The Role of Decision Context and Cognitive Reflection in AI Advice Acceptance

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Abstract

As artificial intelligence (AI) plays an increasing role in decision-making, understanding when and why individuals accept AI advice is crucial. This study titled "The Role of Decision Context and Cognitive Reflection in AI Advice Acceptance" by Tim Sigmund examines whether AI advice acceptance depends on decision context – specifically, whether individuals are more likely to follow AI recommendations in analytical (financial) versus intuitive (travel) decisions. Additionally, it investigates whether cognitive reflection, the ability to engage in deliberative thinking, moderates this effect by stabilizing advice-taking behaviour across contexts.

An experimental study was conducted in which participants made initial decisions in two scenarios before receiving AI-generated advice. The findings showed no significant effects of decision context or cognitive reflection on AI advice acceptance. Instead, participants largely adhered to their original choices, suggesting that egocentric discounting may play a stronger role than decision type or cognitive traits. These results challenge prior assumptions that AI is more readily trusted in structured, data-driven contexts and highlight the complexity of AI advice-taking behaviour.

The study contributes to research on human-AI collaboration by demonstrating that egocentric discounting may outweigh the influence of cognitive traits and decision context. While cognitive reflection was expected to moderate advice acceptance, its impact was minimal, indicating that other factors – such as AI trust, prior experience, or self-confidence – may better predict AI reliance. Future research should explore these variables and consider real-world decision-making contexts to refine our understanding of AI-human interaction.

Keywords: AI advice acceptance, decision context, cognitive reflection, human-AI interaction, egocentric discounting

Resumo

À medida que a inteligência artificial (IA) assume um papel crescente na tomada de decisões, entender quando e por que as pessoas aceitam conselhos da IA torna-se essencial. Este estudo, intitulado "The Role of Decision Context and Cognitive Reflection in AI Advice Acceptance", de Tim Sigmund, investiga se a aceitação de conselhos da IA depende do contexto decisório – especificamente, se os indivíduos tendem mais a seguir recomendações da IA em decisões analíticas (financeiras) do que em decisões intuitivas (viagem). Além disso, examina se a reflexão cognitiva, ou seja, a capacidade de pensar de forma deliberada, modera esse efeito ao estabilizar o comportamento diante de conselhos da IA em diferentes contextos.

Foi realizado um experimento no qual os participantes tomaram decisões iniciais em dois cenários antes de receber conselhos gerados por IA. Os resultados não mostraram efeitos significativos do contexto ou da reflexão cognitiva na aceitação da IA. Em vez disso, os participantes mantiveram suas escolhas iniciais, sugerindo que o viés egocêntrico pode exercer maior influência do que o tipo de decisão ou características cognitivas.

O estudo contribui para a pesquisa sobre colaboração entre humanos e IA ao demonstrar que o viés egocêntrico pode sobrepor-se a traços cognitivos e ao contexto decisório. Fatores como confiança na IA, experiência prévia ou autoconfiança podem prever melhor o uso da IA. Pesquisas futuras devem explorar essas variáveis em contextos reais.

Palavras-chave: aceitação de conselhos da IA, contexto decisório, reflexão cognitiva, interação humano-IA, viés egocêntrico.

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List of Abbreviations

Abbreviation	Definition
AI	Artificial Intelligence
CRT	Cognitive Reflection Test
CRT-L	Cognitive Reflection Test – Long
CRT-V	Cognitive Reflection Test – Verbal

1. Introduction

In 2016, the Artificial Intelligence (AI) AlphaGo defeated the Go world champion, a game far more complex than chess (Silver et al., 2016). During the historic game, AlphaGo made unconventional and irritating moves that later played out to be a highly effective strategy that went far beyond human understanding (Silver et al., 2016).

Over the last few decades, AI has evolved from a futuristic vision to an indispensable technology influencing decisions in almost every area of our lives: From low-stakes contexts such as personalized recommendations in online shopping (Linden et al., 2003), music (Koenigstein et al., 2011) or movies (Steck et al., 2021) to high-stakes domains such as medical diagnosis (Buch et al., 2018; Bulten et al., 2022), investment decisions (Zhang et al., 2021), hiring (Diab et al., 2011) and even prison sentence recommendations (Hao, 2019). AI is expected to have a tremendous impact on the global economy, with some projections estimating that the technology could contribute up to $15.7 trillion to the global economy in 2030 (Rao & Verweij, 2017).

Humans are already collaborating with AI in various fields. In the education sector, it assists teachers by supplying learning materials or acting as a practice partner for students (Ji et al., 2023). In medicine, AI collaborates with human doctors by analyzing medical images to help identify skin cancer or by calculating target zones for radiotherapy – far more quickly and accurately than a human ever could (Buch et al., 2018). In research, the AI AlphaFold has been used to accurately predict three-dimensional protein structures – a feat that used to require months or years of dedicated effort, just to determine a single protein structure (Jumper et al., 2021). For this discovery, Jumper and Hassabis, the Co-Founder and CEO of DeepMind, the company behind AlphaFold, have been awarded the 2024 Nobel Prize in chemistry (The Royal Swedish Academy of Sciences, 2024).

Beyond technical applications, AI is playing an increasingly important role is decision-making, where it is used both to replace human decision makers and to support human judgment (Agrawal et al., 2019). Recent advancements in AI technology have significantly reduced the cost of prediction tasks – for instance in the case of AlphaFold – which allows AI systems to handle more data-driven decisions, while humans remain responsible for more nuanced judgment calls (Agrawal et al., 2019).

Yet, automating decision-making entirely is often not ideal, especially in high-stakes environments like healthcare, where mistakes could have potentially deadly consequences

(Vodrahalli et al., 2022). For this reason, AI is more commonly used to support human decision-making by providing recommendations that individuals can either accept or reject (Lai et al., 2021).
However, whether people choose to follow AI advice often depends on the decision context. Some decisions, for instance financial decisions, are rather analytical and data-driven, others, such as deciding on a vacation destination, are more subjective and heavily influenced by personal preference and emotions (Vodrahalli et al., 2022). Research by Gino & Moore (2007) suggests that individuals trust AI more in structured, objective domains but prefer human input in more intuitive, preference-based decisions. This study extends their work by comparing AI advice-taking in financial and travel decisions to see if cognitive reflection shapes how people respond across these contexts.

As task-complexity rises and AI becomes better at making predictions, humans may increasingly cede decision-making authority to AI in order to increase efficiency – even when human judgement would be superior (Agrawal et al., 2019). Yet, AI is still faced with a lot of skepticism and apprehension. Research by Dietvorst and colleagues (2015) suggests that individuals rely on AI only reluctantly because they see errors made by algorithms as systematic and irremediable, as compared to human errors that are seen as more flexible and correctable. Additionally, as algorithmic reasoning does not always align with human cognitive processes, this can lead to frictions in human-AI collaboration (Einhorn, 1986; Gigerenzer & Todd, 1999). Understanding these factors is crucial for improving human-AI interaction and designing AI systems that foster trust and acceptance.

While existing research shows that people tend to trust AI more in analytical decisions while preferring human input for more subjective choices (Gino & Moore, 2007; Vodrahalli et al., 2022), there is a gap in literature on how individual differences in cognitive reflection shape this process. Since cognitive reflection promotes analytical thinking (Frederick, 2005), it may influence AI advice-taking across decision types. This thesis aims to explore whether AI advice acceptance is dependent on decision context and if this effect is moderated by cognitive reflection.

1.1. Problem Statement

Early research has shown that, even though simple algorithms consistently outperform human intuition, people show significant psychological and ethical resistance against their implementation (Dawes, 1979), a phenomenon that has been coined algorithmic aversion (Dietvorst et al., 2015). Dietvorst et al. (2015) showed that people prefer human judgment over algorithm predictions after seeing the algorithm make mistakes. This phenomenon occurs even when the algorithm outperforms human judgement and when its mistakes are smaller and less frequent than those of humans. However, more recent research challenges this traditional view of "algorithm aversion", with Logg et al. (2019) introducing the juxtaposed concept of "algorithm appreciation". Through a range of experiments, the researchers found that participants consistently trusted and preferred advice they were told came from an algorithm over advice that they were told came from a human (Logg et al., 2019).
Existing research found that AI is increasingly integrated into the decision-making process across industries, for instance by giving recommendations that humans can choose to accept or reject (BaniHani et al., 2024; Shrestha et al., 2019). However, whether AI advice is accepted is highly context-dependent. Some studies showed that individuals were more likely to trust AI in rational, data-driven tasks but preferred human advice when human intuition or emotional understanding was required (Gino & Moore, 2007; Vodrahalli et al., 2022). Additionally, individual differences play a crucial role in AI advice-taking: Research by Chong et al. (2022) identified self-confidence as a primary determinant of reliance on AI. Furthermore, cognitive biases, such as egocentric discounting, are barriers to external advice acceptance (Yaniv, 2004). While cognitive reflection has been shown to influence deliberative reasoning and reduce biases (Frederick, 2005; Toplak et al., 2011), its role in AI advice acceptance is currently still underexplored.

This dissertation aims to examine how decision context and individual differences in cognitive reflection influence the acceptance of AI advice. Specifically, it investigates whether people are more likely to accept AI advice in in decisions that are more analytical and data-driven (e.g., financial choices) compared to those that are more intuitive and preference-based (e.g., travel decisions) and whether cognitive reflection moderates this effect by stabilizing advice-taking behaviour across contexts. To adequately address the identified research gap, the central research question was divided into the following sub-questions:

RQ1: Are individuals more likely to accept AI advice in analytical versus intuitive decision contexts?

RQ2: Does cognitive reflection moderate the influence of decision context on AI advice acceptance, such that individuals with higher cognitive reflection show less variability in advice acceptance across contexts?

1.2. Managerial & Academic Relevance

This study aims to contribute to academic literature by addressing two significant gaps in the existing literature. First, while research on AI advice acceptance in decision making is growing, findings are ambivalent. Currently, research shows both a preference of AI-advice over that from humans (Logg et al., 2019), as well as an aversion to algorithm-based advice, even when it outperforms human forecasters (Dietvorst et al., 2015) and is correct (Schemmer et al., 2022). Second, there is a gap in research regarding the role individual differences play in the context of AI advice acceptance. While there is research showing that AI advice acceptance is closely linked to self-confidence (Chong et al., 2022), so far, to the best of my knowledge, there has been no research examining the influence of cognitive reflection on AI advice acceptance. By investigating this relationship, this study hopes to shed light onto the psychological mechanisms that drive AI advice acceptance. Furthermore, current research suggests that people are more likely to accept AI advice in scenarios that are more rational and data-driven and less likely to do so in decisions that involve emotions or intuition (Vodrahalli et al., 2022). However, the influence of cognitive processes on these context-dependent choices remains underexplored. By investigating the interaction between cognitive reflection and decision context this dissertation hopes to add depth to the understanding of Dual-Process Theories and how they apply to human-AI interactions.

