



# Trusting the Machine: The Impact of Framing, Emotional Intelligence, and Personality Traits on the Acceptance of AI-Generated Financial Advice

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## **Abstract**

**Title:** Trusting the Machine: The Impact of Framing, Emotional Intelligence, and Personality Traits on the Acceptance of AI-Based Financial Advice

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The rise of AI-based financial advisory tools has significantly transformed the investment management landscape, making it essential to understand the factors shaping trust and user acceptance of AI-generated advice.

This thesis investigates how psychological traits including emotional intelligence, personal innovativeness in the domain of information technology (PIIT), and agreeableness influence trust and advice-taking behavior in the context of AI-generated investment recommendations. In addition, it examines how positively versus negatively framed informational texts about robo-advisors affect user perception and behavior. An online survey was conducted with  $N = 324$  participants, who were randomly assigned to one of the framing conditions. Participants then evaluated the AI-generated advice and completed validated psychological assessments.

The results show that framing consistently influenced advice-taking behavior, with participants in the positive framing condition being significantly more likely to accept the AI's recommendation. Emotional intelligence showed a marginally significant positive effect on advice acceptance, offering partial evidence for its role. In an exploratory model predicting trust, emotional intelligence emerged as a consistent positive predictor. Agreeableness demonstrated a robust and reliable effect across models, making it a key factor in predicting trust in and acceptance of AI-generated financial advice. In contrast, PIIT did not significantly predict either outcome.

In summary, these findings underscore the importance of how AI tools are presented to users. They also highlight that individual psychological traits, particularly agreeableness and emotional intelligence, play an important role in shaping trust and acceptance of AI-based financial advice.

**Keywords:** robo-advisors, financial decision-making, human-AI interaction, emotional intelligence, personal innovativeness in the domain of information technology, agreeableness, framing effects, behavioral finance, trust, technology acceptance

## **Resumo**

**Título:** Confiando na Máquina: O Impacto do Enquadramento, da Inteligência Emocional e dos Traços de Personalidade na Aceitação de Conselhos Financeiros Baseados em IA

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O surgimento de ferramentas de consultoria financeira baseadas em IA transformou a gestão de investimentos, tornando essencial compreender os fatores que moldam a confiança e a aceitação dos utilizadores perante conselhos gerados por IA.

Esta dissertação investiga como traços psicológicos como inteligência emocional, inovação pessoal em tecnologia da informação (IPTI) e amabilidade influenciam a confiança e o seguimento de recomendações de investimento geradas por IA. Além disso, examina como textos informativos com enquadramento positivo ou negativo sobre robôs de investimento afetam a percepção e o comportamento dos utilizadores. Realizou-se um inquérito online com  $N = 324$  participantes, aleatoriamente atribuídos a um dos enquadramentos. Os participantes avaliaram o conselho da IA e completaram avaliações psicológicas validadas.

Os resultados mostram que o enquadramento influenciou consistentemente a aceitação do conselho, com participantes no enquadramento positivo significativamente mais propensos a aceitar a recomendação da IA. A inteligência emocional apresentou um efeito positivo marginalmente significativo na aceitação, fornecendo evidência parcial do seu papel. Num modelo exploratório para prever a confiança, a inteligência emocional revelou-se um preditor positivo consistente. A amabilidade revelou um efeito robusto e fiável em todos os modelos, sendo fator-chave para prever confiança e aceitação de conselhos financeiros gerados por IA. Em contraste, a IPTI não previu significativamente nenhuma das variáveis.

Em síntese, os resultados sublinham a importância da forma como as ferramentas de IA são apresentadas. Também mostram que traços psicológicos individuais, particularmente amabilidade e inteligência emocional, são relevantes na formação da confiança e na aceitação de conselhos financeiros baseados em IA.

**Palavras-chave:** robôs de investimento, tomada de decisão financeira, interação humano-IA, inteligência emocional, inovação pessoal no domínio da tecnologia da informação, amabilidade, efeitos de enquadramento, finanças comportamentais, confiança, aceitação de tecnologia

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## List of Abbreviations

AI	Artificial intelligence
AIDUA	AI device use acceptance
$\alpha$	Cronbach's alpha
$b$	Unstandardized regression coefficient
$df$	Degrees of freedom
EI	Emotional intelligence
ESG	Environmental, social, governance
FFM	Five-factor model
GFP	General factor of personality
H	Hypothesis
IQ	Intelligence quotient
IT	Information technology
$M$	Mean
m	Million
$N(n)$	Sample size ( $N$ = total sample size; $n$ = sub sample size)
OEA	Others' emotion appraisal
$p$	P-value
PIIT	Personal innovativeness in the domain of information technology
$r$	Pearson correlation coefficient
RMSR	Root mean square residual
ROE	Regulation of emotion
RQ	Research question
RSMSEA	Root mean square error of approximation
$SD$	Standard deviation
$SE$	Standard error
SEA	Self-emotion appraisal
$t$	t-statistic
TAI	Trust scale for the AI context
TAM	Technology acceptance model
TLI	Tucker-Lewis index
UOE	Use of emotion
UTAUT	Unified theory of acceptance and use of technology
WLEIS	Wong and Law emotional intelligence scale

# 1 Introduction

## 1.1 Opening Thought

*“If your users can't trust the technology, you're not going to bring it into your product.”*

— Aidan Gomez, CEO of Cohere

This statement reflects a growing reality: user trust is not a nice-to-have, but a prerequisite for the adoption of artificial intelligence (AI)-driven technologies (Kelly et al., 2023; Sholevar & Bachmann, 2025; van der Crujjsen et al., 2023). This is especially important in finance, where robo-advisors offer algorithm-based investment recommendations without human intervention (van der Crujjsen et al., 2023).

The rapid evolution of financial technology has significantly transformed the investment management landscape. Among these innovations, robo-advisors have emerged as a central tool that enables the democratizing access to wealth management services (Zhang et al. 2021). Robo-advisors are “digital platforms comprising interactive and intelligent user assistance components that use information technology to guide customers through an automated (investment) advisory process” (Jung et al., 2018a, p. 81). By leveraging AI, machine learning, and big data analytics, robo-advisors can provide personalized investment advice at a low marginal cost (Zhu et al., 2024).

The growth of robo-advisors has been rapid as their assets under management rose from \$1.1m in 2017 to \$1,800m in 2024 and are projected to reach \$2,381m by 2029, with the US accounting for 81.1% (Statista, 2025). User numbers grew from 2.35m to 31.01m over the same period (Statista, 2025).

However, despite many advantages over traditional advisors, robo-advisors have one critical vulnerability which is the difficulty of building trust. Trust is the “willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party” (Mayer et al., 1995, p. 712). Trust in robo-advisors varies significantly by age: While 54% of those aged 25–34 reported trust or complete trust, only 9% of those 65+ did (CFA Institute, 2022).

There are several drivers of mistrust regarding robo-advisors. It often stems from a perceived lack of transparency (Ismatullaev & Kim, 2024; Zhu et al., 2023) and limited individualization (Scherer & Lehner, 2023). Users also fear data misuse (Jung et al., 2018b) and question the fairness and neutrality of AI recommendations (Shin & Park, 2019).

While these structural and technical concerns explain part of the distrust toward robo-advisors, growing research emphasizes the importance of psychosocial factors in shaping users' trust and acceptance of AI systems (Kelly et al., 2023). Understanding why some individuals trust AI-driven advisors while others do not requires looking beyond system performance and considering the user's personality and emotional abilities. The current thesis highlights three such aspects.

First is emotional intelligence (EI), defined as the “ability to perceive, manage, and regulate emotions, promoting adaptive thinking and the understanding of the meaning and consequences of emotions” (Quílez-Robres et al., 2023, p.1). Individuals with higher EI may be better equipped to manage uncertainty or ambiguous contexts and exhibit more adaptive decision-making (Avsec, 2012). Given the emotionally distant nature of robo-advisors, EI may play a role in whether users accept or reject AI financial advice.

Second is personal innovativeness in the domain of information technology (PIIT), which is the “willingness of an individual to try out any new information technology“ (Agarwal & Prasad, 1998, p. 206). People with high PIIT are more likely to adopt and trust emerging technologies earlier than others (Agarwal & Prasad, 1998; Thatcher & Perrewe, 2002; Park & Woo, 2022).

Third is the personality trait agreeableness from the Big Five framework which is linked to trustfulness, prosocial behavior, and cooperation (Costa & McCrae, 1992; Jensen-Campbell et al., 2002). Individuals high in agreeableness may be more inclined to perceive algorithmic advisors as trustworthy agents (Böckle et al. 2021; Sindermann et al., 2022).

By combining these psychological and behavioral variables and applying an experimental approach using trust framing, this thesis aims to enhance the understanding of trust formation in the context of AI-driven financial advice.

## 1.2 Problem Statement and Research Objective

Despite their increasing technological sophistication and potential to democratize financial services, many individuals remain hesitant to fully trust and follow recommendations generated by algorithmic systems (Jung et al., 2018b; Lockey et al., 2021; Scherer & Lehner, 2023). While prior research has explored system-level factors and demographic influences on trust (e.g. Glikson & Woolley, 2020; Zhang et al., 2021), there is limited understanding of how individual psychological traits shape trust in AI-driven financial advice. This thesis addresses the gap by investigating how individual-level factors, including EI, PIIT, and the personality trait of agreeableness, affect users' trust in robo-advisors and their willingness to follow AI-generated investment advice.

To strengthen causal interpretation, this thesis incorporates an experimental manipulation using two contrasting but scientifically grounded information texts (positive vs. negative framing) about robo-advisors. The thesis aims to address the identified research gap by answering the following research questions:

Main research question: How do information framing and individual differences in emotional intelligence, personality, and PIIT influence users' trust and acceptance of AI-generated financial advice?

- RQ1: Does the framing of information (positive vs. negative) about robo-advisors significantly influence users' trust and willingness to follow the AI financial recommendations?
- RQ2: To what extent does emotional intelligence affect the likelihood of following AI financial recommendations?
- RQ3: To what extent does PIIT affect the likelihood of following AI financial recommendations?
- RQ4: To what extent does the personality trait of agreeableness affect the likelihood of following AI financial recommendations?

### 1.3 Academic and Managerial Relevance

Academic relevance: While the academic literature already offers a solid foundation on the relationship between personality traits and AI-acceptance, most research have relied on correlational designs. In contrast, the present thesis adopts an experimental approach to explore causal relationships in the context of AI-driven financial advice. A study by Oehler et al. (2022), which is considered the closest paper to this thesis, examined the relationship between personality traits, risk attitudes, life orientation, locus of control, and the use of robo-advisors. In contrast, the present thesis focuses on a different set of psychological traits, including all facets of EI and PIIT. The only overlap is the personality trait of agreeableness, which is re-evaluated here using a larger and more diverse sample compared to undergraduate business students from a single German university.

Another study by Park & Woo (2022) specifically analyzed the relationship between PIIT and general AI-acceptance, but not in the context of financial advice. Furthermore, the link between EI and technology adoption remains an underexplored and nuanced area. Existing research has primarily focused on how EI influences general decision-making (e.g. Hess & Bacigalupo, 2011; Moon, 2021) or financial behavior (e.g. Ameriks et al., 2009; Chaturvedi Sharma, 2025), but not how it shapes trust in AI-driven financial advice.

Managerial relevance: Managers in fintech, wealth management, brokerage, and traditional financial services can use the findings of this thesis to identify which user profiles are more likely to trust robo-advisors. User groups may benefit from more tailored support, personalized communication, or simplified onboarding strategies. For example, if framing significantly influences trust, firms can adjust their messaging accordingly, either by emphasizing AI's strengths (e.g., efficiency, data-driven objectivity) or mitigating common concerns (e.g., transparency, individualization, or explainability). Robo-advisor interfaces and feedback mechanisms can also be optimized for users with different EI levels or technology openness to support more inclusive adoption. Beyond robo-advisors, the findings can also improve the design and promotion of AI-driven services, such as automated customer support or digital financial planning tools and could promote the adoption of AI-tools in traditional business areas.

#### 1.4 Dissertation Structure

This dissertation follows a classic structure commonly used in empirical research. The first chapter introduces the topic, outlines the relevance of investigating trust in AI-driven financial advisory services, and presents the research questions and objectives. Building on this, chapter 2 reviews the relevant literature and theoretical concepts to derive relevant hypotheses. It examines key constructs such as EI, PIIT, agreeableness, and their potential relation to trust and advice-taking behavior. Chapter 3 outlines the research methodology, describes the experimental design, participant sample, data collection procedure, and measurement of key variables to answer the research questions. Chapter 4 presents the results of the empirical study, including descriptive statistics and hypothesis testing. Chapter 5 discusses and interprets these findings in the context of the existing literature and derives both theoretical and managerial implications. It also discusses limitations and suggests directions for future research. Finally, chapter 6 concludes the dissertation by summarizing the key findings and highlighting their broader implications.

## 2 Literature Review

### 2.1 Foundations of AI

AI comprises technologies that collect data, recognize patterns, generate responses, and adapt dynamically to external input (Ferràs-Hernández, 2018). It refers to the capacity of machines to execute activities that typically require human intelligence, including reasoning, and decision-making (Pereira et al., 2023). Through its interactional nature, AI adjusts its behavior based on external prompts (Frantz, 2003; Rahwan et al., 2019).

Evolved from rule-based systems to data-driven models, AI is now a cornerstone of the digital economy and Industry 4.0 (Hecklau et al., 2016). A future goal is to make machines think like humans, but to outperform them in task completion (Misselhorn, 2018). While its aim is to replicate and surpass human cognition, AI is not monolithic but an umbrella for sub-disciplines, most notably machine learning, where algorithms learn from data without explicit programming (Glikson & Woolley, 2020).

Core features include analyzing large-scale structured and unstructured data, identifying patterns, and generating predictive insights efficiently (Burton et al., 2020), enabling systems to mimic intelligent behavior (Kelly et al., 2023). Its applications in finance illustrate this potential, ranging from fraud detection and algorithmic trading to robo-advisory services.

### 2.2 Role of Robo-Advisors in AI-based Finance

Robo-advisors are digital platforms that offer investment management and financial planning services with minimal human input (Belanche et al., 2019; Jung et al., 2018b). Powered by algorithms, they collect data from users such as investment goals, risk tolerance, and financial background to generate personalized portfolio recommendations (Gan et al., 2021; Zhu et al., 2024). In essence, robo-advisors leverage software to replicate the role of a human financial advisor. Initially introduced by firms like Betterment and Wealthfront around 2010, robo-advisors have evolved from basic portfolio allocators into sophisticated tools capable of automated portfolio construction, continuous rebalancing, tax-loss harvesting, financial planning, and ESG (environmental, social, governance) integration (Capponi & Lehalle, 2023; Shen et al., 2025; Zhang et al., 2021; Zhu et al., 2024). Conceived as low-cost alternatives after the financial crisis, they aimed to democratize access to investment advice (Abraham et al., 2019). Their rise has been fueled by advances in AI, big data, and rising demand for digital financial self-service. Rather than fully replacing human advisors, robo-advisors often complement them, leading to hybrid models which combine automated portfolios with human guidance to balance efficiency and personalization (Fisch et al., 2019).

