

Differences in Investment Behavior – A Quantitative Study on the Effects of Robo-Advisors and Human Financial Advisors

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This study examines investment behavior differences between static and conversational robo-advisors and human financial advisors, focusing on affective trust, risk, and financial literacy. Using an online factorial experiment (n = 165), U.S. participants evaluated advisor scenarios under positive and negative message framing. MANOVA and Pearson correlations revealed no significant trust or risk differences across advisor types or framings. However, individuals with high financial literacy perceived conversational robo-advisors as riskier under negative framing, while lower-literacy participants trusted robo-advisors more. The study highlights the need for human-like design improvements in robo-advisors and enhanced financial education to support informed, confident decision-making.

Keywords: robo advisors, behavioral finance, affective trust, risk, investment, financial literacy

INTRODUCTION

Have you engaged in online brokerage platforms, traded stocks via a digital app, or set-up an Exchange Traded Fund (ETF) on your smartphone? If so, you are not alone. Considering the increasing digitalization and financialization of the Western world's capital market, innovative financial technology (FinTech) solutions continue to rise. The question arises whether novel FinTech services allow for a higher degree of accessibility of financial products on the one hand, whilst on the other hand promoting an increase of actively participating in the stock market. Following this notion, 62% of U.S. adults invested in the stock market in 2024 – tendency rising (Statista Research Department, "Share of Americans Investing Money in the Stock Market 1999-2024").

At the same time, the FinTech market is continuously evolving, with so-called robo-advisors posing one of the most common digital financial services. Put simply, robo-advisors provide simplified online investment advice to private individuals (Garg et al., 2023). Robo-advisor technology builds on artificial intelligence algorithms to continuously rebalance a user's portfolio through passive investment strategies. At the same time, they allow for a high degree of customization, e.g. by catering to a user's risk preference and investment goals whilst at the same time offering a low-cost asset management service that can be administered digitally (Belanche et al., 2019; Beketov et al., 2018; Garg et al., 2023; Hildebrand & Bergner, 2020; Sironi, 2016; Pietersen, Ferreira-Schenke & Dick-arson, 2021; Wexler & Oberlander, 2021).

According to a Statista Market Forecast (2023), the robo-advisor market reflected by assets under management is forecasted to reach US\$1,800.00 billion by the end of 2024 with a projection of 34.050 million users by 2029. With the key markets being North America, Germany, as well as Singapore and Hong Kong, the providers Vanguard, Schwab Intelligent Portfolios, Betterment, or SoFi are the most renowned for their robo-advisor services (Statista Market Insights, 2023; Tepper & Curry, 2021).

Robo-advisors pose the value proposition to simplify, customize, and optimize investment decisions for users by objectifying the investment process through algorithmic operations instead of human decision-making. Put differently, one could argue that robo-advisor services try to “de-humanize” the investment process to optimize it by minimizing the risk of falling prone to biases, hasty decisions, or mere investment mistakes. This notion starkly contrasts behavioral economics and behavior finance (Eichler & Schwab, 2024), arguing for a humanization of neoclassical economic theory to increase the predictive quality of mathematical models for real-life use cases.

Behavioral finance, a branch of behavioral economics, uses psychological concepts to better understand investment behavior (Costa & Moreira, 2019; Shefrin, 2009). In its essence, the field suggests that investment decisions are shaped by behavioral patterns, cognition, affect and psychological preferences, e.g. risk perception, to enhance modern portfolio and asset pricing theories (Sent, 2004; Shefrin, 2009). Hereby, behavioral economists support the shifting view from the rational homo economicus to the naturally biased human (Simon, 1955; Thaler, 2016). At the same time, the field does not neglect the principles of neoclassical theory but tries to integrate them into real-life examples related to bounded rationality (Ashraf, Camerer & Loewenstein, 2015; Sent, 2004; Thaler, 2016).

Today, different forms of robo-advisors exist that continuously challenge the blending borders between objective technology and humanoid design by integrating new functionalities, such as turn-taking or the use of emojis, into existing robo-advisor models. Therefore, one can commonly differentiate between so-called static robo-advisors and conversational, or generative, robo-advisors which embody the digitalized counterpart to the human financial advisor (Hildebrand & Bergner, 2020).

Problem Statement and Research Objective

Based on the above observations, this study attempts to offer a new perspective on the use of robo-advisors and its effect on consumers’ investment behavior by using behavioral finance as a working model, since the impact of robo-advisors on individual investment behavior and receptivity to non-human financial advice remains underexplored. Despite the technology’s rapid growth, regulatory frameworks are still developing to ensure robo-advisors deliver on their promise: providing accessible, automated, low-cost investment guidance tailored to individual risk preferences and goals, independent of an investor’s financial expertise (Baker & Dellaert, 2018). Yet, a critical review of the technology’s regulatory requirements will be out of this research article’s scope. In addition to the behavioral dimensions, the authors support that financial literacy is pivotal to individual financial health and effective investment strategy execution as required for trading stocks or other assets through robo-advisors. Until today, most individuals still lack even basic financial knowledge, con-straining their ability to engage successfully in investment markets (Ansari et al., 2022).

Furthermore, individuals tend to rely on cognitive shortcuts in processing financial information to simplify their cognitive decision-making. While the influence of heuristics and prospect theory on investment behavior is well-documented, less is known about whether robo-advisors alter these behavioral tendencies (Tversky & Kahneman, 1979; Tversky & Kahneman, 1986; Kahneman, 2003).

Lastly, the financial industry suggests that robo-advisors could mitigate human biases through algorithmic objectivity and consistency (Darškuviene & Lisauskiene, 2021). However, overconfidence – a common bias where individuals overestimate their abilities in areas with limited expertise – can pose a significant investment challenge (De Bondt & Thaler, 1994; Kahneman, 2011). Financial organizations’ claims that robo-advisors can compensate for individual incompetencies might unintentionally foster or bolster overconfidence, increasing the risk of suboptimal financial decisions.

Still little is known about the relationship between the different forms of financial advisors and their effect consumers’ investment behavior as it relates to the above outlined concepts within the field of

behavioral finance. Therefore, this study aims to assess whether individuals perceive financial advice differently when received from a static robo-advisor, a generative robo-advisor, or a human financial advisor. Also, the researchers seek to examine how these perceptions influence investment behavior. Specifically, the study focuses on perceived investment risk, affective trust toward the financial advisor, and individual financial literacy levels.

Research Questions and Hypotheses

To yield initial answers to the questions mentioned above, the researchers have developed five overarching research questions and corresponding hypotheses, utilizing a behavioral finance perspective to examine how robo-advisors, designed to provide rational, quantitative-driven guidance, might influence investment decisions compared to human advisors.

Based on these theoretical assumptions, the researchers hypothesized that robo-advisors may reduce framing effects and loss aversion, promoting more objective, portfolio-maximizing choices. Yet, the researchers decided against directed hypotheses to allow for a higher degree of exploration and to first develop an understanding for whether there is a difference between different forms of financial advisors – or not. Therefore, the five hypotheses place their focus on the role of the financial message sender (static robo-advisor, conversational robo-advisor, or human financial advisor) – amidst positive- and negative framing conditions:

Research Question 1: *Is there a difference in the perceived level of affective trust between the three forms of financial advice, static robo-advisor, dynamic robo-advisor, or human financial advisor, if presented a negative financial message?*

Hypothesis H01: *There will be no difference between individuals receiving a negative financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

Hypothesis H11: *There will be a statistically significant difference between individuals receiving a negative financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

Research Question 2: *Is there a difference in the perceived level of affective trust between the three forms of financial advice, static robo-advisor, dynamic robo-advisor, or human financial advisor, if presented a positive message?*

Hypothesis H02: *There will be no difference between individuals receiving a positive financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

Hypothesis H12: *There will be a statistically significant difference between individuals receiving a positive financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

Research Question 3: *Is there a difference in the perceived level of risk between the three forms of financial advice, static robo-advisor, dynamic robo-advisor, or human financial advisor, if presented a positive financial message?*

Hypothesis H03: *There will be no difference between individuals receiving a positive financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

Hypothesis H13: *There will be a statistically significant difference between individuals receiving a positive financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

Research Question 4: *Is there a difference in the perceived level of risk between the three forms of financial advice, static robo-advisor, dynamic robo-advisor, or human financial advisor, if present-ed a negative financial message?*

Hypothesis H04: *There will be no difference between individuals receiving a negative financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

Hypothesis H14: *There will be a statistically significant difference between individuals receiving a negative financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

Research Question 5: *Is there a difference in the perceived level of risk between the three forms of financial advice, static robo-advisor, dynamic robo-advisor, or human financial advisor, if a participant shows high financial literacy level and is presented a negative message?*

Hypothesis H05: *There will be no difference between individuals showing high financial literacy levels receiving a negative financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

Hypothesis H15: *There will be a statistically significant difference between individuals showing high financial literacy levels receiving a negative financial message by a static robo-advisor, dynamic robo-advisor, or human financial advisor.*

The hypotheses will be tested within one study and online-experiment as outlined in this research article's method section.