From a managerial perspective, it is essential to understand what influences the acceptance or rejection of AI-given advice and how it affects subsequent decision-making. Agrawal and collaborators (2019) show that AI's influence on decision-making is trifold: First, advances in AI's capability to make better, data-based predictions allows for more informed decision-making which enables decision-makers to be more confident in taking actions involving higher risks. Second, its predictions increasingly complement humans in judgement tasks where intuition, ethical considerations, interpersonal dynamics or creative problem-solving is required. Third, as tasks get increasingly complex, AI can help to reduce the cognitive load of workers, which allows them to focus on the areas where human judgement is most valuable. However, the authors also note that due to the increased influence of and reliance on AI, humans will delegate some decisions to AI, even when human input would yield better results. These insights show the need for organizations to understand when to rely on AI, when to rely on humans and how to optimally integrate AI in the decision-making process.

This dissertation aims to provide actionable insights for designing more effective human-AI collaboration systems. Understanding how cognitive reflection influences AI advice acceptance can help organizations in the creation of decision-support systems that optimally fit the needs of their users. For example, the findings of Agrawal and colleagues (2019) suggest that AI recommendations may be more effective in rational contexts where data-driven decision-making is prioritized, whereas in intuitive contexts AI may rather complement human judgment instead of replacing it. Examining cognitive reflection can provide valuable insights into how people interpret and respond to AI advice. These learnings could be used to design AI recommendation systems that align optimally with users' cognitive processing styles and to develop training programs that take individual cognitive differences into account. In turn, this could help to foster trust in AI systems while reducing the current problem of over-reliance or overall rejection of AI recommendations (Chong et al., 2022). Ultimately, by examining the influence of AI advice in intuitive or rational decision contexts, this study provides strategic guidance on how to effectively operationalize AI, depending on the type of task at hand.

1.3. Structure of the Dissertation

Following this introductory chapter, Chapter 2 lays the theoretical foundation of this thesis by reviewing and discussing existing literature on the concept of AI, its role in decision making and its current relationship with human decision-makers. Furthermore, this chapter will have a closer look at dual-process theories and cognitive reflection. This chapter also outlines the hypotheses guiding this study. Chapter 3 details the study's experimental methodology, including research design, participant selection, experimental procedure, and the measurement of key variables. Chapter 4 presents its results, including data preparation, scale reliability, and hypothesis testing. Chapter 5 discusses the findings in relation to existing literature, derives theoretical and managerial implications while also addressing the study's limitations and suggestions for future research. Finally, Chapter 6 concludes the dissertation by summarizing key insights and contributions to both research and practice.

2. Literature Review

2.1. Artificial Intelligence

The term Artificial Intelligence was first coined by McCarthy et al. in 1955 who stated that artificial intelligence is essentially to make a machine behave in a way that would be called intelligent if a human behaved the same way . Today, AI is broadly defined as a computer system's ability to interpret data, learn from it, and apply those learnings to achieve specific goals (Kaplan & Haenlein, 2019), though no universally agreed upon definition exists.

The concept of AI encompasses several other technologies like Machine Learning, Deep Learning, Natural Language Processing and Computer Vision (BaniHani et al., 2024). Machine Learning refers to algorithms and statistical models that learn from data in order to improve their performance on a specific task, while not being specifically programmed to do so (Mitchell & Mitchell, 1997). Deep Learning is a significantly more complex and advanced sub-category of Machine Learning, which employs artificial neural networks with multiple layers to automatically process and learn from vast and complex data sets. It is therefore especially powerful in processing images, videos, natural language and audio (LeCun et al., 2015). Computer Vision refers to the training of computers to understand and interpret visual data, like images and videos, in a human-like way (Szeliski, 2009). This variety in AI technology shows the complexity of universally defining AI – each of these technologies is considered AI in and by itself, yet they are often combined to create even more capable AI systems (BaniHani et al., 2024).

Kaplan and Haenlein (2019) provide a comprehensive framework for classifying AI into three stages based on its intelligence level relative to humans: Artificial Narrow Intelligence, Artificial General Intelligence and Artificial Super Intelligence. According to their framework, Artificial Narrow Intelligence, or weak AI, describes the first generation of AI which encompasses all AI applications and solutions available today. Here, AI is applied to a certain area that it has been specifically trained for and in which it equals or surpasses human performance. Examples that the authors mention in this regard are self-driving car technology or AI assistants like Apple's Siri. While such an AI might drive a car equally well or even better than the average driver, it is unable to solve problems in other, unrelated areas, like writing an e-mail (Kaplan & Haenlein, 2019). Building on this, Kaplan and Haenlein (2019) introduce the second stage of their framework – Artificial General Intelligence – which applies AI to several areas at once. This enables AI to autonomously solve tasks that it was never specifically trained for, thus equaling or outperforming humans in several areas simultaneously. Finally, the last stage of this framework, Artificial Super Intelligence, describes a fully autonomous and self-aware system that applies AI to any area and can solve even the most complex problems almost instantaneously, thus outperforming humans in any field and essentially making them redundant. For this reason, only Artificial Super Intelligence is considered to be true AI by some (Kaplan & Haenlein, 2019).

The focus of this thesis lies on the use of AI –specifically Artificial Narrow Intelligence – in decision making, to which the literature review turns next.

2.2. AI in Decision Making

In recent years the adoption of AI technology has increased significantly due to big data, algorithms advancements, computing power improvements, storage capacity increases and resulting cost decreases (Duan et al., 2019). In a recent systematic literature review exploring the role of AI in decision-making, BaniHani et al. (2024) show that AI and its various subtypes – for example deep learning – are increasingly used across sectors like healthcare, finance and technology, where it aims to foster more accurate and data-driven decision-making. For example, machine learning and deep learning technology enables algorithms to independently learn from data over time, improve their pattern recognition and subsequently improve their ability to make decisions based on the selected data (Mahmud et al., 2022). It must be noted that decision-making is not a single action, but rather a process spanning multiple stages. Building on previous literature (Belton & Stewart, 2012; Linstone & Turoff, 1975; Simon, 1955), BaniHani et al. (2024) propose the following, systematic model for decision-making processes: 1) recognizing the need for a decision, 2) defining the problem or opportunity, 3) gathering information, 4) generating alternative solutions, 5) evaluating alternatives, 6) making the decision, 7) implementing the decision, 8) monitoring and feedback. BaniHani and collaborators (2024) show that AI already contributes at all stages of this decision-making process: In healthcare, AI assists in a variety of use cases, like diagnostics (3, gathering information) (Aldahiri et al., 2021), drug-design (4, generating alternative solutions) (Selvaraj et al., 2022) and even patient care (8, monitoring and feedback) (Ben-Israel et al., 2020). In fact, AI is already so omnipresent in even the most sensitive areas of decision-making, including the medical and financial fields, that we are forced to accept and adopt this technology (BaniHani et al., 2024). Besides AI's contributions across the decision-making process, its rising adoption also leads to fundamental shifts in traditional decision-making dynamics and the role of human decision-makers.

As AI systems are increasingly embedded in digital systems across industries, their impact on human decision-making rises significantly (Duan et al., 2019). The growing collaboration of humans and AI leads to a shift where the role of decision-makers changes from developing solutions to evaluating and selecting options proposed by AI (Shrestha et al., 2019). However, algorithms currently still serve more as tools supporting the decision-making process, rather than acting as independent decision makers (Acharya et al., 2018). One reason for this is the current state of AI technology. All AI solutions available today fall under the category of artificial narrow intelligence or weak AI (Kaplan & Haenlein, 2019), which is task-specific and requires human intervention for context changes, thus limiting its use for multi-faceted decision-making scenarios (Goertzel, 2014). Therefore, the AI applications discussed in this dissertation are assumed to fall into this category as well. This fundamental transformation in the decision-making dynamic is reflected in the diverse decision-making structures involving AI, as described by Shrestha and collaborators (2019). The authors distinguish between three different decision-making structures involving AI: In the first – full human to AI delegation – AI makes decisions without human intervention. This can be considered to fall under the category of full automation, as outlined by Parasuraman and Riley (1997). While this form of fully AI-based decision making is still relatively rare, it is characterized through a rapid decision-making speed resulting from the lack of human involvement (Shrestha et al., 2019). The authors mention examples such as recommender systems (e.g., Spotify, YouTube), dynamic pricing schemes (e.g., Uber prices varying depending on demand) or traffic planning. In the second structure, sequential decision-making, AI and humans sequentially make decisions and the input of one decision maker provides the input for the other one (Shrestha et al., 2019). This category is further divided into two hybrid structures: 1) AI to human: AI acts as an initial filter that presents a pre-selected choice of alternatives to the human decision maker, who then selects the best option(s). This approach is commonly found in hiring or idea evaluation scenarios and allows the human decision maker to handle situations involving large sets of alternatives effectively. 2) Human to AI: Here, humans narrow down the options, AI selects the best one. This is common in medical settings, where AI helps doctors monitor high-risk patients and detect potential acute disorders.

In aggregated human-AI decision-making, tasks are distributed between humans and AI based on their respective strengths and later combined into a final decision. In hiring, for example, humans might focus on more interpersonal aspects like social fit, whereas AI might evaluate more objective, data-driven aspects like productivity.

The focus of this dissertation lies primarily on AI to human sequential decision-making, where AI advice serves as an input that the human decision-maker can either accept or reject, thus staying in charge of the final decision (Shrestha et al., 2019). This cooperation of man and machine is commonly referred to as augmentation in literature, and is considered by many to be the future of how humans will interact and work with AI (Hollnagel & Woods, 2005; Daugherty & Wilson, 2018). Yet, besides these advancements, there remain significant barriers to the widespread adoption and acceptance of AI, especially in safety-critical fields like healthcare, as misdiagnosis or erroneous advice from a machine might have fatal consequences (Vodrahalli et al., 2022). Overcoming these barriers requires more than just technological advancements – it depends on fostering trust in and reliance on AI systems.