### 2.3 Technology Acceptance

Given the growing relevance of AI across industries, understanding user adoption is essential. The Technology Acceptance Model (TAM) is one of the most fundamental frameworks, explaining technology acceptance through two beliefs: perceived usefulness, which is the belief that the technology is useful to perform a task, and perceived ease of use, which is the belief that using the technology requires minimal effort (Davis, 1989). Both shape attitudes and behavioral intention, with perceived usefulness often being the stronger predictor (Wu et al., 2011).

Building on this, the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) integrates eight earlier models and identifies four core predictors of adoption: Performance expectancy, effort expectancy, social influence, and facilitating conditions.

However, such models mainly apply to non-intelligent technologies (Gursoy et al., 2019). To capture AI-specific adoption, the AI Device Use Acceptance model (AIDUA) (Gursoy et al., 2019) incorporates both cognitive and emotional processes. It proposes a three-stage appraisal: 1) primary appraisal, where users consider social influence, hedonic motivation, and anthropomorphism; 2) secondary appraisal, focusing on usefulness and ease of use; and 3) an outcome stage of acceptance or rejection, allowing for a more nuanced distinction between favorable and unfavorable attitudes compared to traditional models (Gursoy et al., 2019).

Nowadays, trust is increasingly seen as a predictor of technology acceptance (Hildebrand & Bergner, 2021; Kelly et al., 2023; Komiak & Benbasat, 2006), as the next section details.

### 2.4 Trust in AI-Driven Financial Advice

Trust is central in decision-making, particularly under uncertainty, complexity, or vulnerability (Glikson & Woolley, 2020). Mayer et al. (1995) define trust as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor” (p. 712). Researchers describe trust as a dynamic concept (Glikson & Woolley, 2020). It could be distinguished in cognitive trust, grounded in beliefs about reliability and performance (Schoorman et al., 2007) and emotional trust, linked to warmth and emotions (Komiak & Benbasat, 2006; McAllister, 1995). While interpersonal trust relies on empathy and morality, trust in AI depends more on competence, transparency, and reliability (Lee & See, 2004; McKnight et al., 2011). Yet, emotion-driven trust remains vital for user acceptance of complex systems (Hoff & Bashir, 2015).

Trust is a strong predictor of adoption and compliance with AI-advice, regardless of whether it is from human or AI (Baines et al., 2024; Jung et al., 2018b; Rossi & Utkus, 2020; Wise, 2000). Conversely, anxiety and skepticism reduce perceived usefulness and therefore AI-adoption (Meuter et al., 2003). Unlike interpersonal trust which builds over time due to several interactions, trust in AI often declines as users detect errors (Madhavan & Wiegmann, 2007). Empirical evidence showed that expert human advisors are trusted more than robo-advisors, while low-expertise humans are not (Zhang et al., 2021). Robo-advisors were perceived as less competent and emotionally trustworthy, though they attributed similar levels of integrity to both (Zhang et al., 2021). Surprisingly, hybrid (human + AI) forecasts were trusted less compared to purely human analysts (Stradi & Verdickt, 2024).

Key antecedents of trust in robo-advisors include perceived developers' expertise (Lourenço et al., 2020), explanation quality (Lehmann et al., 2022), and anthropomorphic features (Chen & Park, 2021; Plotkina et al., 2024). In contrast, lack of personalization and empathy fosters distrust, especially in complex financial situations (Scherer & Lehner, 2023). Further barriers include concerns over data misuse (Jung et al., 2018b) and mass data extraction (Lockey et al., 2021). Other critical system level factors include transparency, accuracy, and reliability (Lockey et al., 2021).

Additionally, research demonstrates that the way information is framed can significantly influence decision-making, a phenomenon known as the framing effect (Tversky & Kahneman, 1981). In the context of AI-generated recommendations, positively framed messages have been shown to enhance trust and increase compliance with advice (Hou & Jung, 2021; Prinz et al., 2025). Thus, I propose:

**H1:** Positive framing of AI financial advice leads to higher trust and advice-taking compared to negative framing.

#### 2.4.1 Acceptance of AI Advice vs. Human Advice

Overall, most research showed that individuals tend to prefer human advice over AI-advice, a phenomenon known as algorithm aversion (Dietvorst et al., 2015). Conversely, other studies highlighted algorithm appreciation, where AI-advice was preferred (Kennedy et al., 2022). The literature identified several key factors that influenced whether AI or human advice was preferred.

First, perceived competence played a central role. Human advisors are preferred in social and emotional domains (Longoni & Cian, 2022; Baines et al., 2024), while AI is considered more capable in analytical and utilitarian tasks (Hertz, 2018). Although AI performance in emotional

contexts has improved (Logg et al., 2019), it still falls short in meeting moral principles and responsibility (Hakli & Mäkelä, 2019).

Second, anthropomorphism generally increases acceptance levels (Pak et al., 2012; Plotkina et al., 2024; Seymour et al., 2021; Verberne et al., 2015). However, this effect is reversed when the advisor becomes too human (uncanny valley effect; Duffy, 2003).

Third, transparency and comprehensibility influence advice acceptance, but with mixed findings (Bonaccio & Dalal, 2006; Lehmann et al., 2022). While user-friendly transparency can improve adoption, overly simple explanations may increase skepticism, and opacity fuels algorithm aversion (Bertrand et al., 2022; Jung et al., 2018b).

Fourth, experience and perceived expertise shape advice acceptance, with people trust advisors more with proven performance and high status (Fischer & Harvey, 1999; Önköl et al., 2017). For AI, this trust extends to the credibility of the algorithm and its developers (Lourenço et al., 2020). Moreover, advice is more likely to be accepted when it aligns closely with one's prior opinion (Mesbah et al., 2021; Schultze et al., 2015).

Fifth, decision-makers penalize AI-advice more harshly for mistakes which lead to a long-lasting loss of trust, even if the AI's overall performance is superior (Prahll & van Swol, 2017; Baines et al., 2024; Dietvorst et al., 2015). Even small errors lead to questioning of the whole system due to the perfection schema while human errors are seen as natural (Madhavan & Wiegmann, 2007).

Finally, demographic factors also shape AI-advice acceptance. Younger individuals trust AI more (CFA Institute, 2022; Lee et al., 2017). Furthermore, higher numeracy increases trust (Logg et al., 2019), while the education level showed mixed effects (Lourenço et al., 2020; Saragih & Morrison, 2022). Beyond these factors, personality traits also influence advice-taking, as discussed in the next section.

## 2.5 Personality

### 2.5.1 Personality and the Five Factor Model

Personality is commonly defined as a relatively stable set of predispositions that influence how individuals think, feel, and behave across various situations (McAdams & Pals, 2006; McKenna & Bargh, 2000). It includes enduring patterns of thoughts, emotions, attitudes, and behaviors that distinguish different persons (Funder, 2009). Cervone & Pervin (2023) emphasize two core aspects of personality: consistency and distinctiveness. Abood (2019) further outlines three foundational assumptions of personality traits: Traits are almost stable over time, remain consistent across different situations, and allow for the prediction of related behaviors. One of

the most widely accepted frameworks to capture the structure of personality is the Five-Factor Model (FFM) (McCrae & Costa, 1987; John & Srivastava, 1999; John et al., 2008; Soto & John, 2017a). It proposes that an individual's personality can be described using five dimensions, each representing a range between two extremes (Barrick & Mount, 1991; Gosling et al., 2003).

First, openness to experience is characterized by imagination, creativity, and a desire for novelty (Jani & Han, 2014). Individuals high in openness are more open to try new ideas and experiences, whereas low scorers tend to be conventional and pragmatic (Almlund et al., 2011; Goldberg, 1992; John, 1990).

Second, conscientiousness captures self-discipline, organization, and goal-directed behavior (di Sarno et al., 2023). Highly conscientious individuals tend to be reliable, methodical, and capable of long-term planning (Ross et al., 2009). Low conscientiousness can be associated with flexibility, but also with unreliability and carelessness (Almlund et al., 2011).

Third, extraversion is associated with sociability, assertiveness, and positive emotionality (McCrae & Costa, 1990). Extraverts seek social interaction and stimulation, while low extraversion is linked to reserved or formal behavior (Almlund et al., 2011).

Fourth, neuroticism is characterized by emotional instability and a propensity for negative feelings such as anxiety, anger and depression. (John & Srivastava, 1999). High neuroticism relates to stress and insecurity, while low neuroticism indicates emotional resilience (Almlund et al., 2011).

Fifth, agreeableness which includes compassion, trust, altruism, and cooperativeness (Yoo & Gretzel, 2011). Agreeable individuals value social harmony and tend to be warm and empathetic (Graziano & Eisenberg, 1997). Low scorers are often seen as individualists and competitive (John & Srivastava, 1999).

### 2.5.2 Personality and AI attitudes

Riedl (2022) conducted a literature review summarizing findings until 2021 regarding the correlation between personality traits and trust in AI. Nine papers reported a significant positive relationship between agreeableness and trust in AI-systems (Bawack et al. 2021; Böckle et al. 2021; Chien et al. 2016; Ferronato & Bashir 2020a; Huang et al. 2020; Kraus et al. 2020; Lyons et al. 2020; Müller et al. 2019; Rossi et al. 2018). Beyond this review, several studies support the importance of agreeableness towards AI. Cross-cultural studies show that agreeableness predicts more positive and less negative AI-attitudes in both UK and Arab samples (Babiker et al., 2024), while in China, but not in Germany, agreeableness is linked to higher AI-acceptance

(Sindermann et al., 2022). More broadly, agreeable individuals appear more tolerant of AI's shortcomings (Kaya et al., 2024), show greater trust when customization and feedback are available (Böckle et al., 2021), and are more forgiving of AI's negative aspects (Schepman & Rodway, 2023). Agreeableness is also tied to AI sociality and functionality (Park & Woo, 2022) and was the only trait significantly related to positive AI attitudes in Stein et al.'s (2024) study. Other research indicates that individuals have a higher tendency to seek financial advice if they score high on agreeableness, conscientiousness and low on extraversion (Chatterjee & Fan, 2021). Agreeableness emerged as most consistently linked to AI-acceptance, which is why it will be the focus of the thesis. Thus, I propose:

**H2:** Agreeableness is positively related to acceptance of financial AI advice.

Eight papers from Riedl's (2022) review reported a positive relationship between openness to experience and trust in AI (Aliasghari et al., 2021; Antes et al., 2021; Böckle et al., 2021; Elson et al., 2020; Ferronato & Bashir, 2020a; Oksanen et al., 2020; Schaefer & Straub, 2016; Zhang et al., 2020). This was confirmed in recent literature as openness led to an increased ChatGPT adoption (de Winter et al., 2024) and greater perceived AI functionality (Park & Woo, 2022). Riedl's (2022) review included five studies supporting a positive link between extraversion and trust in AI (Böckle et al., 2021; Haring et al., 2013; Kraus et al., 2020; Merritt & Ilgen, 2008; Müller et al., 2019), while one study reported a negative relationship (Ferronato & Bashir, 2020a). Recent research supports this negative correlation as extraversion has been linked to stronger negative emotions and lower AI functionality perceptions (Park & Woo, 2022) and introverts tend to hold more favorable attitudes toward AI (Rheu et al., 2021; Schepman & Rodway, 2023).

Regarding conscientiousness, Riedl (2022) identified three studies that reported a positive link with AI trust (Bawack et al., 2021; Chien et al., 2016; Rossi et al., 2018) and two that found a negative relationship (Aliasghari et al., 2021; Oksanen et al., 2020). More recently, conscientiousness has been identified as a strong predictor of positive AI-attitudes (Babiker et al., 2024), particularly in hiring contexts where efficiency and reliability matter (Calluso & Devetag, 2025).

For neuroticism, three studies in Riedl's (2022) analysis found a negative correlation with trust in AI (Kraus et al., 2020; Sharan & Romano, 2020; Zhang et al., 2020). Additional findings reinforce this trend in cross-cultural settings (Sindermann et al., 2022). Neuroticism has been linked to greater AI-related fear and negative perceptions (Babiker et al., 2024), stronger negative emotions but also higher AI sociality perceptions (Park & Woo, 2022), and lower trust in AI and human advice (Sharan & Romano, 2020). Overall, personality traits appear to

influence AI acceptance, with agreeableness showing the most consistent positive link. Given the mixed or weaker evidence for other traits, only agreeableness is tested in this thesis.

Beyond personality traits, individual characteristics such as internal locus of control (Oehler et al., 2022; Sharan & Romano, 2020) or high risk-taking tendencies tend to impact trust in AI, but with mixed findings (Ferronato & Bashir, 2020b; Oehler et al., 2022). Individuals with higher self-efficacy showed an increasing willingness to use AI (Oksanen et al., 2020) and emotions like sadness, fear, and anger predict negative AI-attitudes (Montag et al., 2025). These latter findings suggest the relevance of individual emotional dispositions in shaping trust toward automated systems.

## 2.6 Foundations of Emotional Intelligence

Quílez-Robres et al. (2023) defines EI as the “ability to perceive, manage and regulate emotions, promoting adaptive thinking and the understanding of the meaning and consequences of emotions“ (p.1). Emerged as a subset of social intelligence, EI highlights the role of emotions in reasoning, decision-making, and interpersonal interactions (Salovey & Mayer, 1989). Since multiple conceptualizations exist, a brief chronological overview is provided.

The first definition by Salovey & Mayer (1989) described EI as the skill to monitor and utilize emotions to guide thinking and actions, consisting of three components: appraisal and expression of emotions, regulation of emotions, and the utilization of emotions to support reasoning and creativity (Salovey & Mayer, 1989).

Goleman (1995) later popularized EI in leadership, introducing five dimensions (self-awareness, self-regulation, motivation, empathy, and social skills) which enable individuals to manage relationships effectively, influencing, persuading, and leading others (Goleman, 1995, 2000). This approach was the foundation of the “mixed approach”. Bar-On (2000) builds upon Goleman’s (1995) conceptualization but offers a more structured and psychometrically validated framework (Bar-On, 2000; Bar-On, 2004). He conceptualized EI as a broad set of non-cognitive abilities, meaning it includes both self-perceived emotional skills and personality traits (Bar-On, 1997).

In response to Goleman (1995), Mayer & Salovey (1997) refined their original definition by developing the four-branch model of EI, which remains one of the most widely used frameworks today. This model described EI as the skill or ability to perceive and articulate emotions and characterizes EI as an intelligence rather than a trait which can be developed and

improved consisting of four interrelated components: perceiving emotions, facilitating thought, understanding emotions, and managing emotions (Mayer & Salovey, 1997).

A competing perspective emerged from Petrides & Furnham (2001), who argued that EI is better understood as a stable personality trait rather than a cognitive ability. They proposed the trait EI model, which views EI as a set of self-perceived emotional competencies. Trait EI is strongly linked to personality traits and is evaluated through subjective responses rather than objective tasks.

Wong & Law (2002) made a significant contribution to EI research by developing the Wong and Law Emotional Intelligence Scale (WLEIS), a commonly utilized self-report measure of EI that was applied in this thesis.

