference in the perceived *benevolence* of the robo-advisor between experimental groups, in contrast to Hildebrand & Bergner (2021) who were able to demonstrate that perceived benevolence can vary between robo-advisors. Upon closer examination of differences in research design, the results suggest that robo-advisors need to have a conversational interface to evoke a sense of *benevolence*, whereas a static robo-advisor that only provides recommendations without allowing for investor questions, feedback or other forms of interaction is unlikely to have this effect.

5.2 Managerial implications

To enhance the perceived *ability* of a robo-advisor, it may be worthwhile for providers to invest in measures that increase customer confidence. One effective approach is to provide transparent information about the developers' expertise and third-party rankings. Financial firms should ensure that their technology is backed by qualified and experienced professionals, and clearly communicate this to their clients. In addition, highlighting awards and other attributes that demonstrate the robo-advisor's *ability* can further increase acceptance of investment recommendations.

Similarly, perceived integrity can be increased by emphasizing that the robo-advisor is subject to rigorous regulatory requirements and that customer data is highly protected. Therefore, investing in these or similar integrity-enhancing features and actively communicating them to customers can be a smart move for robo-advisor providers. By demonstrating both ability and integrity, firms can establish trust and confidence with their clients.

5.3 Limitations and further research

The study is subject to a number of limitations that should be considered when interpreting the results. Firstly, the sample comprised of young professionals and master students. Replicating the study with a different sample, such as investors with more experience, less formal education, or those who are less receptive to new technologies, could yield different outcomes. Furthermore, while the sample size of 72 is sufficient for the statistical analyses conducted in this study, it is not considered comfortable. A post-hoc power analysis has indicated that a larger sample size would have resulted in a significant finding for H2b, albeit with a small effect size (Cohen's d 0,359). Moreover, a larger sample size would have enabled the examination of mediating effects of trust measures on advice acceptance in addition to the main effects.

Second, the experimental setting may have influenced participants to take more risks than they would in a real investment scenario. Even though we attempted to minimize this effect by offering incentives for performing in the top half rather than being the best investor, and by playing four rounds instead of the announced five, the limitations of the experimental environment cannot be eliminated completely.

A third limitation pertains to the experimental procedure, in which observant participants could potentially infer that the recommendations provided by the robo-advisor were not tailored to their individual risk propensity, as no actual artificial intelligence was utilized. As a result, this may have led to a bias and decreased trust towards the robo-advisor. However, due to the randomization process, this effect should apply equally to both the experimental and control groups, and therefore, any comparative bias should be minimal.

Lastly, the study solely investigates the impact of perceived trustworthiness on the acceptance of robo-advisory. Nonetheless, there are other factors that could influence the acceptance of automated investment recommendations. To gain a more comprehensive understanding, future research may need to incorporate approaches from other disciplines. For example, emotions such as greed or fear could also play a role in shaping behavior and willingness to accept an investment recommendation (Wahren, 2009). Therefore, we suggest that future studies should evaluate the validity of perceived trustworthiness in relation to the personal circumstances and individual characteristics of the investor. By doing so, we could understand better how other factors could potentially impact the acceptance of robo-advisory, and potentially identify additional ways to enhance its acceptance.

References

Amelia, A., Mathies, C., & Patterson, P. G. (2022). Customer acceptance of frontline service robots in retail banking: A qualitative approach. Journal of Service Management, 33 (2), 321–341. https://doi.org/10.1108/JOSM-10-2020-0374

Auge-Dickhut, S., Koye, B., & Liebetrau, A. (2014). Client Value Generation, Springer Gabler, https://doi.org/10.1007/978-3-658-01524-4_1

Ball, J. (2009). The currency of trust: What business leaders can learn from the extreme poor. Ivey Business Journal, 73.