While an analysis of recent literature shows that most scholars are largely optimistic regarding the potential of AI in decision making (BaniHani et al., 2024), a variety of factors currently still limit human trust in and reliance on AI-generated advice. Trust can be defined 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, irrespective of the ability to monitor or control that other party" (Mayer et al., 1995, p. 712). In the context of decision making, Lee and See (2004) define reliance as the conscious behavior of acting upon the advice presented to them (i.e. accepting or rejecting it). They further clarify the role of trust, which they describe as an attitude that an agent (e.g., AI) will help an individual to achieve his goals in uncertain situations. While trust can increase reliance, reliance can also occur independently of trust (Lee & See, 2004) – we might not trust the investment advisor, but still consciously decide that following his advice is the best possible decision (Schemmer et al., 2022). Trust in AI has been identified as a key factor in advice-taking behaviors (Kohn et al., 2021). A variety of factors influence trust in AI advice, including prior beliefs in its effectiveness (i.e., if people believe AI outperforms humans on a given task), confidence (i.e., advice seems reliable and is presented confidently) and task context (e.g., preference for AI advice in data-driven tasks) (Vodrahalli et al., 2022). One issue limiting human trust into AI is the so-called "black-box" nature of some AI systems, which can lead to a lack of transparency and interpretability (BaniHani et al., 2024; Mahmud et al., 2022). As a result, the AI's decision-making process remains opaque, making it hard or even completely impossible to understand for humans (Castelvecchi, 2016). Beyond these trust and interpretability issues, cognitive biases, such as egocentric discounting, play a crucial role in shaping human decision-making processes. To fully understand the dynamics of AI advice acceptance, it is essential to first explore this cognitive bias and its impact on decision-making.

2.2.1. Egocentric Discounting in Decision-Making

Egocentric discounting is a cognitive bias that describes an individuals' tendency to place greater value on their own opinions and judgments compared to external advice, which leads them to discount or undervalue information from others (Yaniv, 2004). As individuals have direct access to the thought process behind their own decisions, they tend to believe that their own knowledge is more accurate or reliable and, in turn, perceive external advice as less informed or credible (Yaniv & Kleinberger, 2000). When individuals have already invested significant effort to form their initial opinion, or when they perceive themselves as competent in the area, this discounting behaviour is amplified (Harvey & Fischer, 1997). Consequently, even when faced with expert or accurate external advice, people are more likely to adhere to their initial judgments (Yaniv & Kleinberger, 2000). This can lead to a biased integration of advice in line with preexisting notions (Yaniv & Milyavsky, 2007) and subsequential decrease in decision quality (Yaniv & Kleinberger, 2000).

While there is currently no research directly examining the influence of egocentric discounting on AI advice acceptance, theoretical parallels can be drawn from research on human advice-taking behaviour (Yaniv, 2004) and known scepticism towards algorithmic recommendations (Dietvorst et al., 2015). In decision contexts involving AI, the resistance of taking external advice might be further amplified due to the perception of AI systems lacking human intuition or emotional intelligence (Vodrahalli et al., 2022). The following section explores this dynamic by examining the factors influencing human and AI advice acceptance.

2.2.2. Human vs. AI advice

Research on advice-taking behaviour reveals that people's acceptance of AI advice is highly context-dependent. One well-documented phenomenon called "algorithm aversion" occurs when people lose confidence in AI systems after witnessing it make mistakes, even if the AI generally outperforms human judgment (Dietvorst et al., 2015). Dietvorst and colleagues show that individuals have unrealistically high expectations towards algorithms, expecting near-perfect performance while simultaneously being highly sensitive to errors. Specifically, people are quick to generalize a single mistake made by the AI to all its future predictions, deeming it as unreliable and subsequently switching to human advice despite its generally lower accuracy (Dietvorst et al., 2015). Mahmud et al. (2022) further identified four key factors influencing algorithm aversion: characteristics of the algorithm (e.g., perceived accuracy and the "black box" issue), individual biases and familiarity with the technology, task complexity and decision

consequences, as well as broader organizational or social influences. These findings suggest that algorithm aversion is strongly context-dependent and varies according to the nature of the decision as well as the decision-maker's background (Mahmud et al., 2022).
Conversely, newer research conducted by Logg and collaborators (2019) shows that people are more likely to follow AI advice when they perceive it as more accurate or reliable compared to human judgment. In fact, individuals showed a preference for algorithmic recommendations even when the advice was identical to that of a human, which indicates a bias towards algorithmic sources – a phenomenon referred to as "algorithm appreciation" (Logg et al., 2019). This suggests that algorithm appreciation may be driven by a perception of objective rationality or data-driven accuracy inherent in AI systems (Logg et al., 2019).
However, it must be noted that the acceptance of AI advice is highly context dependent. Research by Vodrahalli et al. (2022) showed that individuals are more likely to trust AI advice in tasks perceived as objective and data-driven, such as identifying artworks or cities, whereas they preferred human advice in tasks requiring emotional understanding or human intuition, such as detecting sarcasm. This suggests that the perceived nature of the task (rational vs. emotional) significantly moderates AI advice acceptance (Vodrahalli et al., 2022). Similarly, Gino and Moore (2007) demonstrated that advice-taking behaviours are context-dependent and also influenced by the complexity of the task at hand. They found that individuals are more likely to accept external advice in difficult and analytical tasks, as the increased complexity reduces confidence in their own judgment. Conversely, in simpler and more intuitive tasks, individuals rely more strongly on their own assessments and are less receptive to external input. This pattern suggests that more complex, rational and data-driven contexts, such as financial decision-making, may foster greater AI advice acceptance. In contrast, more intuitive, emotional and subjective contexts, such as travel decisions, may lead to a greater reliance on one's own judgment. Therefore, this dissertation proposes:
H1: *The type of decision context will significantly influence the likelihood of AI advice acceptance. Specifically, participants are more likely to accept AI advice in the financial context (a rather rational decision type) compared to the travel context (a rather intuitive decision type).*

Similarly, Agrawal et al. (2019) highlight that as prediction technology advances, humans may increasingly delegate decisions to AI in objective contexts where outcomes are easier to quantify, while maintaining a preference for human judgment in subjective scenarios where nuanced interpretation is required. Interestingly, despite the context-dependence of preferences, Vodrahalli and collaborators (2022) found that, when advice is accepted, the integration of AI and human advice influences decisions to a similar degree. This indicates that, while initial acceptance may differ, the impact of accepted advice is comparable, regardless of its source (Vodrahalli et al., 2022).

Building on these findings, the present study examines whether this dependence on context in AI advice acceptance also applies to decision-making scenarios that involve rational and emotional contexts. To fully understand this dynamic, a closer look at the role of confidence, a crucial factor influencing how people perceive and rely on AI recommendations, is needed. The next section deals with this issue.

2.2.3. AI advice acceptance and confidence

Confidence is often essential to the quality of decision-making processes, as it influences how individuals evaluate options, weigh evidence, and ultimately make choices (Fleming, 2024). It helps individuals decide when to trust their judgment, seek more information, or reconsider their decisions (Fleming, 2024). Despite its importance, there is still limited research on how AI advice impacts or is impacted by confidence. Recently, Chong and collaborators (2022) linked confidence to trust in and reliance on AI, showing that it is not merely confidence in AI itself but rather confidence in one's own abilities (i.e., self-confidence) that drives acceptance or rejection of AI advice. Here, participants were asked to solve chess puzzles with the support of an AI assistant. Due to the abstract and varying definitions of trust, their study focused on two types of confidence closely related to trust: confidence in AI and participants' self-confidence in their ability to make good decisions, based on their skills and competence on the task at hand. Participants were split into two groups where AI performance was manipulated to either improve or deteriorate over time (from 20% to 80% accuracy, or vice versa). Then, confidence in the AI and participants' own abilities was measured through self-reporting after each task. The study found that confidence in AI advice drops rapidly when AI performance deteriorates and recovers slowly, even if the advice improves again. Conversely, confidence in AI increased much more slowly if performance was initially poor (Chong et al., 2022). This shows an asymmetry in trust, which aligns with loss aversion theory – stating that people tend to weigh losses more heavily than gains (Tversky & Kahneman, 1991). When AI gave consistently poor or good advice, self-confidence remained stable. However, when an initially well-performing AI started to deteriorate, so did human self-confidence, suggesting that people misattribute AI failure to themselves. Interestingly, an improvement in AI performance after initial poor performance did not lead to a significant increase in self-confidence. This shows

that negative AI performance can have a negative impact on human self-confidence (Chong et al., 2022).
Surprisingly, the paper found that human self-confidence – not confidence in AI – is the main driver in the decision whether to accept or reject AI advice. Participants with low self-confidence were more likely to rely on the advice given by AI, even if it performed poorly.
Relatedly, an experiment exploring the acceptance of AI decisions in a real-life business context found that employees with low past performance were more likely to accept AI advice (Kawaguchi, 2021). Research suggests that past performance can influence self-confidence, as individuals often use their previous successes or failures as a benchmark for their abilities (Stankov et al., 2015). In contrast, participants with high self-confidence were more likely to reject AI advice and trust in their own abilities. This finding contradicts the common assumption that people rely on AI based primarily on their confidence in AI itself (Chong et al., 2022). Building on these findings, this study proposes the following hypothesis:
H2: *Initial confidence levels are negatively correlated with decision change after receiving AI advice.*
By testing this hypothesis, this study adds to the research by investigating whether initial confidence in fact predicts decision change. Thus, it aims to contribute to the understanding of confidence as a key factor in AI advice acceptance.
The findings of Chong and colleagues (2022) were further supported by Vodrahalli and collaborators (2022), who conducted an experiment showing that advice acceptance depended heavily on participants' perceived confidence in their own answer – if participants were unsure regarding their own assessment, they were more likely to accept the advice. Additionally, advice acceptance was strongly influenced by the perceived confidence of the advice - participants were more likely to use the advice if they were under the impression that it was safe and well-founded (Vodrahalli et al., 2022).
Furthermore, misplaced trust in (faulty) AI advice can lead to a vicious cycle: When participants accepted poor AI advice, the result was a loss of self-confidence (Chong et al., 2022). This made it more likely for them to accept the next suggestion given by the AI, even if it performed poorly, resulting in a vicious loop where people continued to rely on a poorly performing AI because they had lost confidence in their own abilities (Chong et al., 2022).
Finally, Chong and colleagues (2022) discern between good and bad decision makers. Good decision-makers showed a positive correlation between self-confidence and their decision to accept AI advice. They trusted their own judgement and rejected AI advice when confident in their own ability yet relied on it when they were less certain about their judgement, thus

adequately balancing both AI's and their own strengths. Conversely, bad decision makers over-relied on AI even when it performed poorly, which led to worse outcomes (Chong et al., 2022).The study by Chong et al. (2022) reveals that there are individual characteristics, such as self-confidence, that can influence AI advice adoption. In the next section, the thesis turns to an individual difference that may influence AI advice adoption: cognitive reflection.