Literature Research Strategy

The research strategy for this study centered on exploring the intersection of behavioral finance and robo-advisor technology. Using the researchers' institutions library's OneSearch and EBSCO Host, the researchers identified relevant literature on behavioral finance concepts such as heuristics, overconfidence, financial literacy, risk, and message framing, filtering results to include only books and peer-reviewed articles published between 1955 and 2024 in both English and German to cater to the researchers' language abilities. The chosen timeframe ensures coverage of Simon's (1955) foundational work on behavioral economics as an indirect starting point.

Initial searches were refined through additional searches inspired by cross-references and specific subsections within the literature review. Key search terms included but were not limited to *behavioral economics, bounded rationality, robo-advisor, financial literacy, prospect theory, overconfidence, risk, affective trust, bias, investment behavior, and financial decision-making.*

Foundational Theory and Background

The concept of bounded rationality, introduced by Simon (1955, 1991), suggests that individuals face cognitive limitations, time constraints, and knowledge gaps, preventing them from fully processing all available information and understanding every alternative and outcome (Kalantari, 2010; Schwarz, Christensen & Zhu, 2022). In contrast, modern portfolio theory (Markowitz, 1959) assumes that investors are rational actors who maximize their portfolios by satisfying preference axioms in utility theory, such as completeness, reflexivity, and transitivity (Neumann et al., 2007). Rational investors balance risk and utility to achieve the highest possible returns at minimal risk (Costa & Moreira, 2019; Escobar-Anel et al., 2022; Maier-Paape & Zhu, 2018; Mittal & Mandal, 2022). Yet, investment choices inherently involve decision-making under uncertainty. Based on this notion, prospect theory posits that individuals exhibit loss aversion, preferring certain gains over potential ones and assessing options relative to a personal reference point along a value function (Tversky & Kahneman, 1979; Tversky & Kahneman, 1981).

Therein, framing also affects decision-making, as individuals' evaluations depend on whether information is presented neutrally, as a gain, or as a loss (Kahneman, 2003; Kahneman & Tversky, 1979, 1984). Within behavioral finance, framing is crucial in shaping investor behavior. In addition, it is important to note that individuals tend to rely on heuristics to minimize their cognitive load and accelerate their decision-making processes. Heuristics serve as mental shortcuts that use familiar patterns and existing knowledge to simplify judgments, often building on past experiences (Kahneman, 2003; Tversky & Kahneman, 1974). As an example, a common heuristic in investment contexts is overconfidence, where individuals overestimate their skills relative to their actual abilities (De Bondt & Thaler, 1994; Kahneman, 2011). In addition, the anchoring effect and overreliance on past investment experiences and disregarding newly available information proves to be another commonly explored investment heuristic in the field (Kahneman, 2011; Owusu & Laryea, 2023; Upashi & Kadakol, 2023).

Different Forms of Robo-Advisors and Their Operationalization

While this study does not focus on the technological aspects of robo-advisors, a brief overview of their means of operations is provided to contextualize their impact on user interactions in wealth and asset management platforms.

Today's most prevalent type of robo-advisor service, static robo-advisors, include first- and second-generation algorithmic models that employ questionnaire-driven risk assessments to determine a user's risk profile. By doing so, they predominantly pursue passive investment strategies on behalf of the consumer (Alsabah et al., 2019; Beketov et al., 2018; Semko, 2019). More advanced third- and fourth-generation robo-advisors incorporate higher levels of automation via artificial intelligence models, gradually enabling the full transfer of investment decision-making from the client to the robo-advisor (Beketov et al., 2018; Semko, 2019).

A review of 219 robo-advisor platforms has outlined the functionality's common operational framework and mathematical basis: First, assets are preselected and matched to a client's risk preferences through a questionnaire on the asset management provider's website. Then, Modern Portfolio Theory is applied to optimize the portfolio, which can be continuously monitored and rebalanced on the user's chosen platform (Beketov et al., 2018; Semko, 2019). Many platforms employ sample portfolios as a simplified alternative to complex quantitative models. However, these portfolios often restrict customization and thus attract less assets under management (Beketov et al., 2018).

In contrast, artificial neural networks (ANNs), a subset of machine learning, offer a promising enhancement to the limitations of the first-generation models. By leveraging non-linear learning algorithms that emulate biological neural activity, ANNs can adaptively learn from the environment and user behavior, increasing the potential for personalized investment strategies. This adaptability may help detect and counteract irrational behavioral patterns and biases in human investment behavior, which traditional portfolio models cannot fully address (Beketov et al., 2018; Guresen & Kayakutlu, 2011; Semko, 2019).

In response to this trend and technological evolution, conversational or generative robo-advisors are on the rise. In essence, they function similarly to chatbots. These advisors engage with clients through anthropomorphic features, such as personalized names, informal language, emojis, or a distinct tone of voice via voice-bots, simulating human interaction through anthropologic design measures (Hildebrand & Bergner, 2021; Thomaz et al., 2020). The current state of research indicates that the more conversational robo-advisors are tailored to individual consumers, the more likely clients are to perceive the interaction as social rather than mechanistic, fostering affective trust (Hildebrand & Bergner, 2021; Thomaz et al., 2020).

Finally, robo-advisors aim – and claim – to enhance efficiency and customer experience within financial services and reduce the risk of suboptimal investment decisions by leveraging supportive technology.

Processing (Financial) Information Amidst Dual-Processing Theories

Research on dual-processing theories, also known as dual-system theories, draw a distinction between so-called Type 1 and Type 2 cognitive processes (Evans & Stanovich, 2013; Kahneman, 2011). Following this theory, Type 1, or System 1, thinking is intuitive and automatic, relying on past experiences and

associations to quickly access information with minimal effort. Often, this is done through heuristics and mental shortcuts (Evans & Stanovich, 2013; Kahneman, 2011). In contrast, Type 2, or System 2, thinking is deliberate, requiring substantial cognitive effort to apply analytical reasoning and draw well-founded conclusions, though it remains prone to errors under high complexity or limited cognitive capacity (Evans & Stanovich, 2013; Kahneman, 2011).

Implications of the Elaboration Likelihood Model

Herein, the Elaboration Likelihood Model (ELM) offers a framework to understand how attitudes are formed or changed, depending on the cognitive elaboration and involvement level. High elaboration activates the central route, where message quality and rational arguments drive persuasion, while low elaboration engages the peripheral route, relying on superficial cues such as the source's credibility or design elements (Petty & Cacioppo, 1984). High-involvement scenarios tend to engage deeper cognitive processing, potentially fostering resistance or acceptance based on message content, while low-involvement scenarios facilitate persuasion through peripheral features (El Hedhli & Zourrig, 2023; Petty & Cacioppo, 1979).

Applying dual-processing and ELM principles to the different forms robo-advisors, research suggests that these technologies could prompt Type 2 processing, encouraging rationality by leveraging algorithmic objectivity, thereby reducing heuristic biases typical of Type 1 thinking (Darškuvienė & Laisauskiene, 2021; Jung, Puzmaz, & Weinhardt, 2018). Moreover, as robo-advisors vary in complexity, consumer engagement can shift between central and peripheral information processing routes. For example, when a financial message's quality is perceived to be high, robo-advisors may promote central-route processing. Instead, dominantly superficial cues, such as design elements or emojis, may activate the peripheral route, affecting trust and perceived credibility of the robo-advisor (Algarni, 2019; Hildebrand & Bergner, 2021). Following this notion, robo-advisors can influence investment decisions by shaping both the cognitive and emotional dimensions of financial decision-making.

Framing and Prospect Theory in Financial Decisions

A judgement refers to evaluating uncertain events and attributing probabilities to uncertain outcomes – per definition, any investment opportunity poses a decision under uncertainty. In the context of financial decision-making, judgment accuracy refers to the correct processing of financial information to make decisions that are unbiased (Krueger, 2012; Wilcox, 2022). The amount and frequency of the presented information influences an individual's ability to make accurate decisions. Both an increasing amount as well as an increasing frequency of repeated informational cues have been associated with impaired judgement accuracy (Hwang & Lin, 1999).

In addition, how information is presented is known to significantly affect how (financial) information is perceived, processed and ultimately judged. The select presentation or focus of information, called framing, has the potential to shape perception, risk preferences, and decision-making without changing the content itself (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). According to prospect theory, individuals will evaluate choices as gains or losses relative to a reference point, showing greater sensitivity toward losses than equivalent gains. This concept is known as loss aversion (Tversky & Kahneman, 1979). According to the theory, people simplify complex decisions by using mental shortcuts, which, while facilitating faster judgment, can lead to biases in uncertain contexts (Kahneman, 2003).