Bhatia, A., Chandani, A., & Chhateja, J. (2020). Robo advisory and its potential in addressing the behavioral biases of investors – A qualitative study in Indian context. Journal of Behavioral and Experimental Finance, 25 (5), 100281. https://doi.org/10.1016/j.jbef.2020.100281

Bluethgen, R., Meyer, S., & Hackethal, A. (2008). High-Quality Financial Advice Wanted. SSRN Electronic Journal, http://dx.doi.org/10.2139/ssrn.1102445

Breidbach, C. F., Keating, B. W., & Lim, C. (2020). Fintech: research directions to explore the digital transformation of financial service systems. Journal of Service Theory and Practice, 30(1), 1–24. https://doi.org/10.1108/JSTP-08-2018-0185

Breidbach, C. F., & Maglio, P. (2016). Technology-enabled value co-creation: an empirical analysis of actors, resources, and practices. Industrial Marketing Management, 56(7), 73–85. https://doi.org/10.1016/j.indmarman.2016.03.011

Calcagno, R., Giofré, M., & Urzì-Brancati, M. C. (2017). To trust is good, but to control is better: How investors discipline financial advisors' activity. Journal of Economic Behavior & Organization, 140, 287–316. https://doi.org/10.1016/j.jebo.2017.04.010

Cassell, J., & Bickmore, T. (2000). External manifestations of trustworthiness in the interface. Communications of the ACM, 43(12), 50–56. https://doi.org/10.1145/355112.355123

Chan, R., Troshani, I., Hill, S. R., & Hoffmann, A. (2022). Towards an Understanding of Consumers' FinTech Adoption: The Case of Open Banking. International Journal of Bank Marketing, 40(4), 886–917. https://doi.org/10.1108/IJBM-08-2021-0397

Chang, L. J., Doll, B. B., van 't Wout, M., Frank, M. J., & Sanfey, A. G. (2010). Seeing is believing: trustworthiness as a dynamic belief. Cognitive psychology, 61(2), 87–105. https://doi.org/10.1016/j.cogpsych.2010.03.001

Chi, O. H., Jia, S., Li, Y., & Gursoy, D. (2021). Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) social robots in service delivery. Computers in Human Behavior, 118, https://doi.org/10.1016/j.chb.2021.106700.

Colquitt, J.A., Lepine, J.A., & Wesson, M.J. (2009). Organizational behavior: Improving performance and commitment in the workplace. McGraw-Hill.

Davis, F. D. (1985). A Technology Acceptance Model for Empirically Testing New End-User Information Systems, Doctoral dissertation, Massachusetts Institute of Technology.

Delgado, M. R., Frank, R. H., & Phelps, E. A. (2005). Perceptions of moral character modulate the neural systems of reward during the trust game. Nature neuroscience, 8(11), 1611–1618. https://doi.org/10.1038/nn1575

Edelman (2022). Edelman Trust Barometer 2022 - Global Report: Trust in Financial Services Sector. www.edelman.com

Eisend, M., & Tarrahi, F. (2022). Persuasion Knowledge in the Marketplace: A Meta-Analysis. Journal of Consumer Psychology, 32(1), 3–22. https://doi.org/10.1002/jcpy.1258

Emons, W. (2001). Credence goods monopolists. International Journal of Industrial Organization, 19(3–4), 375–389. https://doi.org/10.1016/S0167-7187(99)00023-5

Freedy, A., DeVisser, E., Weltman, G., & Coeyman, N. (2007). Measurement of trust in human-robot collaboration. CTS 2007, Proceedings of the Symposium on Collaborative Technologies & Systems, 106–114. https://doi.org/10.1109/CTS. 2007.4621745

Gambino, A., Fox, J., & Ratan, R. A. (2020). Building a stronger CASA: Extending the computers are social actors paradigm. Human-Machine Communication, 1, 71–85. https://search.informit.org/doi/10.3316

Gennaioli, N., Shleifer, A., & Vishny, R. (2015). Money Doctors. Journal of Finance, 70(1), 91–114. https://doi.org/10.1111/jofi.12188

Georgarakos, D., & Pasini, G. (2011). Trust, Sociability, and Stock Market Participation. Review of Finance, 15(4), 693–725. https://doi.org/10.1093/rof/rfr028

Gold, N. A., & Kursh, S. R. (2017). Counterrevolutionaries in the Financial Services Industry: Teaching Disruption – A Case Study of Rob Advisors and Incumbent Responses. Business Education Innovation Journal, 9(1), 139–146. http://dx.doi.org/10.2139/ssrn.3539122