2.3. Dual-Process Theories: Intuition vs. Reason

To understand how individuals accept or reject AI advice, it is essential to examine the cognitive processes underlying decision-making, as conceptualized by Dual-Process Theories. Researchers distinguish between two systems of information-processing and decision-making, commonly referred to as System 1 and System 2 (Kahneman, 2011; Kahneman & Frederick, 2002; Stanovich, 1999; Tversky & Kahneman, 1974). System 1 is characterized by fast, unconscious and automatic processes requiring low effort (Evans, 2008), and is engaged while recognizing familiar objects or faces, forming first impressions or reacting to simple or routine stimuli (Tversky & Kahneman, 1974). It is optimal for (subconscious) routine tasks but is prone to errors and biases (Evans, 2008). In contrast, System 2 is defined through conscious, deliberate and slow reasoning processes requiring high cognitive effort. It involves higher-order cognition, like conscious decision-making and analytical reasoning (Evans, 2008). It comes into operation when engaging in complex or unfamiliar tasks that require concentration and dedicated effort, such as comparing values or checking the validity of logical arguments (Kahneman, 2017). When it comes to reasoning and decision-making tasks, System 1 relies on previous experience and knowledge to make quick, intuitive judgments, whereas System 2 allows for more precise, logical and reflective reasoning (Kahneman, 2017). However, reliance on System 1 can lead to cognitive biases such as matching bias – focusing on superficial similarities – or belief bias – where conclusions are accepted based on plausibility rather than logic (Evans, 2008). In this regard, System 2 can be applied to correct or rationalize decisions that have initially been made on an intuitive basis (Tversky & Kahneman, 1974).

In this context, the Cognitive Reflection Test (CRT) has become a valuable tool for measuring individual differences in reflective decision-making ability. Developed by Frederick (2005), it measures an individual's ability to override intuitive responses in favour of more reflective and analytical solutions. The original test encompasses three numeracy-based problems that elicit intuitive and seemingly easy, but incorrect answers. For example:

"A bat and a ball cost $1.10. The bat costs $1.00 more than the ball. How much does the ball cost? ___ cents."

The intuitive answer is 10 cents, whereas the correct one is 5 cents (Frederick, 2005).

Research has consistently shown that individuals scoring high on the CRT demonstrate more consistent and reflective decision-making patterns compared to those scoring low (Frederick, 2005; Toplak et al., 2011). This research found that individuals with high CRT scores engage in deliberate reasoning more strongly, which reduces susceptibility to cognitive biases and leads them to make more consistent choices.

In recent years, some adaptations to the original CRT have been introduced to provide a more accurate assessment of cognitive reflection while addressing its limitations. The Verbal CRT (CRT-V) developed by Sirota and colleagues (2021) uses verbal items to reduce the effect of numeracy skills, which was an issue in the original version. The CRT – Long (CRT-L), developed by Primi and collaborators (2016), increases sensitivity by including easier questions and thus managed to eliminate the floor effects present in the original version.

The ability to measure the balance between intuitive and reflective thinking makes the CRT relevant in examining how individuals process advice from AI. Higher CRT scores indicate a greater capacity for deliberative reasoning, and therefore an improved ability to override intuitive judgments (Frederick, 2005). While cognitive reflection is linked to analytical decision-making and reduced reliance on intuition (Frederick, 2005; Toplak et al., 2011), its impact on AI advice acceptance remains largely unexplored. Research by Frederick (2005) and Toplak and colleagues (2011) proposes that high CRT individuals do not accept external advice more readily unless it offers a clear, rational advantage. While no peer-reviewed studies in high quality journals exist at this time, there are some scientific outputs. For example, a study by Yang and Gosline (2020) found that, in financial decision-making contexts, individuals with higher CRT scores were more likely to accept AI advice compared to human advice. Conversely, research by Chernoskutova (2021) focusing on a more intuitive context – a mental health scenario – did not find a significant relationship between CRT scores and AI advice acceptance. This aligns with prior research, showing that people tend to trust AI more in analytical contexts but prefer human judgment in intuitive ones (Vodrahalli et al., 2022; Gino & Moore, 2007). This is further supported by Simmons & Nelson (2006) who show that decision context can significantly impact individuals' confidence regarding their intuitive choices. People tend to prefer their intuitive choices unless their confidence in them is undermined, at which point they become more open to deliberation and external input

(Simmons & Nelson, 2006). If cognitive reflection helps people rely less on the specific context of a decision, those with higher CRT scores might be more consistent in accepting AI advice, regardless of whether the decision is more intuitive or analytical. This would mean that, rather than directly increasing AI advice acceptance, cognitive reflection may shape how much the decision context influences that acceptance. It is therefore proposed that:
H3: *Cognitive reflection will moderate the relationship between the type of decision context and AI advice acceptance. Specifically, participants with higher cognitive reflection will show less variability in AI advice acceptance across decision contexts, whereas participants with lower cognitive reflection will display a greater influence of the decision context on AI advice acceptance.*

3. Methodology

3.1. Research Design

To test how decision context influences AI advice acceptance in a decision-making scenario, and to evaluate the role of cognitive reflection in this context, this study used a quantitative, experimental and correlational approach with data collected through Qualtrics. Participants were presented with two decision-making scenarios: one of which was designed to trigger rather intuitive reasoning, whereas the other aimed to foster more deliberative reasoning. After choosing their preferred option, participants received advice from AI.

The study followed a mixed experimental design, that combined within-subjects and between-subjects elements. The within-subjects component exposed each participant to both decision contexts, while the between-subjects component varied the AI's advice, so it recommended either the first or second option in both scenarios. As a result, AI advice acceptance was measured without being tied to a specific choice. Cognitive reflection was measured using selected items from established tests to assess participants' decision-making behavior. This ensured that AI advice acceptance was measured independently of the specific choices participants made.

The decision contexts were based on hedonic vs. utilitarian decision-making according to Dhar and Wertenbroch (2000). The first scenario was designed to reflect rather hedonic, experience-driven reasoning, where individuals tend to rely more on intuition (Lu et al., 2016). Here, participants had to choose between two vacation destinations differing in attributes such as emotional appeal, atmosphere, and personal preference. The second scenario was selected to reflect more utilitarian, deliberation-driven reasoning, where people typically engage in systematic, analytical thought (Lu et al., 2016). Here, participants had to choose between two financial investment options that varied in terms of expected return and risk, which required a more rational evaluation. After making their initial decision in each scenario, participants received a recommendation they were told came from AI. This setup allowed for an examination of how decision context interacts with cognitive reflection in shaping AI advice acceptance.

To also assess the impact of AI advice on participants' decision confidence, a pre-post design was used. After deciding on an option, participants rated their confidence in that choice. Then, they were presented with advice they were told came from an AI and subsequentially had the chance to confirm or change their initial decision, before being asked to report their confidence again. This allowed for a comparison of how AI advice influences decision certainty – whether it reinforces confidence, introduces doubt, or leads to a complete decision change – and if that change goes along with higher or lower confidence.

Measuring confidence in this way is particularly relevant because previous research suggests that self-confidence plays a key role in advice-taking behaviour (Chong et al., 2022) and influences trust in AI recommendations (Vodrahalli et al., 2022). By tracking how confidence shifts in response to AI advice, this study provides deeper insights into how AI affects decision stability and self-assurance across different decision contexts.

3.2. Participants

The minimum required sample size was determined to be 159 by running a power analysis in G*Power (power for each individual coefficient, for a regression at 0.8 power, $\alpha = .05$, two-tailed, $f^2 = .05$). To enhance statistical power, the required sample size was further increased to 200. Data was collected using a nonprobability sampling technique. A first round of recruitment used social media (Reddit, Instagram) and WhatsApp and yielded a total of 126 unpaid participants. To meet the required sample size, another 179 participants were recruited using Amazon's Mechanical Turk. For their participation, they received a monetary compensation of USD 0.30 after the successful completion of the experiment. In total, 305 responses were collected. Data cleaning and analysis was carried out using IBM SPSS. Incomplete responses (n = 17) and those failing the attention check (n = 15) were excluded from the dataset. Furthermore, responses with obvious ChatGPT usage were deleted from the dataset (n = 26) (i.e. several responses to the CRT questions included extensive answer nearly identical between participants, instead of just the numerical answer). Lastly, a dummy variable was created to filter and remove duplicate IP addresses (n = 24). While this approach decreases statistical power, it increases data quality by ensuring that the data used in the analysis referred to attentive participants only (Tsikriktsis, 2005). After the elimination, the sample size totaled 224 participants, of which 62.9% were male. Ages ranged from 18 to 59 years (M = 28.84, SD = 7.76). Most respondents worked either full-time (n = 150; 67.0%) or were students (n = 45; 20.1%) and had a bachelor's (n = 161; 71.9%) or a master's degree (n = 37; 16.5%). Nationality of participants was not collected, but as most MTurk participants are US-based, it is expected that the largest part of participants from this method of recruitment had this nationality. As my personal and professional network is mostly German, these participants are expected to form the second largest group. Lastly, most participants indicated that they had already used AI tools (n = 161; 71.9%). For more details on the sample descriptive statistics, such as frequency distributions for education levels or employment status, please check Appendix 2.

3.3. Procedure & Materials

The experiment was conducted online using Qualtrics and followed a randomized survey design. The flow of the survey was structured into randomized blocks that were presented to participants evenly across groups. This ensured a balanced presentation of scenarios and conditions and allowed to control for order effects and minimize potential biases. Every block featured short instructions explaining the task at hand.

Initially, all participants were presented with a short introduction explaining the purpose of the study and instructions on how to proceed before providing informed consent. Afterwards, participants were randomly and equally split into Group 1 or 2.

In the core part of the experiment, all participants were presented with two decision-making scenarios. In Scenario A, participants were presented with two different vacation destinations, both of which were described as appealing but differed significantly in terms of location, atmosphere, type of accommodation and appeal. Option A – Cala Luna – was described as a peaceful, exclusive retreat in a secluded coastal area, surrounded by pristine nature. It was framed to be ideal for those seeking relaxation, privacy, and an escape from crowds and daily life. Option B – Sunport Bay – was presented as a lively seaside town known for its nightlife that offers a vibrant vacation experience with diverse entertainment options. This destination was framed to appeal to those who enjoy comfort, convenience, and the possibility to participate in a wide range of activities. Scenario A aimed to elicit an intuitive decision from participants by using emotional and sensory descriptions of both destinations, designed to create a quick, emotion-based response rather than a detailed analysis of options.

In Scenario B, participants had to decide between two investment options differing in terms of their level of risk and potential return. Option A – stable fund – was framed as a low-risk investment with annual returns of 4-5% designed for those looking for reliable, long-term growth. Option B – high-growth fund – was presented as a volatile, high-risk investment, offering returns of up to 10% and more, thus appealing to investors willing to take a higher risk for higher rewards in a shorter timeframe. Scenario B aimed to elicit a deliberative response by presenting quantitative trade-offs with an emphasis on risk and return. As this decision is framed to have long-term consequences, its aim was to prompt participants to approach the task more analytically and carefully weigh potential outcomes. Participants first made a choice in each scenario and were subsequently asked to rate their confidence in the decision. Then, participants received advice that they were told came from an AI advisor. The recommendation was presented in a text format and included a brief explanation of why this option was favorable, for example: "The AI analyses your preferences and recommends Destination A - Cala Luna, explaining that this option aligns with your desire for an exclusive, peaceful getaway that allows you to reconnect with nature."