Furthermore, framing can affect how probabilities and outcomes are interpreted, influencing whether an individual adopts risk-seeking or risk-averse behavior. When a choice is framed around collective outcomes rather than individual gains or losses, people tend to focus on outcomes, which can unconsciously shift preferences depending on the presentation of the choice problem (Tversky & Kahneman, 1981; Karlsson et al., 2009).

Framing is also influenced by affective states, which are the emotional reactions individuals experience relative to their environment. Hereby, framing effects may be altered by influencing risk preferences (Russel & Barrett, 1999; Seo, Goldfarb, & Barrett, 2010). For example, positive emotions during gains may reduce risk aversion, leading to risk-seeking behaviors. Conversely, aligning a message's framing with the

recipient's emotions can increase engagement, as messages that resonate with an individual's current beliefs or mood enhance information processing and involvement (Raffaelli et al., 2019).

In the context of robo-advisors, these principles play a critical role. Robo-advisors are designed to minimize the biases associated with framing by presenting information in a consistent, objective format that reduces emotional influences and simplifies complex data, encouraging rational decision-making. Automated systems may be designed to counteract framing biases and loss aversion by structuring information around portfolio optimization rather than short-term gains or losses. This approach could promote Type 2 processing, encouraging more analytical engagement and aligning to reduce biases in human investment behavior (Darškuvienė & LISAUSKIENE, 2021; Jung, PUSMAZ, & WEINHARDT, 2018). Thus, robo-advisors may help mitigate framing effects, enabling users to make more consistent, objective investment decisions aligned with long-term financial goals.

Credibility and Affective Trust as Antecedents for Robo-Advisor Adoption

The perception and processing of a financial message is influenced by its content and the perceived qualities of its source, i.e., the sender. In the study's context, the sender is represented by the form of the financial advisor. The parameters of interest under which a sender is being evaluated primarily include trustworthiness, credibility, and attractiveness (Caudill & Diab, 2020; Wu & Wang, 2011).

Credibility, as defined by Wu and Wang (2011), relates to the degree to which a receiver believes the information provided by a source is accurate and reliable. A message becomes more attractive, valid, and trustworthy when the sender demonstrates confidence and expertise in the content. In traditional financial services, customer engagement heavily relies on trust in the advisor's expertise. Trustworthiness is often fostered through human connection, which has historically been central to financial advising (Johnson & Grayson, 2005; Zhang et al., 2021).

The feeling of trustworthiness refers to affective trust which poses a subjective, emotional dimension of trust between two or more parties. Just like in service relationships, affective trust depends on the perceived level of social connection or relationship quality.

In contrast, cognitive trust relates to an objectively assessed level of competence and an individual's confidence (Hildebrand & Bergner, 2021; Johnson & Grayson, 2005). Accordingly, robo-advisors offer credibility by delivering data-driven advice that minimizes biases and rather removes interpersonal effects (Chua et al., 2023; Wu & Wang, 2011; Zhang et al., 2021). Though they lack the human touch, their perceived accuracy and consistent performance enhance credibility, contributing to increased acceptance among clients who value objective financial guidance. Nevertheless, one may critically argue that this solely reflects the value proposition that robo-advisor providers market to their customers and may not pose an actual benefit, because not integrating human factors does minimize the predictability of the overall robo-advisor data model (Eichler & Schwab, 2024).

Overconfidence and the Role of Financial Literacy

Overconfidence encompasses the phenomenon that individuals' perception of their competence is higher than their actual competence – especially in fields where these individually have little or no knowledge in (De Bondt & Thaler, 1994; Kahneman, 2011). Following the implications of overconfidence, individuals generally tend to overestimate their financial knowledge, which is exacerbated by delayed feedback on their investment decisions (Lewis, 2018). Overconfidence can be observed in both experts and laypersons, particularly through the Dunning-Kruger effect. This dynamic leads to impaired financial choices and discourages individuals from seeking necessary professional advice even though they would most likely benefit from the advisor's know-how (Dunkel et al., 2023; Lewis, 2018; Kruger & Dunning, 1999). A literature review by Mittal (2020) identified 27 articles revealing overconfidence as a significant bias in the existing behavioral finance literature, second only to the broader category of biases and heuristics.

It is important to note that financial markets react differently to varying types of information, e.g. by the press or the media, which can affect individual investment behavior. Specifically, overconfidence and self-attribution bias have been shown to lead individuals to overreact to self-generated, private information

while underreacting to publicly available, diversified information (Daniel, Hirshleifer & Subrahmanyam, 1998; Mittal, 2020).

Furthermore, overconfidence has been repetitively linked to financial literacy and investment knowledge, with mixed effects: while financial literacy can enhance decision-making by reducing bias, it may also amplify overconfidence (Ahmad & Shah, 2022; Lewis, 2018; Mittal, 2020). Objective financial literacy encompasses an individual's ability to perform basic financial calculations and understand key financial concepts (Lusardi & Mitchell, 2011; Moreira Costa et al., 2021). In contrast, subjective financial literacy reflects individuals' beliefs about their financial competence, often manifesting as overconfidence (Ahmad & Shah, 2022; Lewis, 2018; Mittal, 2020; Raut, 2020).

According to current research, higher financial literacy has been identified as an antecedent for stock market participation and contributes to financial well-being (Lusardi & Mitchell, 2011; Raut, 2020). However, many individuals struggle to interpret statistics and probabilities effectively due to a lack of training in these areas (Pachur & Bröder, 2013; Tversky & Kahneman, 1974). While traditional financial advice aims to enhance financial literacy and provide strategies for informed decision-making, robo-advisors typically offer a more passive service, making decisions for users without necessarily improving their financial knowledge (Lusardi & Mitchell, 2011; Tan, 2020).

MATERIAL AND METHODS

A hypothetical choice experiment has been conducted online to understand and explore the effect of different forms of financial advisors – those being a robo-advisor or a human advisor. More specifically, participants have been exposed to a static robo-advisor, a conversational robo-advisor, and a human financial advisor in the form of fictional scenarios which shall be later explained in more detail. In addition to the three levels, participants have been presented with either a positive message or a negative message; the framing condition. The research design sought to understand the difference in the effect of the independent variables on participants' perceived level of affective trust and perceived risk.

The quantitative nature of the research design allows for a systematic and formal testing of the outlined hypothesis. In fact, hypothetical choice experiments pose a common research design approach in the behavioral sciences and serve as the preferred method in the foundational literature in the field (Tversky & Kahneman, 1979; Tversky & Kahneman, 1986; Kahneman, 2003).

Target Sample and Recruitment of Participants

An a priori power analysis using the software G*Power version 3.1.9.7 for Windows was conducted to determine the desired target sample size for a F-test MANOVA. For special effects and interactions, effect size of 0.15 was used with an alpha error of $\alpha = .05$ and power of $\beta = .80$. in addition to the three advisor levers and two framing conditions.

The required target sample size equal $n = 43$, however, due to the use of a convenience sample provider, the target sample size was increased to $n = 100$ to meet the screening criteria. Inclusion criteria for recruitment included being an U.S. citizen or permanent resident of the age 18 to 65 years old. The age limitation was adhered to, because it can be assumed that individuals of this age can access robo-advisor services in their private lives as well. In addition, the study sought to create a balanced sample by gender (50% female, 50% male).

Exclusion criteria included no access to the internet and therefore inability to participate in the study as well as residency and nationality outside of the United States. Further, participants were asked whether they experience difficulties with reading, spelling, or understanding written language or have been diagnosed with dyslexia or dyscalculia. Participants answering with “yes” were excluded, because the ability to comprehend written texts and numerations was an integral part of the study and otherwise might have led to biased results. Lastly, incomplete data points or aborted participation in the study served as an automatic exclusion criterion.

The researchers employed the convenience sample through the third-party provider SurveyMonkey LLC to meet the required sample size. Convenience sampling is recognized as a cost-effective and efficient

approach in social sciences, though the researchers were aware that the quality of participants can vary with different providers. SurveyMonkey LLC leverages a crowdsourcing model with a pay-by-task system to generate samples (Antoun et al., 2016; Henry, 1990). Participants were randomly assigned to either a positive or negative message scenario, ensuring equal assignment probability across conditions. This random assignment approach facilitates simplified sampling and analysis (Henry, 1990).