Grillo, T. L. H., & Pizzutti, C. (2021): Recognizing and Trusting Persuasion Agents: Attitudes Bias Trustworthiness Judgments, but not Persuasion Detection. Personality and Social Psychology Bulletin, 47(5), 796–809. http://dx.doi.org/10.1177/0146167220946197

Guillemette, M. A., & Jurgenson, J. B. (2017). The Impact of Financial Advice Certification on Investment Choices. Journal of Financial Counseling and Planning, 28(1), 129–139. https://doi.org/10.1891/1052-3073.28.1.129

Hackethal, A., Inderst, R., & Meyer, S. (2010). Trading on Advice. CEPR Discussion Paper No. 8091, Nov. 2010, www.cepr.org/pubs/dps/DP8091.asp

Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y. C., Visser, E. J. de, & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. Human factors, 53(5), 517–527. https://doi.org/10.1177/0018720811417254

Hamilton, E.L., & Winchel, J. (2019). Investors' Processing of Financial Communications: A Persuasion Perspective. Behavioral Research in Accounting, 31(1), 133–156. https://doi.org/10.2308/bria-52211

Hentzen, J. K., Hoffmann, A., Dolan, R., & Pala, E. (2022). Artificial intelligence in customer-facing financial services: a systematic literature review and agenda for future research. International Journal of Bank Marketing, 40(6), 1299–1336. https://doi.org/10.1108/ijbm-09-2021-0417

Hildebrand, C., & Bergner, A. (2021). Conversational robo advisors as surrogates of trust: onboarding experience, firm perception, and consumer financial decision making. Journal of the Academy of Marketing Science, 49(4), 659–676. https://doi.org/10.1007/s11747-020-00753-z

Hoffmann, A. O. I., Franken, H., & Broekhuizen, T. L. J. (2012). Customer Intention to Adopt a Fee-Based Advisory Model: An Empirical Study in Retail Banking. International Journal of Bank Marketing, 30(2), 102–127. https://doi.org/10.1108/02652321211210886

Isaeva, N., Gruenewald, K., & Saunders, M. N. (2020). Trust theory and customer services research: theoretical review and synthesis. The Service Industries Journal, 40(15–16), 1031–1063. https://doi.org/10.1080/02642069.2020.1779225

Jian, J.-Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an Empirically Determined Scale of Trust in Automated Systems. International Journal of Cognitive Ergonomics, 4(1), 53–71. https://doi.org/10.1207/S15327566IJCE0401_04

Jodlbauer, B., & Jonas, E. (2011). Forecasting clients' reactions: How does the perception of strategic behavior influence the acceptance of advice? International Journal of Forecasting, 27(1), 121–133. https://doi.org/10.1016/j.ijforecast.2010.05.008

Jungermann, H. (1999). Advice giving and taking. Proceedings of the 32nd annual Hawaii international conference on system sciences, IEEE Comput. Soc. https://doi.org/10.1109/HICSS. 1999.772745

Jungermann, H., & Fischer, K. (2005). Using Expertise and Experience for Giving and Taking Advice. In Betsch, T. & Haberstroh, S. (eds.), The routines of decision making (pp. 157–173). Lawrence Erlbaum.

Kollock, P. (1994). The Emergence of Exchange Structures: An Experimental Study of Uncertainty, Commitment, and Trust. American Journal of Sociology, 100(2), 313–345. https://doi.org/10.1086/230539

Lusch, R. F., & Nambisan, S. (2015). Service innovation: a service-dominant logic perspective. MIS Quarterly, 39(1), 155–175. https://doi.org/10.25300/MISQ/2015/39.1.07

Madamba, A., & Utkus, S. P. (2017). Trust and Financial Advice. Vanguard Research, 1–11. http://dx.doi.org/10.2139/ssrn.3697232

Maedche, A., Morana, S., Schacht, S., Werth, D., & Krumeich, J. (2016). Advanced User Assistance Systems. Business & Information Systems Engineering, 58(5), 367–370. https://doi.org/10.1007/s12599-016-0444-2

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. The Academy of Management Review, 20(3), 709–734. https://doi.org/10.2307/258792

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and Validating Trust Measures for e-Commerce: An Integrative Typology. Information Systems Research, 13(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

Metzger, M. J., Flanagin, A. J., Eyal, K., Lemus, D. R., & McCann, R. M. (2003). Credibility for the 21st Century: Integrating Perspectives on Source, Message, and Media Credibility in the Contemporary Media Environment. Annals of the International Communication Association, 27(1), 293–335.