Depending on the group participants were initially assigned to, the AI recommended either Option A (Cala Luna / Stable Fund) or Option B (Sunport Bay / High-Growth Fund) in both scenarios. Once they reviewed the AI's advice, participants were asked to reconsider their initial decision and indicate their final choice between either Option A or Option B. Then, they rated their confidence in this final decision.

To assess participants' cognitive reflection, they were asked six open-ended questions taken from different CRT versions – two each from the original CRT (Frederick, 2005), the CRT-L (Primi et al., 2016), and the CRT-V (Sirota et al., 2021). To account for potential order effects, the presentation of the CRT items was randomized and appeared either before or after the experimental scenarios.

Originally, an Intellectual Humility scale was included to explore its potential influence on advice acceptance. However, due to an error in the implementation of the items, the scale was not correctly administered. This led to a very low reliability (Cronbach's α = 0.54) and the scale was deemed unreliable and subsequentially excluded from further analyses.

Finally, participants were asked general demographic questions concerning their age, gender, education, employment status and their familiarity with AI systems. Here, they indicated if they had ever used AI tools, such as chatbots or decision-making tools, before.

3.4. Variable Measurement

3.4.1. Independent Variables

Decision Context: Two distinct decision-making scenarios were included in the study to assess the role of intuition versus deliberation in AI advice acceptance. The travel scenario (A) represented an intuitive context, while the financial scenario (B) represented a deliberative context.

3.4.2. Dependent Variables

Two primary dependent variables were investigated within the context of the two decision-making scenarios:
Advice Acceptance: This variable measured whether participants were influenced by AI advice to change their initial decision. The question was stated as "Reflect on the AI's recommendation. Does this advice influence your choice? Please indicate your final decision:" No change in decision was coded as 0, if the change aligned with AI advice the response was coded as 1, if it went against AI advice, as -1. This coding allowed the analysis of two key aspects: First, the general influence of AI advice (i.e., whether the AI's recommendation led to any decision change at all, regardless of alignment) and, second, the direction of the decision change (i.e., whether participants aligned their decision with the AI's advice or if they chose to actively oppose it). This allows a deeper exploration of the concepts of algorithm appreciation (Logg et al., 2019) and algorithm aversion (Dietvorst et al., 2015) outlined earlier.
Decision Confidence: This variable examined how AI advice influenced participants' decision confidence ("Please rate how confident you feel about your decision."). The measurement was taken both before and after receiving advice from the AI by applying a 7-point Likert scale (1 = *Not at all confident* to 7 = *Extremely confident*).

3.4.3. Moderator

Cognitive Reflection: To measure participants' cognitive reflection, a mixed approach was adopted. The aim of this strategy was avoid to common pitfalls observed in the original CRT such as gender differences and floor effects (Frederick, 2005; Primi et al., 2016). This approach integrated items from the original CRT, CRT-V, and CRT-L to provide an accurate assessment of cognitive reflection while also reducing a) the impact of prior exposure / recognition bias, as the original CRT items have been used extensively and are well-known (Sirota et al., 2021). Research indicates that self-reported prior exposure leads to a noticeable increase in performance on the test. However, it has to be noted that this does not seem to diminish the test's predictive validity (Bialek & Pennycook, 2018), and actual prior exposure, when non self-reported, has only a minimal effect on performance (Meyer et al., 2018). By incorporating less familiar items from the CRT-V and CRT-L, the issue of prior exposure is mitigated reduces the risk that participants retrieve the correct answers from memory (Primi et al., 2016), while keeping overall score validity; b) the influence of numeracy on cognitive reflection by including non-numeric, verbal items from the CRT-V, (Sirota et al., 2021); c) the gender differences present in the original test were eliminated in this version, while still predicting similar outcome variables, such as bias susceptibility and reflective decision-making (Sirota et al., 2021); d) the high difficulty of the items, by adding easier, numeracy-based questions from the CRT-L (Primi et al., 2016). In the original CRT, this led to floor effects, with 33% of participants scoring zero on the test (Frederick, 2005). This limitation reduces the generalizability of the findings and renders the scale unsuitable for populations with lower levels of cognitive reflection (Primi et al., 2016). This adaptation thus made it suitable for a wider range of cognitive abilities, while simultaneously enabling to discriminate more precisely between respondents of these levels. The final test then featured six open-ended questions, two of which were taken from each CRT version. Each correct response was coded as 1, whereas incorrect responses were coded as 0. This led to a final CRT score ranging from 0 to 6.

3.4.4. Control Variables

Several categorical variables were included as control variables and transformed in order to prepare them for the subsequent statistical analysis. Specifically, the variables for gender, employment status and education were recoded into dummy variables. The original gender variable included four categories: male, female, non-binary and prefer not to say. During the

transformation, male participants were recoded as 1, female and non-binary participants as 0. Participants who did not state their gender identification (n = 1) were treated as missing values and subsequently excluded from analyses involving gender. For employment status, two new dummy variables were created: The first one grouped all employed participants (full-time, part-time & self-employed) which were subsequently coded as 1 (n = 170; 75.9%). All non-employed participants (unemployed, students, retired, and other) were coded as 0 (n = 54; 24.1%). It has to be noted that there is a high likelihood that some students are working part-time or as working students (i.e., two participants specified this in the "other" category). For the sake of simplicity, they were added to the non-employed group, as their student status can be considered their primary form of employment. The second variable, labelled student, further distinguished between students coded as 1 (n = 45; 20.1%) and all other participants (n = 179; 79.9%) coded as 0. Lastly, to distinguish between participants with a high and those with a low education, the binary variable high education was created. Here, participants with a bachelor's degree or higher were coded as 1 (n = 199; 88.8%), all other education levels were coded as 0 (n = 25; 11.2%).
To control for the confound between nationality and recruitment platform, an additional dummy variable named recruitment platform was created. This resulted in a final count of 118 MTurk participants (52.7%) and 106 participants recruited through other methods (47.3%).

The variable prior AI use was created to account for participants' prior experience with AI systems. Based on the original question "Have you ever used AI-based systems before?", responses were recoded as follows: "Yes" was coded as 1 (n = 161; 71.9%), while "No" and "I don't know" were coded as 0 (n = 63; 28.1%). This binary coding allowed for a clear distinction between participants who had previous exposure to AI systems and those who did not, helping to control for potential confounds related to familiarity with AI.

The variable AI recommendation was derived from the scenario order variable to indicate whether the AI recommended Option A or Option B in each scenario. Participants with scenario order values of 1 or 3 were coded as 1 (n = 108; 48.2%), indicating an AI recommendation for Option A. Participants with values of 2 or 4 were coded as 0 (n = 116; 51.8%), indicating an AI recommendation for Option B. This variable was essential for analyzing the influence of AI advice on participants' decision-making.

Two variables for the travel and investment decision were created to capture changes in participants' decisions between their initial choice (before receiving AI advice) and their final choice (after receiving AI advice). Decision changes were coded as follows: 1, if the Decision aligned with the AI recommendation, -1 if the decision opposed the AI recommendation and 0 if there was no change in decision. These variables allowed for a detailed analysis of participants' alignment with or opposition to the AI's advice in each scenario and prepared them for later hypothesis testing. For the travel decision variable, n = 22 (9.8%) participants changed their decision against the AI recommendation (coded as -1), while n = 169 (75.4%) participants maintained their initial decision (coded as 0). A total of n = 33 (14.7%) participants changed their decision in alignment with the AI recommendation (coded as 1). Similarly, for the investment decision variable, n = 26 (11.6%) participants changed their decision against the AI recommendation (coded as -1), while n = 158 (70.5%) participants maintained their initial decision (coded as 0). A total of n = 40 (17.9%) participants changed their decision in alignment with the AI recommendation (coded as 1).

To prepare the data for hypothesis testing, the dataset was restructured to ensure that each scenario (travel and investment) was represented as a separate row for every participant. This transformation was necessary because the study employed a within-subjects design, where each participant completed tasks in both scenarios. By restructuring the data, each scenario-specific response could be analyzed independently while still being linked to the corresponding participant.

4. Results

4.1. Data Preparation, Descriptives, and Bivariate Correlations

To account for egocentric discounting, an analysis was conducted to examine how many participants changed their decision after receiving an AI recommendation that differed from their initial choice. To identify participants whose initial choice did not align with the subsequent AI recommendation, the data set was first filtered. Then, the proportion of participants who maintained their initial choice versus those who changed their decision to align with the AI recommendation was calculated and compared using a χ^2 test to assess the presence of egocentric discounting.

In the travel scenario where the AI recommended Option A – Cala Luna, n = 45 (41.67%) of the 108 participants who received this recommendation had initially chosen Option B – Sunport

Bay. Conversely, when the AI recommended Option B, $n = 62$ (53.45%) out of 116 participants had initially chosen Option A. Overall, $n = 107$ (47.77%) of 224 total participants made an initial choice in the travel scenario that differed from the AI recommendation. Of these, $n = 74$ (69.2%) maintained their initial decision, while $n = 33$ (30.8%) changed their choice to align with the AI recommendation. A χ^2 test was conducted to assess whether participants' decisions deviated from what would be expected under a random distribution. The results ($\chi^2 = 15.71$, $p < .001$) indicate that participants were significantly more likely to stick with their initial choice rather than change their decision based on AI advice.

In the investment scenario where the AI recommended Option A, $n = 37$ (34.26%) of the 108 participants who received this recommendation had initially chosen Option B Fund. Conversely, when the AI recommended Option B, $n = 74$ (63.79%) out of 116 participants had initially chosen Option A. Thus, a total of $n = 111$ (49.55%) out of 224 participants made an initial choice in the investment scenario that differed from the AI recommendation. Of these, $n = 71$ (64.0%) maintained their initial decision, while $n = 40$ (36.0%) changed their choice to align with the AI recommendation. A χ^2 test was conducted to determine whether participants' decisions deviated from a random distribution. A χ^2 test again showed that participants significantly favored their original choice over AI advice ($\chi^2 = 8.65$, $p < .01$).

Descriptive statistics were used to summarize participants' confidence levels before and after receiving AI advice. In the travel scenario, participants reported relatively high confidence levels before receiving AI advice ($M = 5.58$, $SD = 1.28$). After receiving AI advice, the mean confidence and variability slightly increased ($M = 5.62$, $SD = 1.41$). Similarly, decision confidence in the investment scenario was relatively high before receiving AI advice ($M = 5.59$, $SD = 1.28$). After receiving AI advice, participants' confidence levels slightly decreased with a similar level of variability ($M = 5.45$, $SD = 1.32$).