Prior research debates whether the WLEIS aligns more closely with the ability model due to its structure (Bru-Luna et al., 2021; LaPalme et al., 2016; Law et al., 2004) or the trait model as it measures individuals' self-reported emotional capabilities (Pérez et al., 2005; Brannick et al., 2009). Wong & Law (2002). Their framework consists of a practical four-factor structure which is derived from the four-branch model (Mayer & Salovey, 1997). It consists of self-emotion appraisal (SEA), which assesses individuals' ability to recognize and understand their own emotions; others' emotion appraisal (OEA), which captures the ability to recognize emotions in others; use of emotion (UOE), which reflects how effectively emotions are used to enhance cognitive functions and decision-making; and regulation of emotion (ROE), which evaluates one's ability to manage and control emotional responses. Their studies bridged the gap between theoretical EI models and applied business research highlighting the role of EI in workplace success. They showed that EI has a positive impact on teamwork, enabling individuals to exhibit greater resilience and demonstrate stronger leadership capabilities (Wong & Law, 2002, 2012).

Research showed that EI enhances decision-making by balancing analytical reasoning with emotional awareness, enabling individuals to regulate biases, manage risk intelligently, and consider the strategic impact of choices (Chauhan & Chauhan, 2007; Fernandez Araoz, 2007; Fernández-Berrocal et al., 2014; Hess & Bacigalupo, 2011; Moon, 2021). EI facilitates risk-intelligent decision-making and more rational judgments (Alkozei et al., 2016; Moon, 2021). In finance, high-EI investors are less prone to biases, impulsivity, and emotional trading, showing greater independence, discipline, and resilience (Ameriks et al., 2009; Bykova et al., 2024; Chaturvedi Sharma, 2025; Johnsi & Sunitha, 2019; Pirayesh, 2014; Sashikala & Chitramani, 2017; Smith, 2009 Song et al., 2023).

### 2.6.1 Link between Emotional Intelligence and Personality Traits

Extensive research has investigated the relationship between personality traits and EI, showing that all five dimensions of the FFM exhibit at least moderate correlations with EI (Joseph & Newman, 2010; Matthews et al., 2006; Siegling et al., 2015; van der Zee et al., 2002). Trait EI strongly correlates with the FFM personality dimensions, particularly high agreeableness, extraversion, conscientiousness, and low neuroticism (Petrides & Furnham, 2001). The study by van der Linden et al. (2017) is a meta-analysis consisting of 142 studies with a combined sample size of  $N = 36,268$  participants investigated the relationship between EI and the General Factor of Personality (GFP), which is considered a higher-order social effectiveness factor derived from the FFM. The study found a very high correlation ( $r \approx .85$ ) between GFP and trait EI, suggesting that the two constructs are almost synonymous (Alegre et al., 2019; van der Linden et al., 2017). Other research found that openness, conscientiousness, and agreeableness positively predicted EI, while neuroticism had a negative effect, reflecting difficulties in emotional regulation (Zewude et al., 2024). Similarly, Alegre et al. (2019) reported a strong negative relationship between neuroticism and EI and a moderate positive link with extraversion.

In contrast, ability EI showed a weaker correlation with the GFP ( $r \approx .28$ ). This suggests that ability EI is partially related to personality traits but remains a distinct construct (van der Linden et al., 2017).

### 2.6.2 Emotional Intelligence and AI acceptance

Exploring how an individual's EI influences their acceptance of AI is a nuanced and quite understudied area. However, initial evidence shows a clear picture as individuals with high EI tend to be more resilient and flexible with new challenges, including technological advancements (Binsaeed et al., 2023). Abu Shanab & Abu Shanab (2022) found that all dimensions of EI positively predict self-efficacy, which in turn enhances performance expectancy. As this is a strong predictor of technology acceptance, people with high EI find technology easier to use, reinforcing their confidence in adopting it (Abu Shanab & Abu Shanab, 2022). A similar result was found by Khasawneh (2018), indicating a positive correlation between EI and technology acceptance.

Rokaya et al. (2022) showed that all five of Goleman's (1995) EI dimensions significantly predicted students' willingness to use chatbot technologies for educational tasks. Similarly, Hernandez et al. (2023) found that specific emotional regulation skills like cognitive reappraisal increased users' preference for emotionally intelligent AI systems, whereas difficulties in

identifying emotions had the opposite effect. Finally, Kambur (2021) shows how EI levels influence the perception of AI technologies. This research found a positive link between EI and the perception of different aspects of AI like comprehensiveness, format, accuracy, reliability, accessibility, flexibility, and timeliness. Although no study has examined the WLEIS subdimensions in this context, the described relationship between EI and AI-advice acceptance justifies the following hypothesis:

**H3:** Emotional Intelligence is positively related to acceptance of financial AI advice.

## 2.7 PIIT and AI Attitudes

PIIT is an individual trait reflecting a person's tendency to embrace new technologies. Agarwal & Prasad (1998) introduced PIIT as “the willingness of an individual to try out any new information technology” (p. 206). They found that PIIT moderates the relationship between perceptions about new technology and the intention to use it (Agarwal & Prasad, 1998). Individuals scoring high in PIIT typically find new technologies useful and easy to use, which enhances their willingness to adopt IT innovations (Agarwal & Prasad, 1998). It is a domain-specific trait, not limited to a particular task or situation (Agarwal & Prasad, 1998; McAdams & Pals, 2006). Notably, PIIT is positively associated with the personality trait of openness to experience, as individuals who are more open to innovation and change also tend to score higher in PIIT (Nov & Ye, 2008; Yang et al., 2012).

A study with Generation Z consumers on AI voice assistants in banking showed that PIIT significantly boosts both attitude toward the AI-enabled voice assistants and the willingness to use it (Alkadi & Abed, 2025). Among accounting students, a significant positive relationship was found between PIIT and the intention to use new technology (Simarmata & Hia, 2020). High levels of PIIT are further associated with willingness to pursue careers in IT (Chen et al., 2016) and with the acceptance of technology-mediated education services (Wang et al., 2012). PIIT is distinct from general adoption models like the UTAUT (Venkatesh et al., 2003), TAM (Davis, 1989), and AIDUA (Gursoy et al., 2019) but often serves as an important personal factor moderating or directly influencing technology acceptance (Simarmata & Hia, 2020). Specifically, it captures individual differences that may not be accounted for by general constructs such as performance expectancy or social influence.

Empirical evidence suggests that individuals high in PIIT tend to show more positive emotions and attitudes about AI systems (Park & Woo, 2022). They are more willing to explore, adopt, and continue using emerging technologies (Agarwal & Prasad, 1998; Thatcher & Perrewé, 2002). Risk-taking attitudes correlate with a greater willingness to innovate (Mittone et al.,

2022), implying that individuals with high PIIT may be more comfortable navigating uncertainty and complexity in decision-making.

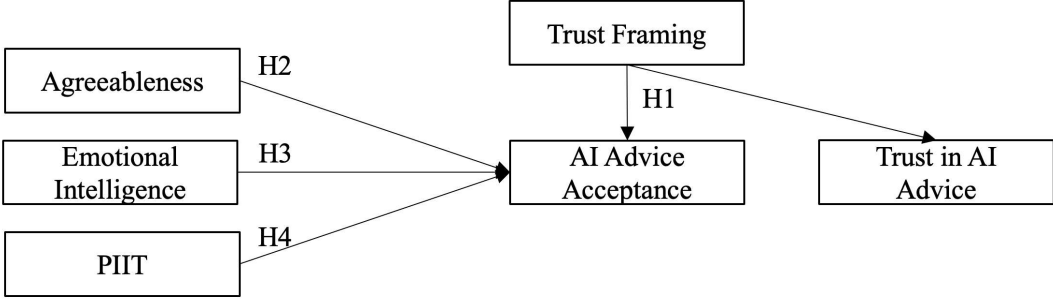
In contrast, individuals low in PIIT may approach AI systems with skepticism, requiring stronger cues for trust and assurance (Park & Woo, 2022). Therefore, I propose:

**H4:** Personal Innovativeness in Information Technology is positively related to acceptance of financial AI advice

2.8 Conceptual Model

Given the reviewed literature, the conceptual model is presented in Figure 1.

**Figure 1:**  
*Conceptual Model*



### **3 Research Methodology**

This chapter begins with the overall research design, proceeds with the scenario development and results of the pre-study, then describes the sample and the procedure of the main study, and concludes with a detailed overview of the applied variables.

#### **3.1 Research Design**

As part of this thesis, I conducted a pre- and main study that examined the influence of EI, personality traits, and individual characteristics such as PIIT on the acceptance of AI financial advice. Given the relevance of causal understanding for both academic insight and practical application, the experimental design approach was chosen. This thesis prioritizes internal validity and uses a controlled design to examine how AI trust framing influences trust and acceptance of AI-generated financial advice. However, the scenario used in the experiment was developed to be as realistic and relatable as possible. A quantitative approach using the online survey platform Qualtrics was selected to answer the research questions and test the hypotheses. This approach is fast, globally accessible, and ensures the data security and privacy of participants (Teo, 2013).

#### **3.2 Pre-Study: Scenario Development and Results**

As part of this thesis, I conducted a study that examined the influence of EI and various individual characteristics on the acceptance of AI-generated financial advice. As a preliminary step, a pre-study was conducted to test how individuals respond to AI-generated financial advice under different framing conditions. To manipulate participants' trust in the AI-financial advice, two conditions with contrasting information were created: One presenting high-trust framing, emphasizing the benefits and reliability of robo-advisors, and the other using a low-trust framing, highlighting potential risks and limitations (see the whole pre-study in appendix A). The goal was to assess whether the manipulation effectively influences participants' trust and willingness to follow AI-financial advice. The texts were designed to have a reading time of approximately one minute to minimize fatigue and maintain attention. This pre-study served to validate the framing stimuli and ensured the credibility and clarity of the manipulation prior to launching the main study. Each text consisted of three concise and thematically parallel sections.

The first section offered an objective framing, stating that robo-advisors either outperform or underperform human advisors in terms of accuracy and risk-adjusted returns.

The second section presented three arguments to reinforce the intended trust framing. The arguments were intentionally structured in a triadic format, 1) a performance-based claim (accuracy), 2) a credibility-based cue (expert reliance), and 3) an emotional or psychological element (bias or personalization), to comprehensively reflect the multifaceted nature of trust formation. The positive framing emphasized the efficiency, credibility, and objectivity of AI-generated financial advice, while the negative framing highlighted data misinterpretation, skepticism, and the superiority of human advisors in handling complex client needs.

The third component addressed trust and potential herding effects by presenting contrasting survey results, indicating that others would trust and follow AI-based advice again (positive framing) or remain skeptical and reluctant to follow such advice again (negative framing).

To enhance perceived realism and credibility, the scenario was tailored to resemble a professional research-based briefing note intended for individual retail investors. Visual and verbal cues such as symbols and headlines were used to support and increase the intended framing and primed participants' interpretation of the content (Roberts et al., 2022). By visually simulating a trustworthy information source, the design aimed to minimize superficial disbelief and increased cognitive engagement with the framing content. The wording was carefully balanced to ensure the manipulation remained ethically appropriate and did not cross into misinformation. The texts aimed to be concise, comprehensive, and persuasive by presenting a range of arguments from performance metrics to emotional dimensions of trust. Both texts nearly had the same wordcount (135 words positive framing vs. 137 words negative framing). After the scenario in the pre-study, a manipulation check was included to verify whether participants had read the text carefully. This was followed by a credibility scale and questions asking whether the framing text changed the prior beliefs about robo-advisors (see chapter 3.5.3). Next, the section on investment preferences, goals and risk behavior was included consisting of four questions to generate realistic AI-based financial advice. After assessing AI-advice acceptance, the trust measurement scale was presented (see chapter 3.5.1).

Results of the pre-study, which can be found in appendix B, showed that out of 42 participants, 35 passed both the attention and manipulation check (failure rate = 16.7%). Participants in the positive framing group had a mean trust score of  $M = 3.02$  ( $SD = 0.56$ ,  $n = 19$ ), compared to  $M = 2.82$  ( $SD = 0.64$ ,  $n = 16$ ) in the negative framing group. Two independent samples t-tests showed no significant differences in trust (scale Cronbach's  $\alpha = .76$ ),  $t(30.1) = 1.01$ ,  $p = .320$ , and credibility (scale Cronbach's  $\alpha = .90$ ),  $t(28.4) = 0.78$ ,  $p = .442$ . Despite the difference not reaching statistical significance, it was in the expected direction. Therefore, no adjustments were made, and the main study proceeded as initially planned.

The results from the prior beliefs section (scale Cronbach's  $\alpha = .88$ ), asking about the participants' willingness to change their opinion based on the framing condition, revealed that the average score ( $M = 3.21$ ,  $SD = 1.27$ ) was significantly lower than the scale midpoint,  $t(34) = -3.65$ ,  $p < .001$ . This indicates that participants were unlikely to change their prior beliefs about robo-advisors after the manipulation.

The mean credibility rating ( $M = 4.38$ ,  $SD = 1.19$ ) was marginally significantly higher than the scale midpoint,  $t(34) = 1.88$ ,  $p = .068$ , indicating that participants perceived the manipulation as moderately credible. Additionally, only 25.7% of participants indicated that they would not follow the investment advice provided, while 37.1% would follow it and 37.1% responded with "not sure". There were no significant differences between the two framing conditions,  $\chi^2(2, N = 35) = 0.01$ ,  $p = .996$ .

### 3.3 Participants

Participants were volunteers and there was no predetermined or systematic selection process in place (Vehovar et al., 2016). Initially, the survey was distributed via word of mouth within the author's personal and professional network. This was followed by a distribution through social media platforms (WhatsApp, Instagram, LinkedIn). After two weeks of data collection through these channels, the survey was additionally distributed via Prolific, a platform widely recognized in academic research for recruiting participants for online questionnaires (Douglas et al., 2023; Peer et al., 2021). On Prolific, several eligibility criteria were defined to ensure data quality. Participants were required to have a minimum approval rate of 95% for previous tasks, at least 500 completed survey submissions, and fluency in English. Participants received £0.82 (approximately €0.97) for their participation. In total, 215 individuals were recruited via Prolific, of which 190 provided valid responses. The median survey completion time on the platform was 9 minutes 51 seconds.

The overall sample comprised 365 participants, of whom 324 passed both the manipulation check and the attention check and were thus considered as the valid sample. Consequently, 41 participants (11.2%) were excluded for failing either one or both checks. While 13 participants failed the attention check, 31 failed the manipulation check (3 failed both).

In the valid sample, 56.8% participants were male, and 43.2% female. Participants came from a diverse range of countries, with the majority coming from Germany (20.4%), followed by South Africa (16.4%), the United States (12.3%), and the United Kingdom (11.1%). The participants had an average age of 34.90 years ( $SD = 12.57$ ). In terms of occupational status, 70.8% were employed, 19.1% were students, 6.5% were unemployed, and 3.7% were retired.

Additionally, 74.8% of participants held a university degree (bachelor's, master's, or doctoral degree).

Due to the removal of participants who failed either the manipulation or attention check, the resulting sample distribution across the experimental conditions was not perfectly balanced. A total of 168 valid participants (51.9%) were exposed to the positively framed scenario, while 156 participants (48.1%) received the negatively framed version.