Data Collection and Instrumentation

The following shall clarify how data was collected and which testing instruments were employed in the online experiment. Data collection went hand in hand with the recruitment of participants and was hosted through the SurveyMonkey LLC software environment as well. In line with IRB standards and the ethical assurances of the research team's academic institution, all eligible participants had to formally consent to participate, through a thorough and transparent consent form, before accessing the online questionnaire. We embrace the values of openness and transparency in science. We believe that such research practices increase our research's informational value and impact, as the data can be reanalyzed and synthesized in future studies. Furthermore, they increase the credibility of the results, as independent verification of the findings is possible. Here, we express a voluntary commitment about how we will conduct our research. Please note that to every guideline there can be justified exceptions. But whenever we deviate from one of the guidelines, we give an explicit justification for why we do so

The online questionnaire allowed to integrate both texts and media files such as videos or graphics, which was applicable for this study to present participants with the three different advisory scenarios. Average questionnaire-completion time was ca. 12 minutes per participant. Data was collected online between August 07, 2024, and August 08, 2024, until the target sample size was reached. Collected raw data was downloaded as an Excel xlsx-workbook and uploaded into the statistics software environment for data analysis.

Instrumentation

The questionnaire was divided into distinct sections to guide participants through the online questionnaire environment. Three introductory items assessed participants' current investment status, invested capital, and primary information sources for investment decisions. Participants were asked if they currently hold an investment (e.g., ETFs, stocks, securities, or other assets), with response options of "yes," "no," or "I do not know." They were then asked to specify their current investment amount in U.S. dollars or decline to answer. Lastly, participants indicated the information sources that most influence their investment choices, choosing among options like advice from friends/relatives (within or outside the financial industry), employer advice, media coverage, personal experience, or advice and information from their bank or investment institute.

Participants were then introduced to a neutral investment scenario and asked to select a preferred portfolio type (stock, security, ETF, or customized) and investment goal (e.g., personal savings, retirement, specific occasion). The intention of these items was to help participants imagine an actual investment situation. With a hypothetical \$1,000 budget, participants were then asked to indicate how much they would invest with financial advice, choosing any amount from \$0 to \$1,000. Finally, rated how much risk they were willing to accept for the investment with the support of financial advice on a Likert scale from 1 (low risk) to 5 (high risk). All responses were hypothetical, with no actual monetary transactions or investments conducted. Afterwards, participants were randomly assigned either a negative or positive financial, the framing condition, that they should consider coming from their trusted source.

Following the framing condition, participants were presented with the three consecutive financial advisor scenarios. Each scenario followed the same structure and contained the same items with the mere difference of referring to either a static robo-advisor, a conversational robo-advisor, or a human advisor in the scenario. Every scenario started with a short, animated video that modeled a fictional interaction between a potential investment customer and a financial advisor. The videos were designed in Microsoft PowerPoint in a text-based manner. Before each video, participants were introduced to the advisor condition. The following outtake introduces the static robo-advisor condition: "You will now be presented

a short video clip showcasing *the fictional interaction between a customer and his or her online robo-advisor. The video clip serves as an example only. An online robo advisor asks customers a set of questions that look like a questionnaire to determine the best investment option for them (see video for reference).*”

Once participants watched the video, they were presented with a text-based scenario to prepare them for the items to follow. For example, this text was used in the static robo-advisor scenario: *“Following the information, your financial institution is offering you advice from an online robo advisor to help you make investment decisions going forward. Again, an online robo advisor is asking customers a set of questions that look like a questionnaire to then determine the best investment option for them (see video for reference). The online robo advisor then makes an investment for you based on your choices.”*

After each of the three scenarios, participants responded to three items on perceived risk and affective trust. First, they were asked how much they would invest, with up to \$1,000 available, under each of the three advisor conditions. This item allowed for comparisons with the baseline condition, reflecting participants’ risk-seeking tendencies. Next, participants rated perceived risk associated with each financial advisor on a 5-point scale (1 = low risk to 5 = high risk).

Three items adapted from Johnson and Grayson (2005) were used to assess affective trust, tailored to each advisor type. For example: *“Given your (human) advisor’s track record, you have no reservations about following its advice,” “How likely are you to use your robo-advisor for future investments?”* and *“You can rely on your robo-advisor to thoroughly analyze the situation before advising you.”* Again, responses were given on a 5-point Likert scale.

In a next section, financial literacy was assessed using selective questions from the OECD Financial Literacy Questionnaire (OECD, 2011). Two items on a 5-point Likert scale measured subjective financial literacy, while two true-or-false items assessed objective financial literacy. Sample items included *“I believe I have good financial knowledge”* (subjective financial literacy) and *“An investment with high returns is likely high risk – true or false?”* (objective financial literacy).

Lastly, the questionnaire collected information on participants’ demographic data: Gender, age (18 and above in 10-year intervals), education level, and any difficulty with reading, spelling, or comprehension, such as dyslexia or dyscalculia (yes/no). This final question determined eligibility for participation. All items were single-choice items.

Data Analysis

The researchers analyzed the data using IBM SPSS version 28, a standard tool in the social sciences known for its robust handling of statistical analyses (IBM, 2023). Initial steps involved screening and cleaning the data by removing incomplete or invalid responses and extreme outliers, including cases of missing data for desired investment amounts in the robo-advisor condition (n = 11), one affective trust item (n = 2), and one participant reporting an age exceeding the study’s threshold (n = 1). Variables were then labeled in SPSS to facilitate analysis, and index scores for key constructs, affective trust, perceived risk, and financial literacy, were calculated.

The mean of two items for subjective financial literacy was computed to yield a score from 1 to 5, while objective literacy scores were dummy-coded based on correct (1) and incorrect (0) answers. Affective trust scores were derived by summing the three items per advisor condition, then computing the mean. The framing condition was also recoded as a binary variable (0 = negative framing, 1 = positive framing).

To address the research questions, the researchers conducted a multivariate analysis of variance (MANOVA), suited to studies with two dependent and two independent variables and univariate analyses (ANOVA) using SPSS’s general linear model function. Bootstrapping with 1,000 iterations at a 95% confidence interval was applied to increase testing power. The MANOVA assumptions included multivariate normal distribution, homogeneity of variances and covariances, and random sampling (Green & Salkind, 2017). In ANOVA, independent variables were categorical, serving as interventions on metric dependent variables; namely, affective trust and perceived risk levels. MANOVA, an omnibus test, extends the analytical scope of ANOVA by assessing mean differences across multiple dependent variables and group levels (Green & Salkind, 2017). Due to the two-level framing condition, post-hoc tests were not universally applied; however, where applicable, Tukey’s Honestly Significant Difference (HSD) was used

with Bonferroni adjustments, alongside bootstrapping for increased precision (Green & Salkind, 2017). The researchers first examined Box’s M and Levene’s tests for equality of covariances and variances, then assessed statistical significance through Pillai’s Trace and Wilks’ Lambda, followed by between-subjects effects analysis to evaluate differences in dependent variables by independent variables (Green & Salkind, 2017).

Further analyses included bivariate Pearson correlations to explore relationships among affective trust, financial literacy, and investment risk, given metric data requirements (Green & Salkind, 2017). The researchers also compared the mean investment amounts across the baseline, static robo-advisor, conversational robo-advisor, and human advisor conditions, computing arithmetic means to analyze risk perception from levels 1 to 5, presuming investment amounts reflect risk-seeking behavior.

Finally, descriptive statistics summarized sample demographics, with arithmetic means and frequencies computed for age, education, and gender, as shall be outlined in the sample description.

RESULTS AND FINDINGS

The following section shall outline the results following the testing of hypotheses as well as those of the descriptive statistics to describe the sample.

Sample Description

SurveyMonkey approached 198 individuals to participate in the study. Of those, 26% did not consent to complete the survey, and an additional 14% disqualified due to the screening criteria. The final sample included 165 individuals (n = 165). 49.1% of participants identified as female (n = 81), 49.7% as male (n = 82), and 1.2% identified with any other gender (n = 2). Table 1 and Table 2 provide an overview of the sample’s age distribution and education level.

Descriptive statistics indicate that 54.6% of participants are at least 40 years old or older and 74.6% stated having at least a bachelor’s degree or higher, whereas 1.2% have no educational degree. Further, 83% (n = 137) of participants stated to currently hold an investment asset. 57% (n = 94) of individuals within the total sample stated to follow the investment goal of personal savings and 32.7% (n = 54) have the investment goal of saving for retirement. In the baseline investment condition, most participants (43.6%; n = 72) chose to invest into a stock portfolio, compared to 24.2% (n = 40) who preferred the security portfolio, the customized portfolio (18.8%; n = 31), or the ETF portfolio (12.1%; n = 20). When asked which sources of information participants felt most influenced by when making an investment, 36.4% (n = 60) referred to the advice of friends or relatives who do not work in the financial services industry, followed by their own experience (21.2%; n = 35).