To further examine confidence changes, difference scores were computed (post-advice confidence minus pre-advice confidence). Positive values indicate increased confidence; negative values indicate decreased confidence. For the travel scenario, most participants ($n = 129$; 57.6%) reported no change in confidence after receiving advice from AI. The second-largest group ($n = 42$; 18.8%) experienced an increase in confidence by one point, while $n = 26$ (11.6%) reported a slight decrease in confidence by one point. Overall, confidence changes ranged from -4 to +4, with a mean change of $M = 0.04$ ($SD = 1.08$). However, changes greater than one point were rare, laying in the single-digit area. Similarly, for the investment scenario, most participants (n = 122; 54.5%) reported no change in confidence. The second-largest group (n = 39; 17.4%) experienced a decrease in confidence by one point, whereas n = 31 (13.8%) participants reported an increase in confidence by the same amount. Here, confidence changes ranged from -4 to +3, with a mean change of M = -0.14 (SD = 1.06). However, similar to the travel scenario, greater changes in confidence only happened rarely.

For the assessment of the CRT questions, a new variable was created for every CRT question, where the correct answer was coded as 1 and all others as 0. To account for the variance in answers, several correct answers were allowed. For example, in the first CRT question concerning the patch of lily pads covering a lake, the correct answer was 47 days. Thus, answers like "47", "47 DAYS" were coded as correct. In the next step, CRT scores were calculated by summing correct responses across six CRT questions (range: 0–6). Descriptive statistics revealed a mean score of $M = 4.26$ ($SD = 1.80$), with a median of 5. A frequency analysis indicated that 29.5% of participants achieved the highest score (6 correct responses), while only 5.8% of participants answered zero questions correctly. The overall high CRT scores led to the suspicion that prior exposure to the items of MTurk participants might have skewed the results. To test this, an independent samples t-test was conducted. Here, CRT scores of MTurk participants were compared to those of participants recruited through my personal network. Levene's test for equality of variances indicated no violation of the assumption of equal variances (F = 1.08, p = .300). In the t-test, no statistically significant difference in CRT scores was detected between MTurk participants (M = 4.08, SD = 1.83) and non-MTurk participants (M = 4.46; SD = 1.76), $t(222) = 1.61$, p = .110, d = 0.22. Interestingly, CRT scores of non-MTurk participants were higher on average. Ultimately, the recruitment platform was found to have no significant impact on participants' CRT scores. Bivariate correlations between the main variables can be found in Appendix 3.

4.2. Hypothesis Testing

An ordinal logistic regression was conducted to examine the influence of decision context, cognitive reflection, and their interaction on AI advice acceptance. First, an interaction term was computed to examine the moderating effect of cognitive reflection on the relationship between decision context and AI advice acceptance. This variable was created as the product of the CRT score and the decision context dummy (coded as 0 = Travel, 1 = Finance). This standardization ensures the comparability across variables with different scales and reduces potential multicollinearity (Gelman, 2008). The interaction variable allowed the analysis to test whether AI advice acceptance varies depending on decision context (H1) and whether cognitive reflection moderates the effect of decision context on AI advice acceptance, such that individuals with higher cognitive reflection show less variability in AI advice acceptance across contexts (H3). The model also included age, gender, education level, employment status, recruitment platform, and prior AI use as covariates.

The overall model fit was not statistically significant, χ^2 (10) = 4.05, p = .945, indicating that the predictors did not meaningfully improve model performance compared to an intercept-only model. Pseudo values (Cox and Snell $R^2 < .01$, Nagelkerke $R^2 < .01$, McFadden $R^2 = .01$) suggested that the model explained a very small proportion of the variance in AI advice acceptance. Parameter estimates revealed that the total CRT score (b = 0.04, SE = 0.08, p = .635), the decision context dummy (b = 0.20, SE = 0.5409, p = .705), and their interaction term (b = -0.03, SE = 0.12, p = .769) were not significant predictors of AI advice acceptance. Among the covariates, none showed a significant effect on the dependent variable (p > .05). These results indicate that the type of decision context did not significantly influence AI advice acceptance, contrary to H1 which posited that participants would accept AI advice more frequently in the more rational financial scenario compared to the rather intuitive travel scenario. Furthermore, the interaction term did also not significantly predict AI advice acceptance, suggesting that cognitive reflection did not moderate the relationship between decision context and AI advice acceptance, as proposed in H3.

Table 1

Results of Ordinal Regression Analysis for AI Advice Acceptance

			95% CI			
Variables	*Beta*	*SE*	*LL*	*UL*	*Z*	*p*

Age	0.02	0.01	-0.01	0.05	1.44	.149
Male	0.18	0.24	-0.30	0.65	0.73	.465
Higher Education	0.03	0.37	-0.70	0.76	0.07	.943
Student	0.11	0.57	-0.99	1.23	0.20	.842
Employed	0.11	0.56	-0.98	1.22	0.20	.845
Recruitment Platform MTurk	-0.24	0.28	-0.79	0.30	-0.88	.378
Prior AI Use	-0.18	0.29	-0.75	0.40	-0.60	.547
Total CRT Score	0.04	0.08	-0.12	0.20	0.47	.635
Scenario Finance	0.20	0.54	-0.86	1.26	0.38	.705
Interaction Term	-0.03	0.12	-0.26	0.19	-0.29	.769

Note. $N = 446$. The dependent variable is *Decision*, which represents AI advice acceptance (-1 = Rejected AI advice, 0 = No change, 1 = Accepted AI advice). The independent variables include CRT_Total (cognitive reflection total score), Decision_Context_Dummy (0 = Travel, 1 = Finance), and their interaction term. Covariates include Age, Gender, Education, Employment Status, Recruitment Platform, and Prior AI Use. **p**-values indicate statistical significance, with $p < .05$ considered significant.

These findings suggest that AI advice acceptance may not be as strongly influenced by decision context or individual cognitive reflection as initially hypothesized.

Afterwards, a separate analysis was conducted to test whether initial confidence levels would be negatively correlated with decision change after receiving advice from AI (testing H2). Spearman's rank correlation was used to analyze the relationship between initial confidence and decision change. This method was chosen because the decision change variable was ordinal, reflecting no change (0), a change in line with AI advice (1), or a change against AI advice (-1).

No significant correlation was found between initial confidence and decision change in either the travel (Spearman's $\rho = .07$, $p = .33$) or the investment scenario (Spearman's $\rho = .03$, $p =$

.667). These results do not support H2, indicating that initial confidence did not significantly influence decision change in either context.

5. Discussion

5.1. Research findings

The purpose of this study was to explore the relationship between decision context, initial confidence, and cognitive reflection in AI advice acceptance. Specifically, it examined whether decision context and initial confidence influence advice acceptance and whether cognitive reflection moderates this relationship. While prior research has extensively examined advice-taking behaviours (Yaniv, 2004), this study aimed to contribute novel insights by focusing on the interplay between decision contexts (rational vs. intuitive), cognitive reflection, and their interaction in shaping AI advice acceptance.

H1 proposed that the type of decision context (financial vs. travel scenario) would significantly influence participants' likelihood of accepting AI advice. The ordinal logistic regression analysis, however, revealed no significant main effect of decision context on advice acceptance. This finding suggests that participants' preferences for AI advice were not strongly dictated by whether the decision involved a rather rational or intuitive context. However, the ordinal logistic regression showed no significant effect, suggesting that AI advice preferences were not dictated by whether a decision was rational or intuitive. These results contrast with earlier research that highlights the context-dependence of advice-taking behaviours (Gino & Moore, 2007). One possible explanation could be the general ambiguity participants perceive in AI reliability, irrespective of the decision type (Hoff & Bashir, 2015). Alternatively, both intuition and deliberation may be perceived as equally valid approaches here.

H2 proposed that the initial confidence levels would be negatively correlated with decision change after receiving advice from AI. This was based on findings from Chong and colleagues (2022), proposing that high self-confidence leads to decision stability and thus resistance to external influence. However, the results did not support this hypothesis, as no significant correlation was found in either scenario. This suggests that initial confidence did not significantly influence decision change in either context.

One possible explanation for the lack of a significant correlation is the consistently high confidence levels that were observed among participants before receiving advice. The median confidence level was 6 out of 7, indicating that most participants were highly confident from the start, thus leaving little room for change after receiving AI advice. This suggests a ceiling effect, where high confidence levels limited the potential for change. These findings are consistent with the existing literature's conclusion that high self-confidence reduces susceptibility to AI influence (Chong et al., 2022). Therefore, the observed stability in confidence levels might be better explained by egocentric discounting described by Yaniv (2004): Participants likely maintained their initial confidence because they valued their own judgments over the AI's recommendation. This interpretation is supported by the moderate variability in confidence change, which suggests that individual differences influenced how participants processed AI advice.

H3 suggested that cognitive reflection moderates the relationship between decision context and AI advice acceptance, such that individuals with higher CRT scores would be less influenced by the decision context when evaluating AI advice, while those with lower CRT scores would show greater variability in their acceptance of AI recommendations. However, the interaction term was not statistically significant in the analysis and failed to support H3. This lack of moderation effect suggests that cognitive reflection does not necessarily stabilize AI advice-taking behaviour across different decision contexts. While prior studies (Simmons & Nelson, 2006) have indicated that cognitive abilities can moderate context effects in decision-making, the absence of a significant interaction in this study suggests that such effects may not extend to AI advice-taking scenarios. One possible explanation is that individuals high in CRT critically evaluate advice rather than automatically accepting it (Frederick, 2005; Toplak et al., 2011). Instead of being generally more open to AI advice, they may apply the same deliberative reasoning process regardless of whether the decision is more intuitive or analytical. Frederick (2005) posited that high CRT individuals only accept external advice when it offers a clear, rational advantage – which was not the case in this study. As the AI did not present a clearly superior option in either scenario, participants with high CRT scores may have simply kept their initial decisions. The lack of a moderation effect also suggests that individuals with low CRT scores were not significantly influenced by the decision context, which might be because they did not perceive a strong enough contrast between the two scenarios. If they perceived both decisions to be similarly complex, intuitive decision-making may not have been as dominant as predicted. As both the travel and investment scenarios show a strong tendency of participants to remain with their initial choices, this suggests the presence of egocentric discounting, where individuals prefer their own judgement over external recommendations

(Yaniv, 2004). Rather than cognitive reflection moderating AI advice acceptance, decision stability driven by egocentric discounting may have been the deciding factor (Yaniv & Kleinberger, 2000). Another possibility is that it is not cognitive ability, but trust in AI that is the more relevant predictor of advice acceptance. Research suggests that AI trust, rather than reflection, influences whether individuals follow algorithmic recommendations (Kohn et al., 2021). If there were different levels of trust among participants, this may have overshadowed the role of CRT. While trust in AI was not explicitly measured in this study, some survey comments suggests AI aversion in some cases ("I would never listen to advice from AI"; "I hate AI").

The findings of this study show the complexity of advice acceptance in the context of AI systems. Contrary to expectations, neither decision context nor cognitive reflection were significant predictors of AI advice-taking. This shows the importance of looking at other psychological factors to better explain variability in advice acceptance, such as trust in AI systems (Hoff & Bashir, 2015) or perceptions of AI competency (Sundar, 2008).