### 3.4 Procedure

The survey began with a brief introductory text that welcomed participants, explained the purpose and topic of the study, and outlined the general procedure. The questionnaire was divided into four sections. The first section presented the previously described scenario in which robo-advisors were either framed positively or negatively. Immediately following this, a manipulation check was included to verify whether participants correctly read the text by asking whether the text emphasized the advantages or disadvantages of robo-advisors.

The second section consisted of four questions aimed at capturing participants' investment preferences, financial behavior, and individual financial objectives. Participants were then shown a screen where an AI-generated investment recommendation was provided. This fictional recommendation was presented as the *Global AllStars Prime* portfolio, an actively managed portfolio composed of well-established and financially secure companies. A short explanatory note was included, stating that the robo-advisor recommended a long-term investment strategy and that its advice was tailored to the current market trends. To assess the AI-advice acceptance, participants were then asked whether they would follow the robo-advisors recommendation.

The following section measured trust in the AI-generated advice. Given that this block included the highest number of questions, an attention check was embedded midway to ensure data quality.

Subsequently, participants responded to scales measuring the main predictors (EI, PIIT, and agreeableness) and control variables (financial literacy and robo-advisor experience).

The final section of the survey captured demographic information, including gender, age, occupation, educational background and country of origin.

### 3.5 Variables

#### 3.5.1 Dependent Variables

Trust in AI: To measure trust in the AI-financial advice, the Trust Scale for the AI Context (TAI) developed by Hoffman et al. (2023) was used as a starting point. The original scale was designed to assess users' confidence in AI systems, including their perceived reliability, predictability, and efficiency.

For the purposes of this thesis, the TAI was adapted to reflect the specific context of AI-driven financial advice. Item phrasing was adjusted to align with the investment scenario presented in the survey and to emphasize aspects relevant to financial decision-making such as perceived competence, its alignment with users' goals, and the perceived safety of following its advice. The complete trust scale, along with all modifications, is presented in appendix C2 (complete pre-study in appendix A, main study in appendix D). Of the eight items used in this thesis, four were retained from the original scale, while the remaining four were modified or newly formulated to better match the use case. First, an additional item for perceived reliability was added: "I believe the AI financial advisor provides reliable investment recommendations." This item supplements the original reliability-focused statements and strengthens construct coverage. Second, an item targeting perceived competence was introduced: "The AI financial advisor demonstrates a high level of expertise in providing financial advice." This addition enhances the measurement of cognitive trust by directly referencing the AI's domain-specific knowledge. Third, the original item "The tool can perform the task better than a novice human user" was replaced by "I trust the AI financial advisor as much as I would trust a human financial advisor." This adaptation allows for a more direct and intuitive comparison between human and AI financial advice. Finally, the item "I feel confident in following the advice given by the AI financial advisor" was included in place of the more general statement "I am confident in the tool. I feel that it works well." This version captures behavioral trust in the specific action of investment decision-making, rather than general tool effectiveness.

Two items from the original scale about the perceived speed and output predictability were excluded given that investment decisions typically involve deliberation rather than immediacy.

AI-advice acceptance: AI-advice acceptance was measured using a single-item behavioral intention question asking participants whether they would follow the investment recommendation provided by the AI financial advisor. This variable was treated as a categorical outcome capturing the participants' immediate willingness to act on AI-generated financial advice with the answer options "Yes", "No" and "Not sure". Prior research found that there is

a positive relationship between trust in robo-advisors and their willingness to adopt them (Hildebrand & Bergner, 2021; Kelly et al., 2023; Komiak & Benbasat, 2006).

### 3.5.2 Predictor Variables

Framing condition: Each participant was randomly allocated to one of the two groups, receiving either the positively or the negatively framed information text about robo-advisors. The goal of this manipulation was to simulate real-world communication strategies used by financial service providers and assess their effect on trust and advice acceptance. This framing variable is categorical (binary) and served as the experimental condition in this study.

EI: EI was measured using the WLEIS (Wong & Law, 2002), a widely used self-report instrument consisting of 16 items, grouped into four subdimensions that reflect key aspects of EI, as described in chapter 2.6. Each subdimension can be evaluated individually while a holistic average score is also possible.

Participants responded to each statement on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). It was initially developed for the application in management and leadership contexts, but has been extended to organizational, behavioral, and educational research settings (Keefer et al., 2018; Law et al., 2004).

The WLEIS was chosen over alternative measures of EI such as the MSCEIT (Mayer et al., 2002) or EQ-i (Bar-On, 1997), primarily due to its time efficiency and suitability for online survey designs. The scale's reliability has been confirmed across cultures, with Cronbach's  $\alpha$  ranging from .88 to .92 in South Korean nurses (Park & Yu, 2021), .80 in an Italian sample (Iliceto & Fino, 2017), and .79 to .91 in a Spanish validation (Extremera Pacheco et al., 2019).

PIIT: PIIT was measured using a validated 4-item scale from Agarwal & Prasad (1998). The PIIT scale has been extensively validated in the context of technology acceptance and reflects a domain-specific personality trait relevant to voluntary technology use (Park & Woo, 2022; Park & Woo, 2025). Participants responded to the statements on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). A composite average score was computed by averaging the responses across all items, with higher scores indicating greater innovativeness. Prior research has reported good internal consistency for this scale, with Cronbach's  $\alpha$  typically exceeding .84 (Agarwal & Prasad, 1998; Park & Woo, 2022; Wu & Yu, 2022).

Agreeableness: Agreeableness was measured using the agreeableness part of the Big Five Inventory-2 Short Form (BFI-2-S), developed by Soto & John (2017a). The BFI-2-S is a 30-item personality inventory that captures the Big Five traits through six items per trait. It is a short form of the Big Five Inventory (BFI-2) (60 items) (Soto & John, 2017b). The agreeableness subscale includes three facets: compassion, respectfulness and trust (two items per facet). Half of the items were reverse-coded in order to control for acquiescence bias. Participants were instructed to indicate the extent to which they agreed with each item using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The BFI-2-S demonstrates a high correlation with the full BFI-2, with part-whole correlations ranging between  $r = .86-.95$ , indicating that the short form preserves the structural and conceptual integrity of the full inventory (Soto & John, 2017a). The BFI-2-S has also shown high internal consistency, with a Cronbach's  $\alpha$  of .75 for agreeableness across a large and diverse sample ( $N = 2,423$ ; Soto & John, 2017a). Furthermore, the scale has been validated for both German (Cronbach's  $\alpha = .65$ ) and US (Cronbach's  $\alpha = .75$ ) participants (Rammstedt et al., 2018). The BFI-2-S was selected as a methodological compromise of less time than the full BFI-2 but higher accuracy and reliability than ultra-short forms such as the BFI-2-XS (Soto & John, 2017a) or the BFI-10 (Rammstedt & John, 2007).

### 3.5.3 Covariates

Credibility: Credibility of the framing condition was measured only in the pre-study using the slightly adapted credibility scale by Appelman & Sundar (2016). This validated scale is widely used in media psychology, online communication, information credibility research and has demonstrated strong internal consistency (Cronbach's  $\alpha = .87$ ; Appelman & Sundar, 2016). In the current study, one item of the original three-item scale (accurate, authentic, believable) was adapted by replacing “authentic” with “trustworthy” to better reflect facets relevant to financial decision-making (see appendix C1).

Financial Literacy: Financial literacy was measured using the widely recognized “Big Three” financial literacy questions developed by Lusardi & Mitchell (2008). These three multiple-choice items assess participants' understanding of key financial concepts: interest, inflation, and risk diversification. The scale has been shown to reliably capture fundamental financial knowledge in a brief yet effective manner. One point was awarded for each correct response, resulting in a total financial literacy score ranging from 0 to 3. This variable was included as a covariate, as prior research suggested that financial literacy may influence trust in and

acceptance of AI-generated financial advice. While some studies found that higher financial knowledge increases willingness to adopt robo-advisors (Isaia & Oggero, 2022; Yi et al., 2023), others observed the opposite (Piehlmaier, 2022) or highlighted indirect effects through reduced anxiety and emotional reactions (Hohenberger et al., 2019).

Robo-advisor experience: Robo-advisor experience was measured using a single-item question asking participants whether they had previously used a robo-advisor, with response options “Yes” or “No”. The variable was treated as a binary indicator to control for prior exposure to AI-based financial tools.

Manipulation and attention checks: To verify that participants processed the framing as intended, a manipulation check was included immediately after the manipulation, giving two answer options asking whether the preceding text highlighted the advantages or disadvantages of robo-advisors. This verified whether participants had read and correctly interpreted the intended framing condition. In addition, an attention check was embedded in the trust measurement block, as it was the longest section of the survey. The item instructed participants to select “strongly disagree” on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). Only participants who selected exactly “1” were retained, all others were excluded from the analysis.

Demographics: Gender, age, occupational status, highest level of education completed, and country of origin were collected and are comparable to other research (e.g., Hyun Baek & Kim, 2023). For a high data quality, Qualtrics accepted only integer values ranging from 0-120 for the age. Moreover, the country of origin needed to be selected from a drop-down menu to avoid misspellings. Prior research found that demographic factors influenced technology adoption in different fields (e.g. Lee et al. 2017).

## 4 Results

### 4.1 Scale Reliability

To assess the internal consistency of the applied scales, Cronbach's  $\alpha$  values were calculated and a factor analysis was performed for all multi-item constructs (see appendix F). Reliability testing ensured that the items within each scale measure the same underlying construct consistently (Tavakol & Dennick, 2011). The results indicated high reliability across all scales as all are above the required threshold of .70 (Bland & Altman, 1997; Peterson, 1994). For all scales, no items were removed, and scale scores were computed by averaging the respective items.

The trust scale, consisting of eight items, showed excellent internal consistency ( $\alpha = .96$ ). The average inter-item correlation was .74 which is above the optimal range of .15 to .50 (Clark & Watson, 1995), suggesting a high degree of item homogeneity and potential redundancy. To further examine the internal structure of the trust scale, a confirmatory factor analysis using maximum likelihood extraction was conducted (see appendix F2). All items loaded strongly on a single factor (loadings between .78 and .94), suggesting that they measure the same underlying construct. The model explained 74% of the total variance, and the model fit was acceptable to excellent (RMSR = .020, TLI = .980, RMSEA = .071), supporting the scale's construct validity.

The four subdimensions of EI from the WLEIS scale also demonstrated strong reliability. SEA ( $\alpha = .92$ ), OEA ( $\alpha = .90$ ), UOE ( $\alpha = .91$ ), and ROE ( $\alpha = .92$ ) all have very strong Cronbach's  $\alpha$ . Across all subscales, no item deletion substantially improved or weakened reliability as the  $\alpha$  changes by -.05 to +.01 if any item across each subscale is removed, supporting the robustness of the original item structure. Each item loaded strongly on its intended factor, with coefficients ranging from .76 to .92 and minimal cross-loadings (see appendix F3, F4, F5, F6). The four factors jointly explained 74% of the total variance, and inter-factor correlations ranged from .43 to .65, indicating related but distinct constructs. Model fit indices revealed a strong model fit (RMSR = .020, TLI = .965, RMSEA = .062).

The scale for PIIT yielded an acceptable reliability with  $\alpha = .81$ . Item one, two and four exhibited similar inter-item correlations and contributed comparably to the overall reliability. Notably, item three stood out, as removing this item would substantially increase Cronbach's  $\alpha$  to .91. As it was the only reverse-coded item, it signals limited attention among the participants. Three items loaded strongly ( $\geq .86$ ), while one item (PIIT\_3) had a notably lower loading (.31), indicating potential weakness (see appendix F7). Nonetheless, all items were

kept. The model explained 61% of the total variance, with acceptable residuals (RMSR = .020) and a high TLI (.995).

The six-item agreeableness scale also reached a satisfactory level of internal consistency ( $\alpha = .81$ ). Inter-item correlations were moderate (average  $r = .43$ ), aligning with the recommended thresholds (Clark & Watson, 1995). All items were kept as none of the six items substantially improved reliability if removed. All items showed moderate loadings between .61 and .72 and the model explained only 43% of the total variance (see appendix F8).

## 4.2 Descriptive Statistics

This section provides an overview of the distribution and central tendencies of the main study variables. Details can be found in appendix G. In contrast to the pre-study, the main study framing resulted in a higher acceptance rate of the AI-investment advice. While 73.8% ( $n = 124$ ) in the high-manipulation group accepted the advice, only 32.1% ( $n = 50$ ) did so in the low-manipulation group.

On average, participants reported high levels of EI, with  $M = 5.35$  ( $SD = 0.93$ ) on a 7-point Likert scale, which was significantly above the scale middle,  $t(323) = 25.97$ ,  $p < .001$ . The highest scores were found on the UOE subscale ( $M = 5.50$ ,  $SD = 1.18$ ), while the OEA subscale yielded the lowest ( $M = 5.10$ ,  $SD = 1.20$ ). However, it was still significantly above scale average,  $t(323) = 16.48$ ,  $p < .001$ . Women reported significantly higher EI ( $M = 5.51$ ) than men ( $M = 5.22$ ),  $t(302) = 2.78$ ,  $p = .006$ . Country-wise, participants from South Africa reported significantly higher EI levels ( $M = 6.14$ ) compared to other nationalities ( $M = 5.19$ ),  $t(81.3) = -8.10$ ,  $p < .001$ .

For PIIT, the mean was 4.83 ( $SD = 1.29$ ) on a 7-point scale, which was significantly higher than the scale midpoint,  $t(323) = 11.56$ ,  $p < .001$ . Men reported significantly higher PIIT scores ( $M = 5.02$ ) than women ( $M = 4.58$ ),  $t(285) = -3.04$ ,  $p = .003$ . Moreover, employed or self-employed participants scored significantly higher ( $M = 5.03$ ) than those in other occupational categories ( $M = 4.36$ ),  $t(166) = -4.22$ ,  $p < .001$ . In terms of nationality, German participants had significantly lower PIIT scores ( $M = 4.25$ ) compared to participants of other nationalities ( $M = 4.98$ ),  $t(104) = 4.33$ ,  $p < .001$ . A marked difference was also observed between participants with prior robo-advisor experience ( $M = 5.42$ ) and those without ( $M = 4.65$ ),  $t(149) = -5.24$ ,  $p < .001$ , suggesting greater openness to new technologies for high PIIT individuals.

Regarding agreeableness, the average score across all participants was  $M = 3.90$  ( $SD = 0.69$ ) on a 5-point scale, significantly above scale average  $t(323) = 23.34$ ,  $p < .001$ . Women scored significantly higher ( $M = 4.09$ ) than men ( $M = 3.75$ ),  $t(308) = 4.66$ ,  $p < .001$ . Additionally,

national differences were also present, with South African participants representing a more collectivist culture, reporting significantly higher agreeableness ( $M = 4.47$ ) than other nationalities ( $M = 3.78$ ),  $t(93.8) = -8.78, p < .001$ .