**TABLE 1
DISTRIBUTION OF THE SAMPLE’S AGE CATEGORIES**

	N	%
18 to 28	21	12.7%
29 to 39	54	32.7%
40 to 50	66	40%
51 to 61	14	8.5%
62 to 65	10	6.1%

TABLE 2
DISTRIBUTION OF THE SAMPLE'S EDUCATION LEVEL

	N	%
High School diploma	35	21.2%
Bachelor's degree	61	37.0%
Master's degree	46	27.9%
Doctoral degree	16	9.7%
No degree	2	1.2%
Other	5	3.0%

Hypotheses Testing and Their Results

To explore the five research questions and the hypotheses, the researchers employed a MANOVA, suitable given the study's structure of two dependent variables and up to two independent factors per research question. To increase confidence in the findings, bootstrapping was applied for a 95% confidence interval, with the MANOVA calculated using the general linear model in SPSS.

Results for Research Questions 1 and 2

Research Questions 1 and 2 investigated whether the perceived level of affective trust differed among three types of financial advisors (robo-advisor, conversational robo-advisor, human advisor) when presented with either positive or negative messages. Box's Test of Covariance Matrices was not statistically significant ($\alpha = .067$), allowing acceptance of the null hypothesis of homogeneity. The multivariate test results indicated no significant difference in affective trust by framing condition, with $F(3, 161) = 1.726$, $p = .164$, Wilks' $\Lambda = .032$, and partial $\eta^2 = .031$. In the Levene's test of equality of variances, the robo-advisor group was significant ($p = .043^*$), but neither the conversational robo-advisor ($p = .333$) nor the human advisor group ($p = .104$) showed significance. The lack of significance in between-subjects tests for dependent variables further supported the acceptance of hypotheses H_{01} and H_{02} for Research Questions 1 and 2.

TABLE 3
MULTIVARIATE TESTS FOR AFFECTIVE TRUST AND THE POSITIVE- AND NEGATIVE FRAMING CONDITION

Effect		Value	F	Hypothesis df	Error df	Sig.	Part. Eta-Square
Framing condition							
	Pillai-Spur	0.031	1,726	3.000	161.000	.164	.031
	Wilks-Lambda	0.969	1,726	3.000	161.000	.164	.031

Designated alpha level of $\alpha = .05$

Results for Research Questions 3 and 4

Research Questions 3 and 4 focused on whether perceived risk levels differed among the three advisor types when presenting positive or negative messages. Box's Test for Equivalence of Covariance Matrices was not significant ($\alpha = .365$), allowing the assumption of equal covariance matrices. As shown in Table 4, MANOVA results revealed no statistically significant difference in perceived risk based on the framing

condition, with $F(3, 161) = 1.505$, $p = .164$, Wilks' $\Lambda = .973$, and partial $\eta^2 = .027$. Levene's test indicated non-significance across all groups (robo-advisor: $p = .824$; conversational robo-advisor: $p = .244$; human advisor: $p = .965$). Given the lack of significance in between-subjects effects, hypotheses H0₃ and H0₄ for Research Questions 3 and 4 were accepted.

TABLE 4
MULTIVARIATE TESTS FOR PERCEIVED LEVEL OF RISK AND THE POSITIVE- AND NEGATIVE FRAMING CONDITION

Effect		Value	F	Hypothesis df	Error df	Sig.	Part. Eta-Square
Framing condition	Pillai-Spur	0.027	1,505	3.000	161.000	.215	.027
	Wilks-Lambda	0.973	1,505	3.000	161.000	.215	.027

Designated alpha level of $\alpha = .05$

Results for Research Question 5

Research Question 5 probed whether perceived risk levels among the advisor types differed when participants with high financial literacy received a negative message. Box's Test for Covariance Matrices was non-significant ($\alpha = .188$), supporting the assumption of homogeneity. In Table 5, MANOVA results showed a statistically significant difference in high objective financial literacy based on framing, with $F(6, 314) = 3.099$, $p = .006$, Wilks' $\Lambda = .891$, and partial $\eta^2 = .056$. Levene's test confirmed non-significance for variance equality across robo-advisor ($p = .435$), conversational robo-advisor ($p = .373$), and human advisor groups ($p = .602$).

Significant effects in the between-subjects analysis emerged only in the human advisor group ($p = .018^*$), whereas the conversational robo-advisor ($p = .064$) and robo-advisor ($p = .781$) groups did not reach significance. Focusing solely on high financial literacy, significance was noted in the conversational robo-advisor group ($p = .006^{**}$). Subsequent LSD post-hoc analysis showed significant differences between high- and low-literacy individuals ($p = .011^*$) and between high- and medium-literacy individuals ($p = .014^*$) concerning perceived risk toward conversational robo-advisors. Thus, hypothesis H1₅ for Research Question 5 was accepted.

TABLE 5
MULTIVARIATE TESTS FOR OBJECTIVE FINANCIAL LITERACY AND A POSITIVE- AND NEGATIVE FRAMING CONDITION

Effect		Value	F	Hypothesis df	Error df	Sig.	Part. Eta-Square
Framing condition	Pillai-Spur	0.109	3.041	6.000	316.000	.007	.055
	Wilks-Lambda	0.891	3.099	6.000	314.000	.006	.056

Designated alpha level of $\alpha = .05$

Findings of Additional Correlation Analysis

To further explore the multivariate analysis related to financial literacy across the three financial advisor groups, the researchers conducted a correlation analysis examining objective and subjective financial literacy, total affective trust, and perceived risk scores. Using the Pearson correlation coefficient r , the

researchers followed Cohen's (1988) guidelines, which classify $|r| = .10$ as a weak correlation, $|r| = .30$ as moderate, and $|r| = .50$ as indicative of a strong correlation between two metric variables (Green & Salkind, 2017).

The correlation analysis demonstrated a statistically significant correlation at $p = .01$ (2-tailed) between subjective financial literacy scores and affective trust toward all advisor types: robo-advisors ($r = .267^{**}$), conversational robo-advisors ($r = .271^{**}$), and human financial advisors ($r = .314^{**}$). Additionally, a significant correlation at $p = .01$ (2-tailed) was found between objective financial literacy scores and affective trust toward robo-advisors ($r = .380^{**}$), conversational robo-advisors ($r = .310^{**}$), and human financial advisors ($r = .413^{**}$). In contrast, perceived investment risk levels showed a significant correlation only at $p = .05$ (2-tailed) between objective financial literacy scores and perceived risk toward conversational robo-advisors ($r = .235^*$), underscoring the nuanced relationship between financial literacy and risk perception across advisor types.

DISCUSSION AND INTERPRETATION OF FINDINGS

This section addresses the research questions in their respective sequence, providing a basis for comparing findings with the existing literature in behavioral finance. The objective is to determine which insights and findings corroborate or extend existing theories and to identify any incongruities with prevailing perspectives.

Analysis of Research Questions 1 and 2

The data analysis yielded no statistically significant variations in perceived affective trust across the three financial advisory types, static robo-advisor, dynamic robo-advisor, and human financial advisor, when financial messages were framed positively or negatively. The analysis of Research Questions 1 and 2 thus indicates that framing financial messages did not differentially impact affective trust toward each advisor type. Although affective trust was not anticipated as a primary factor in preferring robo-advisors over human advisors, prior research indicates that human-like features can enhance affective trust and positively influence clients' receptivity to their advice (Hildebrand & Bergner, 2021).

While the hypotheses did not specify a directional outcome, a significant difference in affective trust among advisor types was expected, irrespective of framing conditions. In particular, the researchers argued that the financial services industry requires a high degree of trust within the service relationship between an investor and her advisor, because investments pose a high level of uncertainty. Through human-to-human interaction, and conversational factors such as turn-taking, relationships may be deepened. However, it can be questioned to what extent a robo-advisor can truly mimic humanoid relationships in comparison to a human financial advisor to establish a bond or elevate the level of affective trust within the service relationship (Eichler & Schwab, 2024). Therefore, a difference between the three advisors was assumed in this study as well.

Other literature also suggests that human-like elements within financial advisors enhance affective trust (Hildebrand & Bergner, 2021; Johnson & Grayson, 2005; Zhang et al., 2021). Behavioral finance studies emphasize that only dynamic, socially interactive robo-advisors can foster trust and encourage acceptance of automated advice, e.g. through the use of chat- or voice-bots. Furthermore, established research suggests that message framing influences affective states, thereby affecting investor behavior and their inclination towards risk-seeking or risk-averse decisions (Kahneman, 2003; Kahneman & Tversky, 1979; Kahneman & Tversky, 1984).