Moorman, C., Deshpandé, R., & Zaltman, G. (1993). Factors Affecting Trust in Market Research Relationships. Journal of Marketing, 57(1), 81–101. https://doi.org/10.2307/1252059

Morgan, D. P. (2002). Rating Banks: Risk and Uncertainty in an Opaque Industry. American Economic Review, 92(4), 874–888. https://doi.org/10.1257/00028280260344506

Nass, C., Reeves, B., & Leshner, G. (1996). Technology and Roles: A Tale of Two TVs. Journal of Communication, 46(2), 121–128. https://doi.org/10.1007/11558651_45

Oliveira, T., Alhinho, M., Rita, P., & Dhillon, G. (2017). Modelling and testing consumer trust dimensions in E-Commerce. Computers in Human Behavior, 71, 153–164. https://doi.org/10.1016/j.chb.2017.01.050

Schoorman, F.D., Mayer, R.C., & Davis, J.H. (2007). An integrated model of organizational trust: Past, present, and future. The Academy of Management Review, 32, 334–354. http://dx.doi.org/10.5465/AMR.2007.24348410

Schlosser, A. E., White, T. B., & Lloyd, S. M. (2006). Converting Web Site Visitors into Buyers: How Web Site Investment Increases Consumer Trusting Beliefs and Online Purchase Intentions. Journal of Marketing, 70(2), 133–148. https://doi.org/10.1509/jmkg.70.2.133

Schütz, T. (2005). Die Relevanz von Unternehmensreputation für Anlegerentscheidungen: Eine experimentelle Studie. Peter Lang.

Serva, M. A., Benamati, J. S., & Fuller, M. A. (2005). Trustworthiness in B2C e-commerce. ACM SIGMIS Database, 36(3), 89–108. https://doi.org/10.1145/1080390.1080397

Steinmann, T. (2013). Vertrauen in Banken: Eine empirische Untersuchung von Determinanten und Konsequenzen, Springer Gabler.

Stolper, O., & Walter, A. (2017). Financial literacy, financial advice, and financial behavior. Journal of Business Economics, 87(5), 581–643. https://doi.org/10.1007/s11573-017-0853-9

Stolper, O. (2018). It takes two to Tango: Households' response to financial advice and the role of financial literacy. Journal of Banking & Finance, 92, 295–310. https://doi.org/10.1016/j.jbankfin.2017.04.014

Tan, Y.-H., & Thoen, W. (2000). Toward a Generic Model of Trust for Electronic Commerce. International Journal of Electronic Commerce, 5(2), 61–74. https://doi.org/10.1007/978-0-387-35692-1_36

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Wahren, H.-K. (2009). Anlegerpsychologie. VS Verlag für Sozialwissenschaften.

Zhang, L., Pentina, I., & Fan, Y. (2021). Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services. Journal of Services Marketing, 35(5), 634–646. https://doi.org/10.1108/IJBM-09-2021-0439

Tobias Schütz, Dr. is a Professor for Marketing and Customer Science at ESB Business School in Reutlingen

Contact information: ESB Business School Reutlingen, Alteburgstraße 150, 72762 Reutlingen, Tel.: +49 (0)7121/271–3099, E-Mail: tobias.schuetz@reutlingen-university.de

Cindy Schröder, M.A. is a Product Manager at Vodafone

Contact information: Vodafone Deutschland GmbH, Betastraße 6–8, 85774 Unterföhring, Tel.: +49 (0)173 6174108, E-Mail: Cindy.Schroeder1@vodafone.com

Carsten Rennhak, Dr. is a Professor for PR and Marketing at the Universität der Bundeswehr in Munich

Contact information: Universität der Bundeswehr München, Werner-Heisenberg-Weg 39, 85577 Neubiberg, Tel.: +49 (0)89/6004–3128, E-Mail: carsten.rennhak@unibw.de