Financial literacy levels were generally high ( $M = 2.50$  out of 3.00,  $SD = 0.79$ ). A total of 65.7% ( $n = 213$ ) of participants answered all three financial knowledge questions correctly. Men were more likely to achieve full marks ( $n = 134, 72.8\%$ ) compared to women ( $n = 79, 56.4\%$ ). Interestingly, educational background had no significant impact, as participants with a university degree didn't score significantly higher ( $M = 2.55$ ) than those without ( $M = 2.35$ ),  $t(120) = -1.76, p = .080$ . However, national differences were also evident, with South African participants scoring significantly lower ( $M = 2.26$ ) than their counterparts ( $M = 2.55$ ),  $t(73.7) = 2.38, p = .020$ .

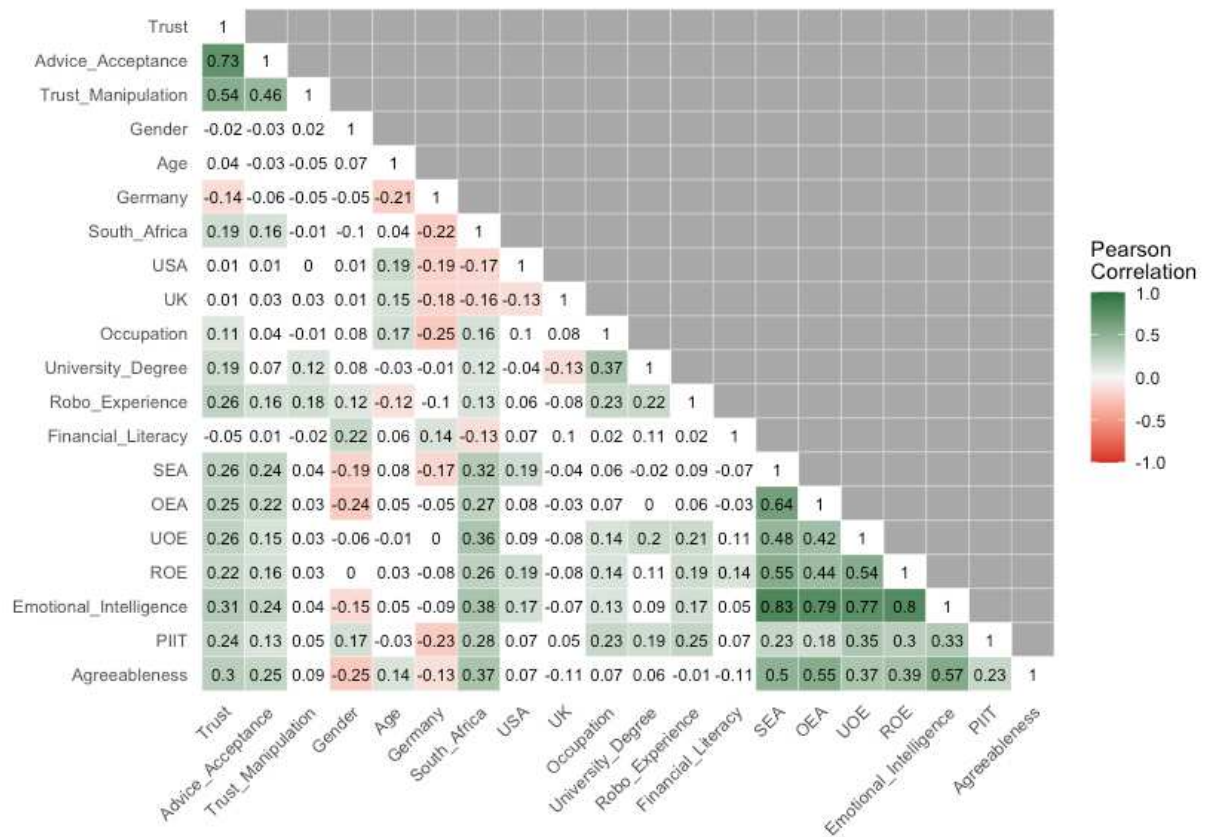
Lastly, concerning the categorical variable of prior robo-advisor use, less than one quarter of participants previously used a robo-advisor ( $n = 76, 23.5\%$ ). Men were slightly more likely to have done so ( $n = 51, 27.72\%$ ) than women ( $n = 25, 17.9\%$ ), however, the result was not significant,  $\chi^2(1, N = 324) = 3.77, p = .052$ . Nonetheless, individuals with a university degree reported significantly higher usage rates ( $n = 70, 28.9\%$ ) than those without ( $n = 6, 7.3\%$ ),  $\chi^2(1, N = 324) = 14.75, p < .001$ .

### 4.3 Bivariate Statistics

To further explore the relationships between the main predictors, the framing condition, and the dependent variables, a Pearson correlation analysis was conducted. Categorical variables were recoded into binary format (see appendix E1 for the full coding scheme). The following correlation matrix illustrates the variable relationships (Field, 2009). Correlation magnitudes were interpreted using Hemphill's (2003) guidelines. Coefficients below .20 are considered weak, values between .20 and .30 are moderate, and values above .30 indicate a strong correlation.

**Figure 2:**

*Pearson Correlation Matrix (significance ( $p < .05$ ) colored)*



Advice acceptance was significantly and positively correlated with trust ( $r = .73, p < .05$ ), indicating a very strong association. This suggests that participants who reported higher levels of trust in the AI system were also much more likely to act on its recommendation. Furthermore, trust showed a strong positive correlation with the positive framing condition ( $r = .55, p < .05$ ), and advice acceptance was also positively related to the framing manipulation ( $r = .46, p < .05$ ). These findings confirm the central assumption that positively framed advice increases both trust and acceptance of AI-generated financial recommendations.

Both trust and AI-advice acceptance also correlated moderately positive with EI ( $r = .33$  and  $r = .24$  respectively,  $p < .05$ ). This indicates that individuals with higher EI tend to place more trust in AI-advisors and are more inclined to follow their advice. Similar trends were observed across the four subdimensions of EI, each showing significant but moderate correlations with trust ( $r$  ranging from .22 to .28,  $p < .05$ ). As expected, the EI subscales show a strong positive correlation with each other, with values ranging from .41 to .64, reflecting the internal consistency of the construct.

PIIT was moderately and positively associated with trust ( $r = .25, p < .05$ ) and showed a weak but still significant correlation with AI-advice acceptance ( $r = .15, p < .05$ ). Also, the expected positive correlation between PIIT and prior robo-advisor experience was confirmed ( $r = .26, p < .05$ ).

Similarly, agreeableness shows a positive relationship with trust ( $r = .31, p < .05$ ) and a moderate yet significant correlation with AI-advice acceptance ( $r = .24, p < .05$ ), suggesting that individuals with more cooperative and trusting dispositions may be more receptive to AI-driven financial tools.

Interestingly, gender, age and financial literacy showed no significant associations with either trust or AI-advice acceptance, which contradicts initial expectations and suggests that demographic factors play a limited role.

#### 4.4 Hypotheses Testing

Despite the performed Shapiro-Wilk test revealing a non-normal distribution of all predictors, parametric tests were still applied in subsequent analyses. Visual inspection of Q-Q plots showed largely linear trends, with only slight and symmetrical deviations at the tails, indicating that the assumption of normality was sufficiently met. Additionally, research supports the use of parametric methods in such cases, particularly for samples above 100 participants (Knief & Forstmeier, 2021).

To test the hypotheses, regression analyses were conducted using trust and AI-advice acceptance as dependent variables. The hypotheses with trust as dependent variable were tested using linear regression models whereas the AI-advice acceptance hypotheses were tested using ordinal logistic regressions.

In the linear regression models predicting trust (Table 1), the framing condition was a significant and robust predictor. In the baseline model (Model 1), including only the trust manipulation and the main predictors, participants exposed to positively framed advice reported significantly higher trust ( $\beta = 1.125, SE = 0.095, p < .01$ ). This effect remained stable and statistically significant when controlling for robo-advisor experience, financial literacy and demographic variables such as gender, age, education, and nationality ( $\beta = 1.064, SE = 0.097, p < .01$ ) (Model 2).

**Table 1:***Linear Regression (Dependent Variable: Trust)*

	Trust (linear regression)			
	(1)		(2)	
	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>
Trust Manipulation	1.125***	0.095	1.064***	0.097
Emotional Intelligence	0.210***	0.064	0.198***	0.067
PIIT	0.103***	0.039	0.065	0.043
Agreeableness	0.197**	0.084	0.189**	0.090
Robo Experience			0.303**	0.123
Financial Literacy			-0.062	0.064
Gender			0.0003	0.105
Age			0.005	0.004
Occupation			-0.009	0.120
University Degree			0.182	0.123
Germany			-0.104	0.134
South Africa			0.066	0.157
USA			-0.154	0.163
UK			0.082	0.167
Constant	0.038	0.320	0.144	0.402
Observations	324		324	
R <sup>2</sup>	.401		.429	
Adjusted R <sup>2</sup>	.393		.404	
Residual Std. Error	0.850		0.842	
<i>F</i> Statistic	53.387*** (df=4; 319)		16.610*** (df=14; 309)	

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ 

AI-advice acceptance was significantly and positively affected by the framing manipulation in both the baseline and full model, as shown in Table 2 (Model 3:  $\beta = 1.960$ ,  $SE = 0.245$ ,  $p < .001$ ; Model 4:  $\beta = 1.957$ ,  $SE = 0.256$ ,  $p < .001$ ). The corresponding odds ratios of 7.10 (Model 3) and 7.08 (Model 4) indicate that participants exposed to the positively framed text were over seven times more likely to be in a higher acceptance category compared to the negatively framed group.

Taken together, these results provide strong empirical support for H1. Participants who received positively framed information texts were significantly more likely to trust and accept the AI-advice, even after adding control and demographic variables.

**Table 2:***Ordinal Logistic Regression (Dependent Variable: Advice Acceptance)*

	AI Advice Acceptance (ordinal logistic regression)					
	(3)			(4)		
	<i>b</i>	<i>SE</i>	Odds Ratio	<i>b</i>	<i>SE</i>	Odds Ratio
No   Not Sure	3.174***	0.804	23.89	2.783***	0.985	16.17
Not Sure   Yes	4.857***	0.834	128.70	4.494***	1.008	89.51
Trust Manipulation	1.960***	0.245	7.10	1.957***	0.256	7.08
Emotional Intelligence	0.350**	0.153	1.42	0.273*	0.163	1.31
PIIT	0.090	0.094	1.09	0.006	0.107	1.01
Agreeableness	0.437**	0.202	1.55	0.487**	0.219	1.63
Robo Experience				0.473	0.329	1.60
Financial Literacy				0.100	0.158	1.11
Gender				0.007	0.263	1.01
Age				-0.008	0.010	0.99
Occupation				0.122	0.298	1.13
University Degree				-0.102	0.297	0.09
Germany				0.046	0.323	1.05
South Africa				0.768*	0.431	2.16
USA				-0.040	0.403	0.96
UK				0.517	0.402	1.68
Observations	324			324		
R <sup>2</sup> Nagelkerke	.302			.323		
Residual Deviance	551.940			543.667		
AIC	563.940			575.667		

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ 

To test the influence of EI, PIIT, and agreeableness on advice-taking behavior, the same ordinal logistic regressions were applied (Table 2, Model 3 and 4).

When EI, PIIT, agreeableness, and the framing condition were jointly entered into the model (Model 3), EI showed a statistically significant positive effect on advice acceptance ( $\beta = 0.350$ ,  $SE = 0.153$ ,  $p < .05$ ), indicating initial support for H3. However, once the covariates were added in Model 4, the effect remained positive but only reached marginal significance ( $\beta = 0.273$ ,  $SE = 0.163$ ,  $p < .10$ ). This suggests a consistent trend, although the effect becomes weaker. Therefore, I interpret H3 as partially supported.

As a brief follow-up analysis, I tested whether the four subdimensions of EI differentially predict AI-advice acceptance (Model 5 and 6, appendix H1). The results revealed that none of

the subdimensions individually reached statistical significance, suggesting that the predictive value of EI in this context may lie in its overall composite rather than in its distinct facets.

PIIT did not emerge as a statistically significant predictor in either AI-advice acceptance model. In Model 3, the coefficient was not statistically significant ( $\beta = 0.090$ ,  $SE = 0.094$ ,  $p = .338$ ), and this remained unchanged in Model 4 ( $\beta = 0.006$ ,  $SE = 0.107$ ,  $p = .955$ ). These results suggest that, despite PIIT showing a significant correlation with AI-advice acceptance in the bivariate table, it loses its independent predictive power when adding other variables, contrary to expectations from prior literature. Thus, H4 is not supported.

Agreeableness showed a consistent and statistically significant positive effect on AI-advice acceptance. In Model 3, it was a significant predictor ( $\beta = 0.437$ ,  $SE = 0.202$ ,  $p < .05$ ), and this relationship remained significant in the full model (Model 4:  $\beta = 0.487$ ,  $SE = 0.219$ ,  $p < .05$ ). This suggests that agreeableness is a strong and independent predictor of accepting AI financial advice. H2 is consistently and robustly supported across all models.

#### 4.5 Exploratory analyses

Although H2, H3, and H4 focused exclusively on AI-advice acceptance, a follow-up analysis was conducted using linear regressions with trust as the dependent variable (Model 1 and 2, Table 1).

This revealed that EI had a consistently positive and statistically significant relationship with trust across both models (Model 1:  $\beta = 0.210$ ,  $SE = 0.064$ ,  $p < .01$ ), and it remains significant after all covariates were added ( $\beta = 0.198$ ,  $SE = 0.067$ ,  $p < .01$ ). However, in these exploratory analyses, PIIT emerged as a statistically significant predictor of trust ( $\beta = 0.103$ ,  $SE = 0.039$ ,  $p < .01$ ) but lost significance in the full model ( $\beta = 0.065$ ,  $SE = 0.043$ ,  $p = .129$ ). Agreeableness, in turn, once again demonstrated a robust effect across all trust models. It had a significant effect when including only the main predictors ( $\beta = 0.197$ ,  $SE = 0.084$ ,  $p < .05$ ), and this significance remained consistent in the full model ( $\beta = 0.189$ ,  $SE = 0.090$ ,  $p < .05$ ).

As a final exploratory step regarding EI, I again decomposed EI into its four subdimensions to examine their individual relationships with trust (Model 7 and 8, appendix H2). The results indicate that none of the EI-subdimensions has a significant effect on trust in AI-advice, similar as for AI-advice acceptance.

## 5 Discussion

### 5.1 Research Findings

This thesis investigated how framing (experimental manipulation) and individual differences in EI, PIIT, and agreeableness (correlational variables) influence trust and acceptance of AI-generated financial advice.

H1 posited that a positively framed robo-advisor information text would increase trust and AI-advice acceptance which was robustly supported. Across two linear and two ordinal regression models, participants exposed to the positively framed condition reported significantly higher trust and a greater likelihood of accepting the AI-generated advice. These findings align with prior research on framing effects (e.g., Glare et al., 2018; Jang & Feng, 2018; Kim & Song, 2020; Kim & Song, 2023; Kühberger, 1998), confirming framing as a low-cost but effective mechanism to enhance receptivity to algorithmic advice.

H2 posited that agreeableness would positively predict AI-advice acceptance, which was robustly supported for AI-advice acceptance and trust. This is in line with existing literature highlighting agreeableness as a trait associated with trust and cooperativeness (Alarcon et al., 2018; Graziano & Eisenberg, 1997). It confirms findings in prior research that found a significant positive relationship between agreeableness and trust in AI systems (e.g. Babiker et al., 2024; Park & Woo, 2022; Stein et al., 2024) for the financial robo-advisor context.