Analysis of Research Questions 3 and 4

Similarly, no significant difference was found in perceived risk among the financial advisor types, regardless of whether messages were positively or negatively framed. This observation contradicts existing findings in the current state of research that emphasize the role of framing in risk perception and affective states, particularly in the context of prospect theory (Gier, Krampe, & Kenning, 2023; Tversky & Kahneman, 1979). The researchers speculate that the hypothetical nature of the experiment may have

diminished participants' emotional engagement, as there were no actual financial consequences associated with the framed messages. In a real-world context, it is plausible that negatively framed messages might have heightened participants' perceived risk and reduced affective trust, contingent upon the support level conveyed by each advisor type. In fact, framing plays a critical role in persuasion and behavior modification and has been extensively studied in health management contexts. However, a meta-analysis by Van't Riet et al. (2014) indicates that loss- or gain-framed messages do not consistently lead to significant behavioral changes, calling into question the applicability of framing effects across different domains.

Although the average perceived risk for each advisor type was moderate, the human advisor condition received the lowest perceived risk rating ($M = 3.41$), followed by the static ($M = 3.54$) and conversational robo-advisors ($M = 3.56$). This trend aligns with participants' hypothetical investment choices, which were highest for human advisors ($M = \$491.62$) and lowest for conversational robo-advisors ($M = \$438.52$). Participants allocated higher investment amounts in the baseline condition ($M = \$515.14$), suggesting that exposure to financial advisors, even hypothetically, heightens risk awareness and decreases willingness to invest substantial sums.

Interestingly, robo-advisor providers commonly claim that using this functionality lowers investment risks, because the foundational data model minimizes human biases or compensates for a lack of financial know-how. Therefore, one could alternatively assume, that layperson might prefer a robo-advisor and associate less risks with this form of financial advice (Beketov et al., 2018). Yet, the researchers argue that amidst all claims, robo-advisors may only minimize individual investment risks but may not limit market fluctuations or systemic investment risks overall (Eichler & Schwab, 2024).

The absence of feedback on investment success or failure in this study limits inferences about participants' judgment accuracy concerning message framing. Prior studies have shown that financial gains can encourage risk-seeking behavior in pursuit of further rewards (Kahneman & Tversky, 1979; Seo et al., 2010). However, such effects were not assessed here, preventing conclusions about framing's influence on judgment accuracy.

Analysis of Research Question 5

In contrast, a significant difference emerged in perceived risk among the financial advisor types in participants with high financial literacy who were exposed to negatively framed messages. Post-hoc analysis identified a notable difference in perceived risk associated with conversational robo-advisors ($p = .006^{**}$), with individuals possessing higher financial literacy reporting significantly greater perceived risk ($p = .011^*$ compared to low literacy, $p = .014^*$ compared to medium literacy).

These findings suggest that financial literacy moderates risk perceptions toward conversational robo-advisors. Participants with lower financial literacy rated conversational robo-advisors as 20.67% less risky under negative framing than their more literate counterparts, indicating that financial knowledge may induce greater skepticism toward these advisors. Financially literate, or knowledgeable, individuals may rely more on their expertise and exhibit greater caution toward advisors, particularly AI-driven ones. On the other hand, individuals with lower financial literacy may rely more on advisors to compensate for their limited expertise. This dependence may foster heightened affective trust, though the study did not directly assess trust as a variable.

The study's findings link back to the line of thought presented by the researchers' recent mini-review (Eichler & Schwab, 2024) and corroborates the argument that enhancing financial literacy through targeted educational initiatives and strategic industry collaboration can substantially elevate individual financial agency and thereby minimize the dependency or reliance on third-party advisors. In the long run, these efforts could create a ripple effect, fostering a financially savvy customer base that benefits individual investors and strengthens institutional performance and societal economic stability.

Correlational analysis reveals a weak to moderate positive relationship between financial literacy and perceived risk toward conversational robo-advisors ($r = .235^*$ at $p = .05$). Higher financial literacy corresponds with heightened risk perceptions, suggesting a tendency among financially knowledgeable individuals to invest conservatively through robo-advisors due to increased skepticism.

Interestingly, objective financial literacy was positively correlated with affective trust across all advisor types, particularly human advisors ($r = .413^{**}$ at $p = .01$), suggesting that financially literate individuals prefer human advisors due to a social connection that complements technical competence. This preference underscores the human element's enduring appeal, even in the presence of advanced AI-driven financial technologies, aligning with research suggesting that clients prioritize relational quality over pure competence (Hildebrand & Bergner, 2021; Johnson & Grayson, 2005). Although one might argue that favoring human advisors is irrational, given AI's potential to minimize human error, trust in AI for high-stakes activities remains low. A global survey by Statista (2024) finds that while 55% of respondents trust AI for low-impact recommendations, only 31% trust it for investment advice, suggesting that financial organizations must address trust barriers in AI-driven financial services.

It remains to be explored, how this behavioral tendency might be minimized in the future to control for consumer risks and instead elevate the level of trust into AI-driven robo-advisor services. For example, offering structured and accessible financial education during the advisory process, could positively impact individuals' perceived self-efficacy and objective financial literacy overall (Eichler & Schwab, 2024).

Implications and Recommendations for Future Research

This study underscores the intricate interplay between financial literacy, affective trust, and perceived risk in response to varying types of financial advisors, namely robo-advisors and human advisors. As technological advancements reshape the landscape of financial advising, a nuanced understanding of the roles played by different forms of financial advisors in influencing individual investment behavior is paramount. The concept of financial literacy is linked to affective trust and risk perception. In their interpretation of findings within this study, the authors suggest that objective financial literacy not only shapes personal financial well-being but may also carry significant implications for economic outcomes due to higher capital market participation (Eichler & Schwab, 2024).

Furthermore, the authors argue that particularly affective trust may pose to be a mediating variable in individuals' acceptance of robo-advisors. Herein, financial literacy can act as a "buffer" against perceived investments risks by empowering individuals with the skills needed to evaluate financial options critically. This aligns with the broader existing literature emphasizing the potential of robo-advisors to democratize access to financial planning, particularly for underrepresented or financially underserved demographics.

When designed with behavioral insights, such as adaptive user interfaces and feedback mechanisms, robo-advisors can reduce cognitive overload, address behavioral biases like overconfidence or anchoring, and ultimately foster greater financial well-being at scale. However, this aspect poses the question to what extent robo-advisors shall or shall not integrate human elements into their data models to optimize predictability and fulfill robo-advisors' value proposition.

Following this notion, future research must delve into optimizing the design and implementation of robo-advisors to enhance individual investment performance and financial well-being. Eichler and Schwab (2024) highlight the importance of tailoring these tools to not only address users' immediate financial goals but also support long-term financial literacy.

Considering the study's fifth significant hypothesis, this study calls for a deeper exploration of financial literacy within the context of behavioral finance. The nuanced relationship between numeracy and financial literacy warrants focused investigation to uncover how these competencies drive investment decisions. Society can build a more informed and resilient investor base by prioritizing financial literacy development through educational initiatives and public-private collaborations. This shift not only benefits individuals and financial institutions but also contributes to economic stability and growth.

The study also emphasizes the value of addressing existing research limitations to refine our understanding of financial decision-making processes. For instance, replicating the study in a controlled laboratory environment while incorporating real-time feedback on financial outcomes could strengthen the reliability of findings. Examining individual responses to financial gains and losses under varying market conditions would yield insights into the cognitive and emotional dynamics underlying financial behavior. decision-making processes.

CONCLUSIONS

This study evaluated how individuals perceive financial advice from three types of advisors, static robo-advisor, conversational robo-advisor, and human advisor, focusing on affective trust and perceived risk. Additionally, it examined whether financial message framing influences these perceptions and the role of financial literacy in shaping these outcomes. The study contributes to the existing behavioral finance literature by addressing five research questions and situating the findings within the current body of knowledge. Contrary to the researchers' hypothesis, no significant differences in affective trust were found between the advisor conditions, regardless of whether the framing was positive or negative. This contradicts previous studies suggesting that human-like or conversational robo-advisors foster greater trust due to their use of social cues (Hildebrand & Bergner, 2021; Zhang et al., 2021). Similarly, no significant differences were observed in perceived risk across the three advisor conditions under either framing condition.

However, the study's key finding, related to the fifth research question, revealed a significant difference between the conversational robo-advisor group and the other two groups regarding participants' objective financial literacy and risk perceptions. Specifically, individuals with higher financial literacy exhibited greater risk perception than those with lower financial literacy. This supports the behavioral finance literature, which suggests that financially literate individuals can better assess risks (Kahneman & Tversky, 1979) and adds complexity to our understanding of robo-advisor adoption, indicating that user competence may influence both trust and risk perceptions. The results suggest that while financial literacy is a significant factor in shaping trust and risk perceptions, message framing alone may not substantially influence investor behavior across advisor conditions. Nonetheless, a slight difference in hypothetical investment amounts was observed between the three advisor conditions. This implies that while framing may not directly impact trust or risk perceptions, it may subtly influence financial decision-making, as evidenced by lower investment amounts attributed to robo-advisors than human advisors.