5.2. Theoretical Implications

This study contributes to the growing body of research on AI advice acceptance by providing new insights into how decision context and cognitive reflection influence individuals' willingness to follow AI-generated recommendations. Contrary to prior research, which suggested that people are more likely to trust AI in analytical, data-driven contexts (Gino & Moore, 2007; Vodrahalli et al., 2022), this study did not find a significant effect of decision context on AI advice acceptance. This suggests that other factors, for example prior AI trust or individual self-confidence, may play a more dominant role than decision context alone. Additionally, no evidence that cognitive reflection moderates AI advice-taking behaviour across contexts was found, despite its established role in analytical thinking and bias reduction (Frederick, 2005; Toplak et al., 2011). This poses the question if cognitive reflection has an effect on AI advice acceptance or whether it mainly affects how individuals process and evaluate information without necessarily increasing their reliance on AI recommendations. Another important consideration is that this study focused exclusively on Artificial Narrow Intelligence, as it is the only form of AI currently in use. This type of AI operates within predefined tasks and lacks the ability to generalize knowledge beyond the borders of its programmed capabilities. Furthermore, it has to be noted that AI is still a relatively new technology and has only recently been applied to decision making, which might explain some of the resistance it still faces. However, the development of Artificial General Intelligence could fundamentally reshape people's engagement with and attitude towards AI recommendations. As Artificial General Intelligence would have the ability to learn across multiple domains and adapt to individual users, its advice would be more personalized and context-aware. This could lead to a potential reduction of algorithm aversion while increasing trust in AI decisions by providing recommendations that feel more intuitive and aligned with human thinking. Similarly, if Artificial Super Intelligence were ever realized, it could lead to a complete shift in decision-making dynamics, where AI acts as the final decision-makers instead of humans – as it would be superior in every domain. Currently, this remains purely hypothetical. However, the findings from this research help to understand how humans process AI-generated advice in its current state and provide insights that may become even more relevant as AI technology continues to evolve.

5.3. Managerial Implications

This study's findings suggest that neither decision context nor cognitive reflection had a significant impact on AI advice acceptance. While this does not rule out the possibility that these factors play a role, any potential effects may be small and outweighed by other influences, such as egocentric discounting (Yaniv, 2004).

To increase AI advice acceptance, organizations should focus on building trust through transparency, clear explanations, and user control (Hoff & Bashir, 2015; Lee & See, 2004). When users understand how AI makes recommendations and feel in charge of final decisions, they are more likely to rely on it since trust and perceived reliability play a bigger role in AI adoption than cognitive traits (Dietvorst et al., 2015; Kohn et al., 2021). Given that decision type and cognitive reflection showed no significant effects, AI adoption strategies should prioritize situational and perceptual factors over assumptions about user cognition.
Lastly, these results highlight the need to explore alternative drivers of AI reliance, such as prior AI exposure, domain expertise, or decision-maker confidence. Future AI integration should be data-driven and adaptable, rather than relying on generalized expectations of when or how people will trust AI advice.

5.4. Limitations and Future Research

There are several limitations in this study that open up areas for future research. First, the lack of significant findings suggests that if decision context and cognitive reflection influenced AI advice acceptance, their effects are likely small. This raises the question of whether other factors play a bigger role. Future studies could take a closer look at variables like trust in AI (Kohn et al., 2021), prior experience with AI, or personality traits such as risk aversion and self-confidence, which have been linked to advice-taking behaviours (Chong et al., 2022). Ultimately, cognitive reflection may not be the best predictor of AI advice-taking. Other traits, such as intellectual humility, or attitudes toward AI, might provide better insights into why people do or don't trust AI recommendations.

Second, the study focused on only two decision contexts – a more analytical investment and a rather intuitive travel scenario. While these were chosen to capture differences in rational vs. intuitive decision-making, they do not fully cover the range of real-world decisions. Future research could examine AI advice-taking in areas like medical or ethical decisions, where emotions and moral values might influence AI trust and reliance more strongly.

Third, participants made an initial decision before receiving AI advice which may have reinforced their original choices due to egocentric discounting (Yaniv, 2004). While this reflects real-world decision-making, it could have limited the effect of cognitive reflection or decision context. Consequentially, the potential effects of cognitive reflection or decision context might have been masked. In the future, different approaches, for example presenting AI advice before the initial choice or measuring confidence levels beforehand, could generate insights on how certainty affects advice acceptance.

Fourth, the study relied on hypothetical scenarios rather than real-world ones. Subsequentially, decision-making in professional or high-stakes settings may be different from what was observed in this study. Future research could use field experiments or longitudinal studies to see how AI advice-taking evolves over time in real-world applications.
If these limitations are addressed in future research, it can help build a clearer understanding of how people integrate AI advice into decision-making and ultimately improve human-AI collaboration.

6. Conclusion

This dissertation investigated whether AI advice acceptance varies across different decision contexts and whether cognitive reflection moderates this effect. While prior research suggested that people might be more likely to trust AI in analytical decisions and rely on personal judgment in intuitive ones, the results of this study did not support this idea. As no significant effects were found, this suggest that other factors, such as decision stability or egocentric discounting may play a larger role in AI advice-taking. The findings show the complexity of AI advice integration as well as the need for future research to closely examine other potential influencing factors in this context.

The findings of this study contribute to research on human-AI interaction by showing the complexity of human-AI cooperation in advice-taking. To better understand this interaction, future research should take a closer look at other possible influencing factors, such as trust in AI, prior experience with the technology as well as advice taking behaviour in real-world decision environments.

As AI's influence in decision-making grows across domains, it becomes essential to understand the nuances of human-AI collaboration. Rather than assuming a universal preference for AI or human advice, future research should explore how individual, contextual, and trust-related factors interact to influence advice acceptance so researchers and practitioners can create AI systems that align more closely with human decision-making processes and thus foster a more effective AI-human collaboration.

7. Bibliography

Acharya, A., Singh, S. K., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision making in fashion industry. *International Journal of Information Management*, *42*, 90–101.

Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Exploring the impact of artificial intelligence: Prediction versus judgment. *Information Economics and Policy*, *47*, 1–6.

Aldahiri, A., Alrashed, B., & Hussain, W. (2021). Trends in Using IoT with Machine Learning in Health Prediction System. *Forecasting*, *3*(1), 181–206. https://doi.org/10.3390/forecast3010012

BaniHani, I., Alawadi, S., & Elmrayyan, N. (2024). AI and the decisio n-making process: A literature review in healthcare, financial, and technology sectors. *Journal of Decision Systems*, 1–11. https://doi.org/10.1080/12460125.2024.2349425

Belton, V., & Stewart, T. (2012). *Multiple criteria decision analysis: An integrated approach*. Springer Science & Business Media. https://books.google.de/books?hl=de&lr=&id=AYYHCAAAQBAJ&oi=fnd&pg=PP12&dq=Belton,+V.,+%26+Stewart,+T.+(2002).+Multiple+criteria+decision+analysis:+An+integrated+approach.+Springer+Science+%26+Business+Media.&ots=8PYq_Riqnu&sig=DDNPWajT_zhO1QYQ_N9It8xPSrY

Ben-Israel, D., Jacobs, W. B., Casha, S., Lang, S., Ryu, W. H. A., de Lotbiniere-Bassett, M., & Cadotte, D. W. (2020). The impact of machine learning on patient care: A systematic review. *Artificial Intelligence in Medicine*, *103*, 101785.

Bialek, M., & Pennycook, G. (2018). The cognitive reflection test is robust to multiple exposures. *Behavior Research Methods*, *50*(5), 1953–1959. https://doi.org/10.3758/s13428-017-0963-x

Buch, V. H., Ahmed, I., & Maruthappu, M. (2018). Artificial intelligence in medicine: Current trends and future possibilities. *British Journal of General Practice*, *68*(668), 143–144. https://doi.org/10.3399/bjgp18X695213

Bulten, W., Kartasalo, K., Chen, P.-H. C., Ström, P., Pinckaers, H., Nagpal, K., Cai, Y., Steiner, D. F., Van Boven, H., Vink, R., Hulsbergen-van De Kaa, C., Van Der Laak, J., Amin, M. B., Evans, A. J., Van Der Kwast, T., Allan, R., Humphrey, P. A., Grönberg, H., Samaratunga, H., … Park, J. (2022). Artificial intelligence for diagnosis and Gleason grading of prostate cancer: The PANDA challenge. *Nature Medicine*, *28*(1), 154–163. https://doi.org/10.1038/s41591-021-01620-2

Castelvecchi, D. (2016). Can we open the black box of AI? *Nature News*, *538*(7623), 20.

Chernoskutova, V., & Nelissen, R. (2021). *How Transparency and Cognitive Reflection Shape Trust in Algorithms*. http://arno.uvt.nl/show.cgi?fid=154703

Chong, L., Zhang, G., Goucher-Lambert, K., Kotovsky, K., & Cagan, J. (2022). Human confidence in artificial intelligence and in themselves: The evolution and impact of confidence on adoption of AI advice. *Computers in Human Behavior*, *127*, 107018. https://doi.org/10.1016/j.chb.2021.107018

Daugherty, P. R., & Wilson, H. J. (2018). *Human+ machine: Reimagining work in the age of AI*. Harvard Business Press. https://books.google.de/books?hl=en&lr=&id=wpY4DwAAQBAJ&oi=fnd&pg=PT14&dq=Daugherty,+P.+R.+%26amp%3B+Wilson,+H.+J.+2018.+Human%2B+machine:+Reimagining+work+in+the+age+of+AI.+Boston,+MA:+Harvard+Business+Press.&ots=Kv9txZhOGO&sig=TR4fZkAWDqYD3_fm6-YU1MISEAw

Dawes, R. M. (1979). The robust beauty of improper linear models in decision making. In *Rationality and Social Responsibility* (pp. 321–344). Psychology Press. https://api.taylorfrancis.com/content/chapters/edit/download?identifierName=doi&identifierValue=10.4324/9780203889695-14&type=chapterpdf

Dhar, R., & Wertenbroch, K. (2000). Consumer Choice between Hedonic and Utilitarian Goods. *Journal of Marketing Research*, *37*(1), 60–71. https://doi.org/10.1509/jmkr.37.1.60.18718

Diab, D. L., Pui, S.-Y., Yankelevich, M., & Highhouse, S. (2011). Lay Perceptions of Selection Decision Aids in US and Non-US Samples: Selection Decision Aids. *International Journal of Selection and Assessment*, *19*(2), 209–216. https://doi.org/10.1111/j.1468-2389.2011.00548.x

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). *Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda (An opinion paper for International Journal of Information Management)*.