H3 proposed a positive relationship between EI and AI-advice acceptance, which received partial support. The effect was significant in the bivariate correlation analysis and when EI was entered alongside PIIT, agreeableness, and the framing condition, but changed to marginally significant once control and demographic variables were added, indicating limited robustness. This finding contributes to a growing body of literature arguing that emotional and psychological traits matter in technology acceptance (e.g., Abu Shanab & Abu Shanab, 2022; Binsaeed et al., 2023; Montag et al., 2025; Oksanen et al., 2020) and are in line with prior findings that emphasize the role of EI in navigating novel or ambiguous environments (Mayer et al., 1990).

H4 suggested that PIIT would positively predict acceptance of AI-generated advice. Contrary to expectations from the literature (e.g., Agarwal & Prasad, 1998; Thatcher et al., 2003), PIIT did not emerge as a significant predictor in any AI-advice acceptance regression model. It showed positive effects at the bivariate level, but its effect did not remain unique when EI and agreeableness were included in the regression models. However, PIIT was a significant predictor in a separate model explaining trust in the AI-generated advice. Its role may operate

indirectly by shaping foundational trust rather than directly affecting immediate behavioral acceptance.

Taken together, these findings provide empirical support for the role of framing and agreeableness in shaping receptiveness to AI-advice. The results on EI offer partial support for its relevance, particularly for fostering trust, while the lack of a unique effect for PIIT suggests that its role may be intertwined with other individual traits such as EI and agreeableness.

## 5.2 Theoretical and Managerial Implications

This research advances theoretical perspectives in several ways. First, the findings showed the significant influence of framing on user trust and AI-advice acceptance. The observed effect aligns with prior work on framing theory and reinforces the view that framing can serve as a psychologically grounded mechanism to shape trust in AI systems (Kim & Song, 2023; Tversky & Kahneman, 1981).

Second, the thesis refines existing insights into EI by demonstrating that the composite EI score partially predicted AI-advice acceptance. The non-significance of individual EI subdimensions further underscores that EI may exert its influence in this area only when considered holistically. The findings nuance prior work that treats EI as a predictor of trust-related behaviors (Christie et al., 2015).

Third, the findings challenge widely accepted assumptions about PIIT. Contrary to the literature that positions PIIT as a core driver of early-stage technology adoption (Agarwal & Prasad, 1998; Thatcher et al., 2003), PIIT showed a weak positive effect in the bivariate analysis but did not significantly predict AI-advice acceptance. This indicates that following AI-advice differs from adopting technologies. Interestingly, PIIT did predict trust in the baseline model, suggesting that while innovation tendency may not directly lead to advice-taking, it still fosters openness to AI-generated input.

Fourth, the consistent predictive power of agreeableness offers further refinement to current personality-based models of AI-advice acceptance. Agreeableness emerged as a stable and significant predictor across models, confirming the findings on general AI-advice acceptance for the finance specific area and supports the idea that trust-prone dispositions play a crucial role in user behavior toward AI systems.

Finally, the results highlight trust as a central mechanism in AI-advice-taking (Hildebrand & Bergner, 2021; Kelly et al., 2023; Komiak & Benbasat, 2006). The observed discrepancy between trust and AI-advice acceptance further implies that both are related but not isomorphic, underscoring the need to integrate trust into models of AI-advice acceptance.

In terms of managerial implications, this thesis offers actionable insights for AI-based decision-support systems, particularly in the financial services sector.

First, the demonstrated effectiveness of framing shows that minor modifications to system communication can significantly boost user trust and acceptance.

Second, user segmentation based on psychological variables could enhance personalization and finally AI-advice acceptance, which enhances product usage (Komiak & Benbasat, 2006). Systems might offer varied levels of support based on personality traits, improving both acceptance and satisfaction (McElroy et al., 2007).

Third, the non-significant role of PIIT implies that targeting only tech-savvy early adopters may not be sufficient for AI-advice solutions. Instead, strategies should also account for users who are open to guidance when trust is effectively established. Communication and onboarding strategies should therefore focus on individuality, credibility, and reliability rather than novelty (Komiak & Benbasat, 2006; Thielsch et al., 2018).

Together, these implications suggest that user acceptance of AI-advice systems can be meaningfully improved by shifting focus from purely technical attributes to psychological, emotional, and contextual variables that influence user trust and decision-making behavior.

### 5.3 Limitations and Future Research

The present thesis offers valuable insights into the factors influencing trust and acceptance of AI-generated financial advice. However, several limitations must be acknowledged which simultaneously open options for future research.

First, the sample was skewed towards younger, well-educated individuals with high financial literacy. While this aligns with typical early adopters of digital financial tools, it limits the generalizability of the findings. Future research should aim for more demographically diverse samples as this might have a significant impact (e.g. Lee et al., 2017).

Second, although the sample included participants from diverse cultural backgrounds, bivariate analyses did not reveal significant differences between cultural groups. Future studies should either replicate the design in specific cultural contexts or apply sampling strategies to examine cultural effects more systematically (e.g. Babiker et al., 2024; Sindermann et al., 2022).

Third, although participants were evenly assigned to both conditions via randomization, a higher proportion of participants in the low-trust framing group failed the attention or manipulation checks which led to a slightly uneven distribution.

Fourth, the thesis relied on self-reported data, which can be prone to social desirability bias (Blome & Augustin, 2015). While anonymity was assured, participants may have answered in ways they perceived as socially acceptable rather than fully reflecting their genuine attitudes. Fifth, the study relied on established measurement instruments, which nonetheless present opportunities for refinement in future research. For example, while a reputable short-form big five scale was used for agreeableness, a longer instrument could capture facets in more detail. Likewise, although the WLEIS is well-respected in measuring EI, its alignment with either the trait-based or ability-based EI model remains unclear. Future research could apply surveys such as the MSCEIT (Mayer et al., 2002) or EQ-I (Bar-On, 1997) which offer greater granularity and are a more objective measurement tool. The trust scale, a core component of this study, was strongly modified and partially self-developed to reflect the specific context of AI-driven financial advice. Future research should consider using a more validated trust scale to enhance comparability.

Moreover, the experimental setting remained artificial. Although the advice scenario was based on realistic questions, the AI recommendation itself, to invest in the *Global AllStars Prime* was generic and did not reflect individual preferences or risk profiles. This reduces the validity of the AI-advice acceptance measure. Future research should aim to personalize AI recommendations more closely, potentially through collaborations with actual robo-advisors that can generate tailored advice based on user input.

Additionally, the framing manipulation included only two conditions, positive and negative framing. Including a neutral or no-information control group would provide a clearer baseline to assess the relative effectiveness of positive versus negative framing as Kim & Song, 2023 found a significant impact. Moreover, the negative framing was slightly asymmetric, as it not only emphasized AI drawbacks but also highlighted the strengths of human advisors. This design reflects a more naturalistic form of framing often encountered in real-world contexts, and it differs from the approach of Prinz et al. (2025), who focused solely on AI-related characteristics.

From a theoretical standpoint, the current models explained only a moderate share of variance, suggesting that relevant variables might have been omitted. Future studies could manipulate other AI characteristics such as perceived expertise (Lourenço et al., 2020; Mesbah et al., 2021), transparency (Bonaccio & Dalal, 2006; Lehmann et al. (2022)), or past performance and status (Önköl et al., 2017) to assess how these factors influence user trust and advice acceptance.

Additionally, future research could explore interaction effects more explicitly, for instance by testing whether trust mediates the relationship between framing and AI-advice acceptance, and

whether individual traits such as EI or PIIT moderate these pathways (e.g. Zhou et al., 2025). Moreover, future research should aim to disentangle the interplay between PIIT, EI, and agreeableness, as their effects may currently overlap.

Short-term longitudinal research designs could also reveal how trust in AI systems evolves over time through repeated interactions. This would help assess whether initial framing effects persist or diminish.

Finally, while the current thesis focused on financial services, the observed dynamics may vary in different sectors, such as healthcare or education. Comparative research across such sectors would enrich the understanding of domain-specific patterns in human–AI interaction.

## **6 Conclusion**

This thesis investigated the psychological and contextual factors that influence the acceptance of AI-generated financial advice, focusing specifically on the roles of trust framing, EI, PIIT, and agreeableness. Using an experimental design, the study explored how users engage with algorithmic recommendations in a simulated robo-advisory setting.

The results revealed the importance of contextual framing in shaping user attitudes toward algorithmic systems. At the trait level, the findings demonstrated that agreeableness emerged as a consistent and robust predictor of AI-advice acceptance. While EI showed a positive but less stable effect, PIIT did not exhibit a direct effect on AI-advice acceptance.

By integrating behavioral science into the study of AI-advice acceptance, this research contributes to a more nuanced understanding of how users evaluate and accept AI-generated financial advice. The findings underscore the importance of both psychological predispositions and contextual cues and suggest that user acceptance cannot be solely attributed to technological performance but rather emerges from a complex interplay of traits, perceptions, and framing effects.

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## Appendix

### Appendix A: Pre Study Questionnaire

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#### Start of Block: Introduction

Dear Participant,

This study is part of my Master's Thesis at Católica Lisbon School of Business and Economics. I am investigating the determinants of **trust and acceptance of AI-driven financial advisors** (also called robo-advisors).

The survey will take approximately **5-6 minutes** to complete. Your participation is completely voluntary and can be discontinued at any time without consequences. All responses are anonymous and confidential, and the data collected will only be used in an aggregated form for academic research purposes.

If you have any questions or comments about this study, please feel free to contact me at [sbsprenger@ucp.pt](mailto:sbsprenger@ucp.pt).

Thank you for your time and support!

#### End of Block: Introduction

---

#### Start of Block: Manipulation High

Display if Manipulation = High

You are presented with an informational text about AI-based financial advisors. Please read the information carefully.



##### AI in Financial Advisory: More Accurate Than Ever

Some recent studies confirm that **AI-driven financial advisors outperform human advisors** in efficiency and risk assessment. In several analyses, robo-advisors have achieved a **higher accuracy** rate in stock predictions and achieved **higher risk-adjusted returns**.

##### Why AI advisors could be superior

- AI algorithms analyze **millions of market data points in real time**, potentially detecting profitable investment patterns earlier than human advisors.
- Leading investment firms are increasingly **experimenting with AI-powered models**.
- AI may **reduce emotional biases** and bases recommendations more strictly on data.

##### Investor Trust in Robo-Advisors is at an All-Time High

Many investors consider AI-driven advisors to be a **reliable, objective and data-backed** option for their investment strategies. Some surveys show that a substantial proportion of users rate them as **trustworthy** and would consider following their advice again.

#### End of Block: Manipulation High

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## Start of Block: Manipulation Low

Display if Manipulation = Low

You are presented with an informational text about AI-based financial advisors. Please read the information carefully.



### AI in Financial Advisory: Still a Risky Bet for Many Investors

Some recent studies confirm that **human advisors outperform AI-driven financial advisors** in reliability and risk assessment. In several analyses, human advisors have achieved a **higher accuracy** rate in stock predictions and achieved higher **risk-adjusted returns**.

#### ⚠️ Why human advisors could be superior

- AI algorithms have been found to sometimes **misinterpret financial data and investment patterns**, leading to investment losses.
- Leading investment firms continue to rely primarily on **experienced human advisors**.
- Human advisors are often seen as more capable of **handling complex client needs**.

#### ● Investor Concerns Around Robo-Advisors Remain

Many investors remain cautious about fully trusting AI-based advice as investment recommendations are **less reliable** and **not personalized**. Some surveys show that a substantial proportion of users rate them as **less trustworthy** and wouldn't consider following their advice again.

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## End of Block: Manipulation Low

### Positive Framing Condition (Sources): Not displayed in the survey

AI in Financial Advisory: More Accurate Than Ever: Some recent studies confirm that AI-driven financial advisors outperform human advisors in efficiency and risk assessment.<sup>1</sup> In several analyses, robo-advisors have achieved a higher accuracy rate in stock predictions and achieved higher risk-adjusted returns.<sup>2</sup>

Why AI advisors could be superior: AI algorithms analyze millions of market data points in real time, potentially detecting profitable investment patterns earlier than human advisors.<sup>3</sup>

Leading investment firms are increasingly experimenting with AI-powered models.<sup>4</sup>

AI may reduce emotional biases and bases recommendations more strictly on data.<sup>5</sup>

Investor Trust in Robo-Advisors is at an All-Time High: Many investors consider AI-driven advisors to be a reliable, objective and data-backed option for their investment strategies. Some surveys show that a substantial proportion of users rate them as trustworthy and would consider following their advice again.<sup>6</sup>

<sup>1</sup> Liu, C., Yang, M., & Wen, M. (2023). Judge me on my losers: Do robo-advisors outperform human investors during the COVID-19 financial market crash? *Production and Operations Management*, 32(10), 3174–3192. <https://doi.org/10.1111/poms.14029>

<sup>2</sup> Tao, R., Su, C.-W., Xiao, Y., Dai, K., & Khalid, F. (2021). Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets. *Technological Forecasting and Social Change*, 163, 120421. <https://doi.org/10.1016/j.techfore.2020.120421>

<sup>3</sup> Chowdhury, E. K. (2019). Use of Artificial Intelligence in Stock Trading. *Portfolio*, 1(22), 17–28. <https://mpira.ub.uni-muenchen.de/id/eprint/118175>

<sup>4</sup> World Economic Forum. (2025, March 17). *AI, wealth management and trust: Could machines replace human advisors?* <https://www.weforum.org/stories/2025/03/ai-wealth-management-and-trust-could-machines-replace-human-advisors/>

<sup>5</sup> Athota, V. S., Pereira, V., Hasan, Z., Vaz, D., Laker, B., & Reppas, D. (2023). Overcoming financial planners' cognitive biases through digitalization: A qualitative study. *Journal of Business Research*, 154, 113291. <https://doi.org/10.1016/j.jbusres.2022.08.055>

<sup>6</sup> Gillespie, N., Lockey, S., Curtis, C., Pool, J., & Ali Akbari. (2023). *Trust in Artificial Intelligence: A global study*. <https://doi.org/10.14264/00d3c94>

### **Negative Framing Condition (Sources):**

AI in Financial Advisory: Still a Risky Bet for Many Investors: Some recent studies confirm that human advisors outperform AI-driven financial advisors in reliability and risk assessment.<sup>1</sup>

In several analyses, human advisors have achieved a higher accuracy rate in stock predictions and achieved higher risk-adjusted returns.<sup>2</sup>

Why human advisors could be superior: AI algorithms have been found to sometimes misinterpret financial data and investment patterns, leading to investment losses.<sup>3</sup>

Leading investment firms continue to rely primarily on experienced human advisors.<sup>4</sup>

Human advisors are often seen as more capable of handling complex client needs.<sup>5</sup>

Investor Concerns Around Robo-Advisors Remain: Many investors remain cautious about fully trusting AI-based advice as investment recommendations are less reliable and not personalized.