In addition, study highlights the persistent role of human trust, especially among those with higher financial literacy, despite the technological advancements represented by robo-advisors. Moreover, the study raises concerns about overconfidence in subjective financial literacy, as a moderate positive correlation was found between higher subjective financial literacy scores and affective trust, potentially leading individuals to overestimate their expertise and impact advisor selection. From a macroeconomic perspective, the study suggests that robo-advisors can democratize financial advice, potentially improving access to investment services and enhancing overall economic outcomes such as market efficiency, productivity, and wages. However, the study also emphasizes the need for robust ethical and regulatory frameworks to address the limitations of this technology and ensure data transparency, security, and user trust.

In conclusion, this study contributes to the behavioral finance literature by underscoring the significance of objective financial literacy in shaping trust and risk perceptions of financial advisors, both human and robo-advisor. While technological advancements are transforming the wealth management sector, human advisors retain a unique position of trust. Future research should optimize robo-advisor technology to improve both micro- and macro-level financial outcomes. Integrating qualitative approaches, experimental feedback mechanisms, and enhanced financial literacy efforts will be crucial in advancing the field and ensuring the effective role of robo-advisors in financial decision-making, while recognizing the irreplaceable value of human judgment.

REFERENCES

- Ahmad, M., & Shah, S.Z.A. (2022). Overconfidence heuristic-driven bias in investment decision-making and performance: Mediating effects of risk perception and moderating effects of financial literacy. *Journal of Economic and Administrative Sciences*, 38(1), 60–90. <https://doi.org/10.1108/JEAS-07-2020-0116>
- Algarni, A. (2019). What Message Characteristics Make Social Engineering Successful on Facebook: The Role of Central Route, Peripheral Route, and Perceived Risk. *Information*, 10(6), 211. <https://doi.org/10.3390/info10060211>
- Alsabah, H., Capponi, A., Lacedelli, O.R., & Stern, M. (2019). Robo-advising: Learning Investors' Risk Preferences via Portfolio Choices. ArXiv.Org. <https://doi.org/10.48550/arxiv.1911.02067>
- Ansari, Y., Albarrak, M.S., Sherfudeen, N., & Aman, A. (2022). A Study of Financial Literacy of Investors—A Bibliometric Analysis. *International Journal of Financial Studies*, 10(2), 36. <https://doi.org/10.3390/ijfs10020036>
- Antoun, C., Zhang, C., Conrad, F.G., & Schober, M.F. (2016). Comparisons of online recruitment strategies for convenience samples: Craigslist, Google AdWords, Facebook, and Amazon Mechanical Turk. *Field Methods*, 28(3), 231–246. <https://doi.org/10.1177/1525822X15603149>
- Ashraf, N., Camerer, C.F., & Loewenstein, G. (2005). Adam Smith, Behavioral Economist. *The Journal of Economic Perspectives*, 19(3), 131–145. <https://doi.org/10.1257/089533005774357897>
- Baker, T., & Dellaert, B. (2018). Regulating Robo Advice Across the Financial Services Industry. *Iowa Law Review*, 103(2), 713–750.
- Belanche, D., Casaló, L.V., & Flavián, C. (2019). Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management + Data Systems*, 119(7), 1411–1430. <https://doi.org/10.1108/IMDS-08-2018-0368>
- Beketov, M., Lehmann, K., & Wittke, M. (2018). Robo Advisors: Quantitative methods inside the robots. *Journal of Asset Management*, 19(6), 363–370. <https://doi.org/10.1057/s41260-018-0092-9>
- Eichler, K.S., & Schwab, E. (2024, October). Evaluating Robo-Advisors through Behavioral Finance: A Critical Review of Technology Potential, Rationality, and Investor Expectations. *Frontiers in Behavioral Economics*, 3(28). <https://doi.org/10.3389/frbhe.2024.1489159>
- Caudill, L.E., & Diab, D.L. (2020). Digital Word of Mouth and Organizational Attraction: Focusing on Message Characteristics and Time. *Corporate Reputation Review*, 23(3), 170–180. <https://doi.org/10.1057/s41299-019-00077-x>
- Chua, A.Y.K., Pal, A., & Banerjee, S. (2023). AI-enabled investment advice: Will users buy it? *Computers in Human Behavior*, 138, 107481. <https://doi.org/10.1016/j.chb.2022.107481>
- Costa, D.F., Carvalho, F. de M., & Moreira, B.C. de M. (2019). Behavioral Economics and Behavioral Finance: A Bibliometric Analysis of the Scientific Fields. *Journal of Economic Surveys*, 33(1), 3–24. <https://doi.org/10.1111/joes.12262>
- Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance* (New York), 53(6), 1839–1885. <https://doi.org/10.1111/0022-1082.00077>
- Darškvienė, V., & Lissauskiene, N. (2021). Linking the Robo-advisors Phenomenon and Behavioural Biases in Investment Management: An Interdisciplinary Literature Review and Research Agenda. *Organizations and Markets in Emerging Economies*, 12(24), 459–477. <https://doi.org/10.15388/omee.2021.12.65>
- De Bondt, W.F.M., & Thaler, R.H. (1994). Financial Decision-Making in Markets and Firms: A Behavioral Perspective. *NBER Working Paper Series*, 4777. <https://doi.org/10.3386/w4777>
- Dunkel, C.S., Nedelec, J., & van der Linden, D. (2023). Reevaluating the Dunning-Kruger effect: A response to and replication of Gignac and Zajenkowski (2020). *Intelligence (Norwood)*, 96. <https://doi.org/10.1016/j.intell.2022.101717>

- El Hedhli, K., & Zourrig, H. (2023). Dual routes or a one-way to persuasion? The elaboration likelihood model versus the unimodel. *Journal of Marketing Communications*, 29(5), 433–454. <https://doi.org/10.1080/13527266.2022.2034033>
- Evans, J., & Stanovich, K.E. (2013). Dual-Process Theories of Higher Cognition: Advancing the Debate. *Perspectives on Psychological Science*, 8(3), 223–241. <https://doi.org/10.1177/1745691612460685>
- Garg, G., Shamshad, M., Gauhar, N., Tabash, M.I., Hamouri, B., & Daniel, L.N. (2023). A Bibliometric Analysis of Fintech Trends: An Empirical Investigation. *International Journal of Financial Studies*, 11(2), 79–. <https://doi.org/10.3390/ijfs11020079>
- Gier, N.R., Krampe, C., & Kenning, P. (2023). Why it is good to communicate the bad: Understanding the influence of message framing in persuasive communication on consumer decision-making processes. *Frontiers in human neuroscience*, 17, 1085810. <https://doi.org/10.3389/fnhum.2023.1085810>
- Guresen, E., & Kayakutlu, G. (2011). Definition of artificial neural networks with comparison to other networks. *Procedia Computer Science*, 3, 426–433. <https://doi.org/10.1016/j.procs.2010.12.071>
- Green, S.B., & Salkind, N.J. (2017). *Using SPSS for Windows and Macintosh: Analyzing and Understanding Data* (8th ed.). Upper Saddle River, NJ: Prentice Hall.
- Henry, G.T. (1990). *Practical sampling*. SAGE. <https://doi.org/10.4135/9781412985451>
- 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>
- Hwang, M.I., & Lin, J.W. (1999). Information dimension, information overload and decision quality. *Journal of Information Science*, 25(3), 213–218. <https://doi.org/10.1177/016555159902500305>
- Johnson, D., & Grayson, K. (2005). Cognitive and affective trust in service relationships. *Journal of Business Research*, 58(4), 500–507. [https://doi.org/10.1016/S0148-2963\(03\)00140-1](https://doi.org/10.1016/S0148-2963(03)00140-1)
- Jung, D., Dorner, V., Weinhardt, C., & Puzmaz, H. (2018). Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets*, 28(3), 367–380. <https://doi.org/10.1007/s12525-017-0279-9>
- Kahneman, D. (2003). A Perspective on Judgment and Choice: Mapping Bounded Rationality. *The American Psychologist*, 58(9), 697–720. <https://doi.org/10.1037/0003-066X.58.9.697>
- Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.
- Kalantari, B. (2010). Herbert A. Simon on making decisions: Enduring insights and bounded rationality. *Journal of Management History*, 16(4), 509–520. <https://doi.org/10.1108/17511341011073988>
- Karlsson, N., Loewenstein, G., & Seppi, D. (2009). Ostrich effect: Selective attention to information. *Journal of Risk and Uncertainty*, 38(2), 95–115. <https://doi.org/10.1007/s1166-009-9060-6>
- Kruger, J., & Dunning, D. (1999). Unskilled and Unaware of It: How Difficulties in Recognizing One's Own Incompetence Lead to Inflated Self-Assessments. *Journal of Personality and Social Psychology*, 77(6), 1121–1134. <https://doi.org/10.1037/0022-3514.77.6.1121>
- Lewis, D.R. (2018). The perils of overconfidence: Why many consumers fail to seek advice when they really should. *Journal of Financial Services Marketing*, 23(2), 104–111. <https://doi.org/10.1057/s41264-018-0048-7>
- Lusardi, A., & Mitchell, O.S. (2011). Financial literacy around the world: An overview. *Journal of Pension Economics & Finance*, 10(4), 497–508. <https://doi.org/10.1017/S1474747211000448>
- Maier-Paape, S., & Zhu, Q.J. (2018). A general framework for portfolio theory. Part I: Theory and various models. *Risks (Basel)*, 6(2), 1–35. <https://doi.org/10.3390/risks6020053>
- Markowitz, H.M. (1959). *Portfolio selection: Efficient diversification of investments*. Yale University Press. <https://doi.org/10.12987/9780300191677>
- Mittal, S., Bhattacharya, S., & Mandal, S. (2022). Characteristics analysis of behavioural portfolio theory in the Markowitz portfolio theory framework. *Managerial Finance*, 48(2), 277–288. <https://doi.org/10.1108/MF-05-2021-0208>