Some surveys show that a substantial proportion of users rate them as less trustworthy and wouldn't consider following their advice again.<sup>6</sup>

<sup>1</sup> Harrison, J. P., & Samaddar, S. (2020). Who Is Better at Investment Decisions: *Man or Machine?* *The Journal of Wealth Management*, 23(3), 70–84. <https://doi.org/10.3905/jwm.2020.1.119>

<sup>2</sup> Puhle, M. (2019). The Performance and Asset Allocation of German Robo-Advisors. *Society and Economy*, 41(3), 331–351. <https://doi.org/10.1556/204.2019.41.3.4>

<sup>3</sup> Lin, T. C. (2019). Artificial Intelligence, Finance, and the Law. *Fordham Law Review*, 88(2), 531. <https://ir.lawnet.fordham.edu/flr/vol88/iss2/6>

<sup>4</sup> Condor Capital Wealth Management. (2024). *The Future of Robo Advisors*. <https://www.condorcapital.com/the-robo-report/reports/the-future-of-robo-advisors-q4-2024/>

<sup>5</sup> Gillespie, N., Lockey, S., Curtis, C., Pool, J., & Ali Akbari. (2023). *Trust in Artificial Intelligence: A global study*. <https://doi.org/10.14264/00d3c94>

<sup>6</sup> Gillespie, N., Lockey, S., Curtis, C., Pool, J., & Ali Akbari. (2023). *Trust in Artificial Intelligence: A global study*. <https://doi.org/10.14264/00d3c94>

**Start of Block: Manipulation Check**

What was the main message of the text you just read about Robo-Advisors?

- The text emphasized the **advantages** of Robo-Advisors
- The text emphasized the **disadvantages** of Robo-Advisors

**End of Block: Manipulation Check**

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**Start of Block: Credibility & Prior Beliefs**

Please indicate your agreement with the following statements on a 7-point scale (1 = Strongly Disagree, 7 = Strongly Agree)

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
The information in the text is <b>accurate</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The information in the text is <b>trustworthy</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The information in the text is <b>believable</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The information in the text <b>influenced my view</b> of robo-advisors	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The text made me <b>reconsider my previous opinion</b> about robo-advisors	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

**End of Block: Credibility & Prior Beliefs**

---

**Start of Block: Robo-advise**

Based on your answers, a robo-advisor will now provide you with an investment recommendation. Please indicate your agreement with the following statements on a 5-point scale (1 = Strongly Disagree, 5 = Strongly Agree)

	Strongly Disagree 1	2	3	4	Strongly Agree 5
I am <b>confident</b> to make personal investment decisions	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I do <b>not feel qualified</b> for making personal investment decisions	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

What is your primary financial objective when investing?

- Saving for retirement
- Wealth accumulation
- Generating passive income (dividends)
- Funding a significant life event (e.g. wedding)
- Speculative gains

What is your investment time horizon?

- Short-term (Less than 1 year)
- Medium-term (1 - 5 years)
- Long-term (above 5 years)

If your investment portfolio declines by 20%, how would you react?

- Sell everything
- Sell some
- Hold
- Buy more

Based on the provided information, the robo-advisor offers you the following investment recommendation:



Given current market trends and financial goals, I would recommend our portfolio „**Global AllStars Prime**“.

This portfolio is designed to **maximize returns while minimizing unnecessary risks**. It offers a broad **diversification across multiple well-established and financially secure companies**. I advise maintaining a **long-term perspective** and staying committed to your strategy, as short-term market fluctuations are a natural part of investing.

Would you follow the investment advice provided by the AI-based financial advisor?

- Yes
- No
- Not Sure

**End of Block: Robo-advise**

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**Start of Block: Trust in Robo-Advisors**

Please indicate your agreement with the following statements on a 5-point scale (1 = Strongly Disagree, 5 = Strongly Agree)

	Strongly Disagree 1	2	3	4	Strongly Agree 5
I believe the AI financial advisor provides <b>reliable investment recommendations</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The AI financial advisor is very <b>reliable</b> . I can count on it to be <b>correct</b> all the time	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The AI financial advisor demonstrates a <b>high level of expertise</b> in providing financial advice	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel <b>safe</b> that when I <b>rely</b> on the AI financial advisor, I will get the <b>right answers</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel <b>confident in following the advice</b> given by the AI financial advisor	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am <b>wary</b> of AI financial advisors	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I <b>trust the AI</b> financial advisor as much as I would trust a <b>human financial advisor</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like using the AI financial advisor for <b>decision-making</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Please select “ <b>Strongly Disagree</b> ” to show you are paying attention to this question	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

**End of Block: Trust in Robo-Advisors**

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## Appendix B: Pre Study Results

**Table B1:** Attention and Manipulation Checks

Condition	Attention Check		Manipulation Check	
	Frequency ( <i>N</i> )	Percentage (%)	Frequency ( <i>N</i> )	Percentage (%)
Passed	39	92.9	37	88.1
Failed	3	7.1	5	11.9
Total	42	100	42	100

**Table B2:** Manipulation Exposure

Trust_Framing	Frequency ( <i>N</i> )	Percentage (%)
High	19	54.3
Low	16	45.7
Total	35	100

**Table B3:** AI-Advice Acceptance

Manipulation	High		Low	
	Frequency ( <i>N</i> )	Percentage (%)	Frequency ( <i>N</i> )	Percentage (%)
Adv_Acceptance				
Yes	7	36.8	6	37.5
No	5	26.3	4	25.0
Not Sure	7	36.8	6	37.5
Total	19	100	16	100

**Table B4:** Credibility scale (continuous variable)

Trust	Frequency ( <i>N</i> )	Mean	Std. Deviation	Likert Scale
Credibility_1	35	4.37	1.40	7
Credibility_2	35	4.43	1.44	7
Credibility_3	35	4.43	1.22	7
Credibility_4	35	4.29	1.23	7
Credibility	35	4.38	1.19	7

**Table B5:** Prior Beliefs (continuous variable)

Trust	Frequency ( <i>N</i> )	Mean	Std. Deviation	Likert Scale
Prior Beliefs_1	35	3.31	1.25	7
Prior Beliefs_2	35	3.11	1.43	7
Prior Beliefs	35	3.21	1.27	7

**Table B6:** Trust scale (continuous variable)

Trust	Frequency ( <i>N</i> )	Mean	Std. Deviation	Likert Scale
Trust_1	35	3.09	0.85	5
Trust_2	35	2.51	0.92	5
Trust_3	35	2.83	0.92	5
Trust_4	35	2.77	1.09	5
Trust_5	35	2.89	0.96	5
Trust_6	35	3.14	0.94	5
Trust_7	35	2.86	1.03	5
Trust_8	35	3.31	1.08	5
Trust	35	2.93	0.59	5

**Table B7:** Internal Consistency of Scales (Cronbach's  $\alpha$ )

Variable	Cronbach's $\alpha$	Number of Items
Trust	.76	8
Credibility	.88	3
Prior Beliefs	.92	2

## Appendix C: Scale amendments

**Table C1:** Credibility scale amendments

Item Number	Original Scale	Selected and adapted items
1	The information in the text is accurate.	The information in the text is accurate.
2	The information in the text is authentic.	The information in the text is trustworthy.
3	The information in the text is believable.	The information in the text is believable.

**Table C2:** Trust scale amendments

Item Number	Original Scale	Selected and adapted items
1		I believe the AI financial advisor provides reliable investment recommendations.
2	The tool is very reliable. I can count on it to be correct all the time.	The AI financial advisor is very reliable. I can count on it to be correct all the time.
3		The AI financial advisor demonstrates a high level of expertise in providing financial advice.
4	I feel safe that when I rely on the [tool], I will get the right answers.	I feel safe that when I rely on the AI financial advisor, I will get the right answers.
5	I am confident in the [tool]. I feel that it works well.	I feel confident in following the advice given by the AI financial advisor.
6	I am wary of the [tool]. (reverse-coded)	I am wary (skeptical) of AI financial advisors.
7	The [tool] can perform the task better than a novice human user.	I trust the AI financial advisor as much as I would trust a human financial advisor
8	I like using the system for decision-making.	I like using the AI financial advisor for decision-making
X	The outputs of the [tool] are very predictable.	Not selected
X	The [tool] is efficient in that it works very quickly.	Not selected

## Appendix D: Main Study Questionnaire

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### Start of Block: Introduction

Dear Participant,

This study is part of my Master's Thesis at Católica Lisbon School of Business and Economics. I am investigating the determinants of **trust and acceptance of AI-driven financial advisors** (also called robo-advisors).

The survey will take approximately **8-10 minutes** to complete. Your participation is completely voluntary and can be discontinued at any time without consequences. All responses are anonymous and confidential, and the data collected will only be used in an aggregated form for academic research purposes.

If you have any questions or comments about this study, please feel free to contact me at [sbsprenger@ucp.pt](mailto:sbsprenger@ucp.pt).

Thank you for your time and support!

### End of Block: Introduction

---

### Start of Block: Manipulation High

Display if Manipulation = High

You are presented with an informational text about AI-based financial advisors. Please read the information carefully.



#### ▶ AI in Financial Advisory: More Accurate Than Ever

Some recent studies confirm that **AI-driven financial advisors outperform human advisors** in efficiency and risk assessment. In several analyses, robo-advisors have achieved a **higher accuracy** rate in stock predictions and achieved **higher risk-adjusted returns**.

#### ✔ Why AI advisors could be superior

- AI algorithms analyze **millions of market data points in real time**, potentially detecting profitable investment patterns earlier than human advisors.
- Leading investment firms are increasingly **experimenting with AI-powered models**.
- AI may **reduce emotional biases** and bases recommendations more strictly on data.

#### 📊 Investor Trust in Robo-Advisors is at an All-Time High

Many investors consider AI-driven advisors to be a **reliable, objective and data-backed** option for their investment strategies. Some surveys show that a substantial proportion of users rate them as **trustworthy** and would consider following their advice again.

### End of Block: Manipulation High

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## Start of Block: Manipulation Low

Display if Manipulation = Low

You are presented with an informational text about AI-based financial advisors. Please read the information carefully.



### AI in Financial Advisory: Still a Risky Bet for Many Investors

Some recent studies confirm that **human advisors outperform AI-driven financial advisors** in reliability and risk assessment. In several analyses, human advisors have achieved a **higher accuracy** rate in stock predictions and achieved higher **risk-adjusted returns**.

#### ⚠️ Why human advisors could be superior

- AI algorithms have been found to sometimes **misinterpret financial data and investment patterns**, leading to investment losses.
- Leading investment firms continue to rely primarily on **experienced human advisors**.
- Human advisors are often seen as more capable of **handling complex client needs**.

#### ● Investor Concerns Around Robo-Advisors Remain

Many investors remain cautious about fully trusting AI-based advice as investment recommendations are **less reliable** and **not personalized**. Some surveys show that a substantial proportion of users rate them as **less trustworthy** and wouldn't consider following their advice again.

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## End of Block: Manipulation Low

### Start of Block: Robo-advise

What was the main message of the text you just read about Robo-Advisors?

- The text emphasized the **advantages** of Robo-Advisors
- The text emphasized the **disadvantages** of Robo-Advisors

Based on your answers, a robo-advisor will now provide you with an investment recommendation. Please indicate your agreement with the following statements on a 5-point scale (1 = Strongly Disagree, 5 = Strongly Agree)

	Strongly Disagree 1	2	3	4	Strongly Agree 5
I am <b>confident</b> to make personal investment decisions	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

What is your primary financial objective when investing?

- Saving for retirement
- Wealth accumulation
- Generating passive income (dividends)
- Funding a significant life event (e.g. wedding)
- Speculative gains

What is your investment time horizon?

- Short-term (Less than 1 year)
- Medium-term (1 - 5 years)
- Long-term (above 5 years)

If your investment portfolio declines by 20%, how would you react?

- Sell everything
- Sell some
- Hold
- Buy more

Based on the provided information, the robo-advisor offers you the following investment recommendation:



Given current market trends and financial goals, I would recommend our portfolio „**Global AllStars Prime**“.

This portfolio is designed to **maximize returns while minimizing unnecessary risks**. It offers a broad **diversification across multiple well-established and financially secure companies**. I advise maintaining a **long-term perspective** and staying committed to your strategy, as short-term market fluctuations are a natural part of investing.

Would you follow the investment advice provided by the AI-based financial advisor?

- Yes
- No
- Not Sure

End of Block: Robo-advise

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**Start of Block: Trust in Robo-Advisors**

Please indicate your agreement with the following statements on a 5-point scale (1 = Strongly Disagree, 5 = Strongly Agree)

	Strongly Disagree 1	2	3	4	Strongly Agree 5
I believe the AI financial advisor provides <b>reliable investment recommendations</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The AI financial advisor is very <b>reliable</b> . I can count on it to be <b>correct</b> all the time	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The AI financial advisor demonstrates a <b>high level of expertise</b> in providing financial advice	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel <b>safe</b> that when I <b>rely</b> on the AI financial advisor, I will get the <b>right answers</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel <b>confident in following the advice</b> given by the AI financial advisor	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am <b>wary</b> (skeptical) of AI financial advisors	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I <b>trust the AI</b> financial advisor as much as I would trust a <b>human financial advisor</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like using the AI financial advisor for <b>decision-making</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Please select “ <b>Strongly Disagree</b> ” to show you are paying attention to this question	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Have you ever used an AI-driven financial advisor (robo-advisor)?

- Yes
- No

**End of Block: Trust in Robo-Advisors**

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**Start of Block: Financial Literacy**

The following questions assess your financial knowledge. Please answer them to the best of your ability.

Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

- More than \$102
- Exactly \$100
- Less than \$102
- Do not know

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

- More than today
- Exactly the same
- Less than today
- Do not know

Please tell me whether this statement is true or false. “Buying a single company’s stock usually provides a safer return than a stock mutual fund (diversified investment fund).”

- True
- False
- Do not know

**End of Block: Financial Literacy**

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**Start of Block: Emotional Intelligence**

In this section, I am interested in learning more about yourself. Please answer as honestly as possible and notice that there are no right or wrong answers. Please indicate your agreement with the following statements on a 7-point scale (1 = Strongly Disagree, 7 = Strongly Agree)

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
I have a good sense of why I have certain <b>feelings</b> most of the time	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I have good understanding of my <b>own emotions</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I really understand what I <b>feel</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I always know whether or not I am <b>happy</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate your agreement with the following statements on a 7-point scale (1 = Strongly Disagree, 7 = Strongly Agree)

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
I always know <b>my friends' emotions</b> from their behavior	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am a <b>good observer</b> of others' emotions	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am <b>sensitive to the feelings</b> and emotions of others	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I have good <b>understanding of the emotions</b> of people around me	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate your agreement with the following statements on a 7-point scale (1 = Strongly Disagree, 7 = Strongly Agree)

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
I always <b>set goals</b> for myself and then try my <b>best to achieve them</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I always tell myself I am a <b>competent person</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am a <b>self-motivated</b> person	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would always <b>encourage</b> myself to <b>try my best</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate your agreement with the following statements on a 7-point scale (1 = Strongly Disagree, 7 = Strongly Agree)

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
I am able to <b>control my temper</b> and handle difficulties <b>rationally</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am quite capable of <b>controlling my own emotions</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I can always <b>calm down quickly</b> when I am very angry	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I have good <b>control of my own emotions</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

End of Block: Emotional Intelligence

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**Start of Block: Personal Innovativeness in the Domain of Information Technology**

Please indicate your agreement with the following statements on a 7-point scale (1 = Strongly Disagree, 7 = Strongly Agree)

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
If I heard about a <b>new information technology</b> , I would <b>look for ways to experiment</b> with it	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Among my peers, I am usually the <b>first to try out new information technologies</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In general, I am <b>hesitant to try out new information technologies</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like to <b>experiment</b> with new information technologies	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

**End of Block: Personal Innovativeness in the Domain of Information Technology**

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**Start of Block: Agreeableness**

Please indicate your agreement with the following statements on a 5-point scale (1 = Strongly Disagree, 5 = Strongly Agree) I am someone who...

	Strongly Disagree 1	2	3	4	Strongly Agree 5
is <b>compassionate</b> , has a soft heart	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
is sometimes <b>rude</b> to others	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
assumes the <b>best about people</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
can be <b>cold</b> and <b>uncaring</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
is <b>respectful</b> , treats others with respect	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
tends to find <b>fault with others</b> (criticize others)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

**End of Block: Agreeableness**

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### Start of Block: Demographics

What is your gender?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

How old are you?

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Which of the following options best describes your current occupation?

- Student
- Employed or Self-employed
- Unemployed
- Retired

What is the highest level of education you have completed?

- Less than high school
- High school graduate
- Bachelor Degree
- Master Degree
- Doctoral Degree
- Others

Which country are you from?

▼ Austria ... Zimbabwe

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### End of Block: Demographics

## Appendix E: Data Preparation

**Table E1:** Recoding scheme of binary variables for Analysis

Variable	Coded as 1	Coded as 0
Trust_Framing	High	Low
Robo_Experience	Yes	No
Demographics_1	Male	Female
Demographics_3	Employed or Self-employed	Student, Retired, Unemployed
Demographics_4	Bachelor Degree, Master Degree, Doctoral Degree	Less than high school, High School Graduate, Others

## Appendix F: Scale Reliability

**Table F1:** Internal Consistency of Scales (Cronbach's  $\alpha$ )

Variable	Cronbach's $\alpha$	Number of Items
Trust	.96	8
SEA	.92	4
OEA	.90	4
UOE	.91	4
ROE	.92	4
PIIT	.81	4
Agreeableness	.81	6

**Table F2:** Exploratory Factor Analysis for the Trust Scale

Item	Factor Loading	Communality ( $h^2$ )	Uniqueness ( $u^2$ )
Trust_1	.88	.77	.23
Trust_2	.87	.76	.24
Trust_3	.89	.80	.20
Trust_4	.92	.85	.15
Trust_5	.94	.88	.12
Trust_6	.78	.60	.40
Trust_7	.81	.66	.34
Trust_8	.79	.63	.37
Eigenvalue	5.94		
Variance Explained	.74		

**Table F3:** Exploratory Factor Analysis for the SEA Subscale

Item	Factor Loading	Communality ( $h^2$ )	Uniqueness ( $u^2$ )
SEA_1	.85	.73	.27
SEA_2	.92	.86	.14
SEA_3	.91	.82	.18
SEA_4	.78	.62	.38
Eigenvalue	3.02		
Variance Explained	.76		

**Table F4:** Exploratory Factor Analysis for the OEA Subscale

Item	Factor Loading	Communality ( $h^2$ )	Uniqueness ( $u^2$ )
OEA_1	.76	.58	.42
OEA_2	.88	.78	.22
OEA_3	.80	.64	.36
OEA_4	.92	.85	.15
Eigenvalue	2.86		
Variance Explained	.71		

**Table F5:** Exploratory Factor Analysis for the UOE Subscale

Item	Factor Loading	Communality ( $h^2$ )	Uniqueness ( $u^2$ )
UOE_1	.82	.67	.33
UOE_2	.79	.63	.37
UOE_3	.89	.79	.21
UOE_4	.91	.82	.18
Eigenvalue	2.91		
Variance Explained	.73		

**Table F6:** Exploratory Factor Analysis for the ROE Subscale

Item	Factor Loading	Communality ( $h^2$ )	Uniqueness ( $u^2$ )
ROE_1	.88	.78	.22
ROE_2	.91	.82	.18
ROE_3	.77	.59	.41
ROE_4	.92	.84	.16
Eigenvalue	3.03		
Variance Explained	.76		

**Table F7:** Exploratory Factor Analysis for the PIIT Scale

Item	Factor Loading	Communality ( $h^2$ )	Uniqueness ( $u^2$ )
PIIT_1	.88	.78	.22
PIIT_2	.86	.74	.26
PIIT_3	.31	.10	.90
PIIT_4	.91	.84	.16
Eigenvalue	2.45		
Variance Explained	.61		

**Table F8:** Exploratory Factor Analysis for the Agreeableness Scale

Item	Factor Loading	Communality ( $h^2$ )	Uniqueness ( $u^2$ )
Agreeableness_1	.72	.52	.48
Agreeableness_2	.61	.37	.63
Agreeableness_3	.62	.38	.62
Agreeableness_4	.66	.43	.57
Agreeableness_5	.67	.45	.55
Agreeableness_6	.64	.41	.59
Eigenvalue	2.57		
Variance Explained	.43		

## Appendix G: Descriptive Statistics Main Study

**Table G1:** Attention and Manipulation Checks

Condition	Attention Check		Manipulation Check	
	Frequency ( <i>N</i> )	Percentage (%)	Frequency ( <i>N</i> )	Percentage (%)
Passed	352	96.4	334	91.5
Failed	13	3.6	31	8.5
Total	365	100	365	100

**Table G2:** Manipulation Exposure

Trust_Framing	Frequency ( <i>N</i> )	Percentage (%)
High	168	51.9
Low	156	48.1
Total	324	100

**Table G3:** AI-Advice Acceptance

Manipulation	High		Low	
	Frequency ( <i>N</i> )	Percentage (%)	Frequency ( <i>N</i> )	Percentage (%)
Adv_Acceptance				
Yes	124	73.8	50	32.1
No	7	4.2	54	34.6
Not Sure	37	22.0	52	33.3
Total	168	100	156	100

**Table G4:** Distribution by prior robo-advisor experience

Robo-advisor experience	Frequency ( <i>N</i> )	Percentage (%)
Yes	76	23.5
No	248	76.5
Total	324	100

**Table G5:** Distribution by financial literacy score

Financial Literacy Score	Frequency ( <i>N</i> )	Percentage (%)
3 out of 3	213	65.7
2 out of 3	70	21.6
1 out of 3	31	9.6
0 out of 3	10	3.1
Total	324	100

Financial Literacy Score	Mean	Std. Deviation
Total	2.50	0.79

**Table G6:** Trust scale (continuous variable)

Trust	Frequency ( <i>N</i> )	Mean	Std. Deviation	Likert Scale
Trust_1	324	3.35	1.17	5
Trust_2	324	2.73	1.31	5
Trust_3	324	3.19	1.20	5
Trust_4	324	2.94	1.25	5
Trust_5	324	3.10	1.25	5
Trust_6	324	2.62	1.26	5
Trust_7	324	2.90	1.32	5
Trust_8	324	3.20	1.09	5
Trust	324	3.01	1.09	5

**Table G7:** Emotional Intelligence scale (continuous variable)

Emotional Intelligence	Frequency ( <i>N</i> )	Mean	Std. Deviation	Likert Scale
SEA_1	324	5.41	1.17	7
SEA_2	324	5.52	1.24	7
SEA_3	324	5.34	1.30	7
SEA_4	324	5.56	1.28	7
SEA	324	5.46	1.12	7
OEA_1	324	4.80	1.35	7
OEA_2	324	5.23	1.35	7
OEA_3	324	5.16	1.43	7
OEA_4	324	5.19	1.31	7
OEA	324	5.10	1.20	7
UOE_1	324	5.48	1.32	7
UOE_2	324	5.27	1.39	7
UOE_3	324	5.57	1.29	7
UOE_4	324	5.68	1.29	7
UOE	324	5.50	1.18	7
ROE_1	324	5.48	1.27	7
ROE_2	324	5.42	1.27	7
ROE_3	324	5.02	1.49	7
ROE_4	324	5.38	1.25	7
ROE	324	5.32	1.19	7
Emotional Intelligence	324	5.35	0.93	7

**Table G8:** PIIT (continuous variable)

PIIT	Frequency ( <i>N</i> )	Mean	Std. Deviation	Likert Scale
PIIT_1	324	4.98	1.49	7
PIIT_2	324	4.55	1.73	7
PIIT_3	324	4.77	1.77	7
PIIT_4	324	5.02	1.49	7
PIIT	324	4.83	1.29	7

**Table G9:** Agreeableness (continuous variable)

Agreeableness	Frequency ( <i>N</i> )	Mean	Std. Deviation	Likert Scale
Agreeableness_1	324	4.07	0.85	5
Agreeableness_2	324	3.83	1.04	5
Agreeableness_3	324	3.66	1.02	5
Agreeableness_4	324	3.77	1.09	5
Agreeableness_5	324	4.38	0.70	5
Agreeableness_6	324	3.67	1.05	5
Agreeableness	324	3.90	0.69	5

**Table G10:** Distribution by gender

Gender	Frequency ( <i>N</i> )	Percentage (%)
Male	184	56.8
Female	140	43.2
Total	324	100

**Table G11:** Distribution by age

Age	Mean	Median	Std. Deviation
Total	34.90	31	12.57

Age	Frequency ( <i>N</i> )	Percentage (%)
18	1	0.3
19	3	0.9
20	8	2.5
21	5	1.5
22	12	3.7
23	17	5.2
24	27	8.3
25	10	3.1
26	17	5.2
27	22	6.8
28	12	3.7
29	13	4.0
30	11	3.4
31	9	2.8
32	11	3.4
33	8	2.5
34	6	1.9
35	11	3.4
36	6	1.9
37	8	2.5
38	10	3.1
39	7	2.2
40	11	3.4
41	2	0.6
42	3	0.9
43	4	1.2
44	4	1.2
45	5	1.5
46	2	0.6
47	2	0.6
48	3	0.9
50	2	0.6
51	6	1.9
52	6	1.9
53	4	1.2
54	2	0.6
55	4	1.2
56	2	0.6
57	2	0.6

58	4	1.2
59	4	1.2
60	4	1.2
61	2	0.6
62	1	0.3
63	2	0.6
64	1	0.3
66	1	0.3
67	1	0.3
68	1	0.3
69	1	0.3
70	1	0.3
71	1	0.3
77	1	0.3
81	1	0.3
Total	324	100

**Table G12:** Distribution by occupation

Occupation	Frequency ( <i>N</i> )	Percentage (%)
Employed or self-employed	229	70.7
Retired	12	3.7
Student	62	19.1
Unemployed	21	6.5
Total	324	100

**Table G13:** Distribution by highest educational degree

Education	Frequency ( <i>N</i> )	Percentage (%)
Less than high school	2	0.6
High school graduate	74	22.8
Bachelor Degree	128	39.5
Master Degree	95	29.3
Doctoral Degree	19	5.9
Other	6	1.9
Total	324	100

**Table G14:** Distribution by nationality

Nationality	Frequency (N)	Percentage (%)
Germany	66	20.4
South Africa	53	16.4
United States of America	40	12.3
United Kingdom of Great Britain and Northern Ireland	36	11.1
Italy	12	3.7
Poland	10	3.1
Nigeria	10	3.1
Portugal	9	2.8
Canada	8	2.5
Ireland	6	1.9
Netherlands	6	1.9
Denmark	5	1.5
Chile	5	1.5
Spain	5	1.5
France	4	1.2
Kenya	3	0.9
Iceland	3	0.9
Sweden	3	0.9
Algeria	3	0.9
Switzerland	3	0.9
Norway	3	0.9
Austria	3	0.9
Greece	3	0.9
Mexico	3	0.9
Philippines	2	0.6
Uruguay	2	0.6
Morocco	2	0.6
Lithuania	2	0.6
Malta	1	0.3
China	1	0.3
Monaco	1	0.3
Estonia	1	0.3
Argentina	1	0.3
Finland	1	0.3
Belgium	1	0.3
Albania	1	0.3
Turkey	1	0.3
Russian Federation	1	0.3
Cyprus	1	0.3
Slovenia	1	0.3
Egypt	1	0.3
Luxembourg	1	0.3
Total	324	100

## Appendix H: Main Study follow-up ordinal and linear regression models

**Table H1:** Follow-up Analysis: Ordinal logistic regressions EI subdimension split

	AI Advice Acceptance (ordinal logistic regression)					
	(5)			(6)		
	<i>b</i>	<i>SE</i>	Odds Ratio	<i>b</i>	<i>SE</i>	Odds Ratio
No   Not Sure	3.170***	0.811	23.81	2.982***	1.014	19.73
Not Sure   Yes	4.864***	0.840	129.55	4.711***	1.038	111.14
Trust Manipulation	1.979***	0.247	7.24	1.971***	0.257	7.18
SEA	0.219	0.141	1.24	0.249*	0.151	1.28
OEA	0.143	0.131	1.15	0.145	0.136	1.16
UOE	0.007	0.120	1.01	-0.079	0.128	0.92
ROE	-0.012	0.122	0.99	-0.046	0.129	0.96
PIIT	0.115	0.096	1.12	0.021	0.107	1.02
Agreeableness	0.396*	0.207	1.49	0.464**	0.223	1.59
Robo Experience				0.543	0.333	1.72
Financial Literacy				0.151	0.161	1.16
Gender				0.089	0.270	1.09
Age				-0.010	0.010	0.99
Occupation				0.144	0.301	1.16
University Degree				-0.004	0.303	1.00
Germany				0.143	0.331	1.15
South Africa				0.815*	0.438	2.26
USA				-0.016	0.406	0.98
UK				0.536	0.406	1.71
Observations	324			324		
R <sup>2</sup> Nagelkerke	.308			.334		
Residual Deviance	549.608			539.694		
AIC	567.608			577.694		

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

**Table H2:** Follow-up Analysis: Linear Regression EI subdimension split

	Trust (linear regression)			
	(7)		(8)	
	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>
Trust Manipulation	1.126***	0.095	1.065***	0.098
SEA	0.037	0.061	0.034	0.063
OEA	0.069	0.055	0.076	0.056
UOE	0.095*	0.051	0.078	0.054
ROE	0.013	0.052	0.013	0.054
PIIT	0.100**	0.040	0.064	0.043
Agreeableness	0.195**	0.086	0.185**	0.091
Robo Experience			0.305**	0.124
Financial Literacy			-0.060	0.065
Gender			0.011	0.106
Age			0.005	0.004
Occupation			-0.010	0.121
University Degree			0.176	0.125
Germany			-0.116	0.137
South Africa			0.061	0.159
USA			-0.140	0.165
UK			0.078	0.168
Constant	0.034	0.323	0.146	0.409
Observations	324		324	
R <sup>2</sup>	0.403		0.431	
Adjusted R <sup>2</sup>	0.390		0.399	
Residual Std. Error	0.852		0.845	
<i>F</i> Statistic	30.479*** (df = 7; 316)		13.632*** (df = 17; 306)	

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$