- OECD. (2011). *Measuring Financial Literacy: Questionnaire and Guidance Notes for Conducting an Internationally Comparable Survey of Financial Literacy*. Retrieved from <https://www.oecd.org/finance/financial-education/49319977.pdf>
- Owusu, S.P., & Laryea, E. (2023). The impact of anchoring bias on investment decision-making: Evidence from Ghana. *Review of Behavioral Finance*, 15(5), 729–749. <https://doi.org/10.1108/RBF-09-2020-0223>
- Pachur, T., & Bröder, A. (2013). Judgment: A cognitive processing perspective. *Wiley Interdisciplinary Reviews. Cognitive Science*, 4(6), 665–681. <https://doi.org/10.1002/wcs.1259>
- Petty, R.E., & Cacioppo, J.T. (1979). Issue involvement can increase or decrease persuasion by enhancing message-relevant cognitive responses. *Journal of Personality and Social Psychology*, 37(10), 1915–1926. <https://doi.org/10.1037/0022-3514.37.10.1915>
- Petty, R.E., & Cacioppo, J.T. (1990). Involvement and Persuasion: Tradition Versus Integration. *Psychological Bulletin*, 107(3), 367–374. <https://doi.org/10.1037/0033-2909.107.3.367>
- Pietersen, J., Ferreira-Schenk, S., & Dickason, Z. (2021). Are Robots Taking Over? Technological Advancements and Investor Risk Tolerance. *Acta Universitatis Danubius. Economica*, 17(4), 7–27.
- Raffaelli, R., Glynn, M.A., & Tushman, M. (2019). Frame flexibility: The role of cognitive and emotional framing in innovation adoption by incumbent firms. *Strategic Management Journal*, 40(7), 1013–1039. <https://doi.org/10.1002/smj.3011>
- Raut, R.K. (2020). Past behaviour, financial literacy and investment decision-making process of individual investors. *International Journal of Emerging Markets*, 15(6), 1243–1263. <https://doi.org/10.1108/IJOEM-07-2018-0379>
- Russell, J.A., & Barrett, L.F. (1999). Core Affect, Prototypical Emotional Episodes, and Other Things Called Emotion: Dissecting the Elephant. *Journal of Personality and Social Psychology*, 76(5), 805–819. <https://doi.org/10.1037/0022-3514.76.5.805>
- Schwarz, G., Christensen, T., & Zhu, X. (2022). Bounded Rationality, Satisficing, Artificial Intelligence, and Decision-Making in Public Organizations: The Contributions of Herbert Simon. *Public Administration Review*, 82(5), 902–904. <https://doi.org/10.1111/puar.13540>
- Sent, E.-M. (2004). Behavioral Economics: How Psychology Made Its (Limited) Way Back Into Economics. *History of Political Economy*, 36(4), 735–760. <https://doi.org/10.1215/00182702-36-4-735>
- Seo, M.-G., Goldfarb, B., & Barrett, L.F. (2010). Affect and the Framing Effect Within Individuals Over Time: Risk Taking in a Dynamic Investment Simulation. *Academy of Management Journal*, 53(2), 411–431. <https://doi.org/10.5465/AMJ.2010.49389383>
- Statista. (2024, October 8). *Share of Americans Investing Money in the Stock Market 1999-2024*. Statista Research Department. Retrieved November 3, 2024, from www.statista.com/statistics/270034/percentage-of-us-adults-to-have-money-invested-in-the-stock-market/
- Shefrin, H. (2009). Behavioralizing Finance. *Foundations and Trends® in Finance*, 4(1–2), 1–184. <https://doi.org/10.1561/05000000030>
- Simon, H.A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, 69(1), 99–118. <https://doi.org/10.2307/1884852>
- Sironi, P. (2016). *FinTech innovation: From robo-advisors to goal based investing and gamification*. Wiley.
- Statista. (2023). *Robo-Advisors - Worldwide | Statista Market Forecast*. Retrieved November 3, 2024, from www.statista.com/outlook/fmo/wealth-management/digital-investment/robo-advisors/worldwide
- Statista Market Insights. (2023, August 1). *Robo-Advisors – Worldwide. Statista Market Forecast*. Statista. Retrieved from <https://www.statista.com/outlook/fmo/wealth-management/digital-investment/robo-advisors/worldwide>

- Statista Research Department. (2024). *Consumer Trust in AI Activities Globally in 2024*. Statista. Retrieved from www.statista.com/statistics/1475638/consumer-trust-in-ai-activities-globally/#:~:text=When%20surveyed%20in%202024%2C%20more
- Tan, G.K.S. (2020). Robo-advisors and the financialization of lay investors. *Geoforum*, 117, 46–60. <https://doi.org/10.1016/j.geoforum.2020.09.004>
- Tepper, T., & Curry, B. (2021, December 1). Best Robo-Advisors of December 2021. *Forbes Advisor*. Retrieved from <https://www.forbes.com/advisor/investing/best-robo-advisors/>
- Thaler, R.H. (2016). Behavioral Economics: Past, Present, and Future. *The American Economic Review*, 106(7), 1577–1600. <https://doi.org/10.1257/aer.106.7.1577>
- Thomaz, F., Salge, C., Karahanna, E., & Hulland, J. (2020). Learning from the Dark Web: Leveraging conversational agents in the era of hyper-privacy to enhance marketing. *Journal of the Academy of Marketing Science*, 48(1), 43–63. <https://doi.org/10.1007/s11747-019-00704-3>
- Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, 185(4157), 1124–1131. <https://doi.org/10.1126/science.185.4157.1124>
- Tversky, A., & Kahneman, D. (1979). *Prospect Theory: An Analysis of Decision under Risk*. IDEAS Working Paper Series from RePEc.
- Tversky, A., & Kahneman, D. (1986). Rational Choice and the Framing of Decisions. *The Journal of Business (Chicago, Ill.)*, 59(4), S251–S278. <https://doi.org/10.1086/296365>
- Upashi, R., & Kadakol, A.M. (2023). Impact of Behavioral Biases on Investment Decision Making: Evidence from the Review of Literature. *Abhigyan (New Delhi)*, 41(1), 35–. <https://doi.org/10.56401/Abhigyan/41.1.2023.35-49>
- Van't Riet, J., Cox, A.D., Cox, D., Zimet, G.D., De Bruijn, G.J., Van den Putte, B., . . . Ruiter, R.A. (2014). Does perceived risk influence the effects of message framing? A new investigation of a widely held notion. *Psychology & Health*, 29(8), 933–949. <https://doi.org/10.1080/08870446.2014.896916>
- Wexler, M.N., & Oberlander, J. (2021). Robo-advisors (RAs): the programmed self-service market for professional advice. *Journal of Service Theory and Practice*, 31(3), 351–365. <https://doi.org/10.1108/JSTP-07-2020-0153>
- Wilcox, J. (2022). *Human Judgment: How Accurate Is It, and How Can It Get Better?* Springer.
- Wu, P.C.S., & Wang, Y.-C. (2011). The influences of electronic word-of-mouth message appeal and message source credibility on brand attitude. *Asia Pacific Journal of Marketing and Logistics*, 23(4), 448–472. <https://doi.org/10.1108/13555851111165020>
- Zhang, L., Pentina, I., & Fan, Y. (2021). Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services. *The Journal of Services Marketing*, 35(5), 634–646. <https://doi.org/10.1108/JSM-05-2020-0162>