Einhorn, H. J. (1986). Accepting Error to Make Less Error. *Journal of Personality Assessment*, *50*(3), 387–395. https://doi.org/10.1207/s15327752jpa5003_8

Evans, J. St. B. T. (2008). Dual-Processing Accounts of Reasoning, Judgment, and Social Cognition. *Annual Review of Psychology*, *59*(1), 255–278. https://doi.org/10.1146/annurev.psych.59.103006.093629

Fleming, S. M. (2024). Metacognition and Confidence: A Review and Synthesis. *Annual Review of Psychology*, *75*(1), 241–268. https://doi.org/10.1146/annurev-psych-022423-032425

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives*, *19*(4), 25–42.

Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. *Statistics in Medicine*, *27*(15), 2865–2873. https://doi.org/10.1002/sim.3107

Gigerenzer, G., & Todd, P. M. (1999). Fast and frugal heuristics: The adaptive toolbox. In *Simple heuristics that make us smart* (pp. 3–34). Oxford University Press. https://pure.mpg.de/rest/items/item_2102905/component/file_2102904/content

Gino, F., & Moore, D. A. (2007). Effects of task difficulty on use of advice. *Journal of Behavioral Decision Making*, *20*(1), 21–35. https://doi.org/10.1002/bdm.539

Goertzel, B. (2014). Artificial General Intelligence: Concept, State of the Art, and Future Prospects. *Journal of Artificial General Intelligence*, *5*(1), 1–48. https://doi.org/10.2478/jagi-2014-0001

Hao, K. (2019, January 19). AI is sending people to jail—And getting it wrong. *MIT Technology Review*. https://www.technologyreview.com/2019/01/21/137783/algorithms-criminal-justice-ai/

Harvey, N., & Fischer, I. (1997). Taking advice: Accepting help, improving judgment, and sharing responsibility. *Organizational Behavior and Human Decision Processes*, *70*(2), 117–133.

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors*, *57*(3), 407–434.

Hollnagel, E., & Woods, D. D. (2005). *Joint cognitive systems: Foundations of cognitive systems engineering*. CRC press. https://www.taylorfrancis.com/books/mono/10.1201/9781420038194/joint-cognitive-systems-erik-hollnagel-david-woods

Ji, H., Han, I., & Ko, Y. (2023). A systematic review of conversational AI in language education: Focusing on the collaboration with human teachers. *Journal of Research* *on Technology in Education*, *55*(1), 48–63. https://doi.org/10.1080/15391523.2022.2142873

Jumper, J., Evans, R., Pritzel, A., Green, T., Figurnov, M., Ronneberger, O., Tunyasuvunakool, K., Bates, R., Žídek, A., & Potapenko, A. (2021). Highly accurate protein structure prediction with AlphaFold. *Nature*, *596*(7873), 583–589.

Kahneman, D. (2011). Thinking, fast and slow. *Farrar, Straus and Giroux*. https://www.pdcnet.org/pdc/bvdb.nsf/showopenaccess?open&repid=852577BA0050DC0D&docid=2BE9C7FA6C507E4DC1257ADA0072A186&solarid=inquiryct_2012_0027_0002_0054_0057

Kahneman, D. (2017). *Thinking, fast and slow*. http://dspace.vnbrims.org:13000/jspui/bitstream/123456789/2224/1/Daniel-Kahneman-Thinking-Fast-and-Slow-.pdf

Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. *Heuristics and Biases: The Psychology of Intuitive Judgment*, *49*(49–81), 74.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kawaguchi, K. (2021). When Will Workers Follow an Algorithm? A Field Experiment with a Retail Business. *Management Science*, *67*(3), 1670–1695. https://doi.org/10.1287/mnsc.2020.3599

Koenigstein, N., Dror, G., & Koren, Y. (2011). Yahoo! music recommendations: Modeling music ratings with temporal dynamics and item taxonomy. *Proceedings of the Fifth ACM Conference on Recommender Systems*, 165–172. https://doi.org/10.1145/2043932.2043964

Kohn, S. C., De Visser, E. J., Wiese, E., Lee, Y.-C., & Shaw, T. H. (2021). Measurement of trust in automation: A narrative review and reference guide. *Frontiers in Psychology*, *12*, 604977.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444.

Lee, J. D., & See, K. A. (2004). Trust in Automation: Designing for Appropriate Reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392

Linden, G., Smith, B., & York, J. (2003). Amazon. com recommendations: Item-to-item collaborative filtering. *IEEE Internet Computing*, *7*(1), 76–80.

Linstone, H. A., & Turoff, M. (1975). *The delphi method*. Addison-Wesley Reading, MA. https://www.academia.edu/download/29694542/delphibook.pdf

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103.

Lu, J., Liu, Z., & Fang, Z. (2016). Hedonic products for you, utilitarian products for me. *Judgment and Decision Making*, *11*(4), 332–341.

Mahmud, H., Islam, A. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technological Forecasting and Social Change*, *175*, 121390.

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

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. *AI Magazine*, *27*(4), 12–12.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. *AI Magazine*, *27*(4), 12–12.

Meyer, A., Zhou, E., & Frederick, S. (2018). The non-effects of repeated exposure to the Cognitive Reflection Test. *Judgment and Decision Making*, *13*(3), 246–259.

Mitchell, T. M., & Mitchell, T. M. (1997). *Machine learning* (Vol. 1). McGraw-hill New York. http://www.pachecoj.com/courses/csc380_fall21/lectures/mlintro.pdf

Musiolik, J., Markard, J., Hekkert, M., & Furrer, B. (2020). Creating innovation systems: How resource constellations affect the strategies of system builders. *Technological Forecasting and Social Change*, *153*, 119209.

Parasuraman, R., & Riley, V. (1997). Humans and Automation: Use, Misuse, Disuse, Abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *39*(2), 230–253. https://doi.org/10.1518/001872097778543886

Primi, C., Morsanyi, K., Chiesi, F., Donati, M. A., & Hamilton, J. (2016). The Development and Testing of a New Version of the Cognitive Reflection Test Applying Item Response Theory (IRT). *Journal of Behavioral Decision Making*, *29*(5), 453–469. https://doi.org/10.1002/bdm.1883

Rao, A. S., & Verweij, G. (2017). *Sizing the prize: What's the real value of AI for your business and how can you capitalise?* https://policycommons.net/artifacts/10771878/sizing-the-prize/11649558/

Schemmer, M., Hemmer, P., Kühl, N., Benz, C., & Satzger, G. (2022). *Should I Follow AI-based Advice? Measuring Appropriate Reliance in Human-AI Decision-Making* (arXiv:2204.06916). arXiv. http://arxiv.org/abs/2204.06916

Selvaraj, C., Chandra, I., & Singh, S. K. (2022). Artificial intelligence and machine learning approaches for drug design: Challenges and opportunities for the pharmaceutical industries. *Molecular Diversity*, *26*(3), 1893–1913. https://doi.org/10.1007/s11030-021-10326-z

Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational Decision-Making Structures in the Age of Artificial Intelligence. *California Management Review*, *61*(4), 66–83. https://doi.org/10.1177/0008125619862257

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., & Lanctot, M. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, *529*(7587), 484–489.

Simmons, J. P., & Nelson, L. D. (2006). Intuitive confidence: Choosing between intuitive and nonintuitive alternatives. *Journal of Experimental Psychology: General*, *135*(3), 409.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 99–118.

Sirota, M., Dewberry, C., Juanchich, M., Valuš, L., & Marshall, A. C. (2021). Measuring cognitive reflection without maths: Development and validation of the verbal cognitive reflection test. *Journal of Behavioral Decision Making*, *34*(3), 322–343. https://doi.org/10.1002/bdm.2213

Stankov, L., Kleitman, S., & Jackson, S. A. (2015). Measures of the trait of confidence. *Measures of Personality and Social Psychological Constructs*, 158–189.

Stanovich, K. E. (1999). *Who is rational?: Studies of individual differences in reasoning*. Psychology Press. https://www.taylorfrancis.com/books/mono/10.4324/9781410603432/rational-keith-stanovich

Steck, H., Baltrunas, L., Elahi, E., Liang, D., Raimond, Y., & Basilico, J. (2021). Deep learning for recommender systems: A Netflix case study. *AI Magazine*, *42*(3), 7–18.

Sundar, S. S. (2008). *The MAIN model: A heuristic approach to understanding technology effects on credibility*. MacArthur Foundation Digital Media and Learning Initiative Cambridge, MA. https://betterlegalinfo.ca/wp-content/uploads/2019/12/Sundar-paper.pdf

Szeliski, R. (2009). *Computer vision: Algorithms and applications*. Springer Nature. https://books.google.de/books?hl=de&lr=&id=QptXEAAAQBAJ&oi=fnd&pg=PR9&dq=Szeliski,+R.+(2011).+Computer+vision:+Algorithms+and+applications.+Springer&ots=BNwiBZREzn&sig=EyhC5VTMgO3lrX0iMOo1cApfeb0

The Royal Swedish Academy of Sciences. (2024). *The Nobel Prize in Chemistry 2024*. https://www.nobelprize.org/uploads/2024/10/press-chemistryprize2024-2.pdf

Toplak, M. E., West, R. F., & Stanovich, K. E. (2011). The Cognitive Reflection Test as a predictor of performance on heuristics-and-biases tasks. *Memory & Cognition*, *39*(7), 1275–1289. https://doi.org/10.3758/s13421-011-0104-1

Tsikriktsis, N. (2005). A review of techniques for treating missing data in OM survey research. *Journal of Operations Management*, *24*(1), 53–62.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, *106*(4), 1039–1061.

Vodrahalli, K., Daneshjou, R., Gerstenberg, T., & Zou, J. (2022). Do Humans Trust Advice More if it Comes from AI?: An Analysis of Human-AI Interactions. *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*, 763–777. https://doi.org/10.1145/3514094.3534150

Yang, H., & Gosline, R. R. (2020). Cognitive style impacts preference for advice seeking from AI. *Management Science*, *64*(3), 1155–1170.

Yaniv, I. (2004). Receiving other people's advice: Influence and benefit. *Organizational Behavior and Human Decision Processes*, *93*(1), 1–13.

Yaniv, I., & Kleinberger, E. (2000). Advice taking in decision making: Egocentric discounting and reputation formation. *Organizational Behavior and Human Decision Processes*, *83*(2), 260–281.

Yaniv, I., & Milyavsky, M. (2007). Using advice from multiple sources to revise and improve judgments. *Organizational Behavior and Human Decision Processes*, *103*(1), 104–120.

Zhang, L., Pentina, I., & Fan, Y. (2021). Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services. *Journal of Services Marketing*, *35*(5), 634–646.

Appendices

Appendix 1: Dissertation Survey

Start of Block: Introductory Information

Welcome and thank you for participating in this research study. The purpose of this survey is to understand how people evaluate advice from artificial intelligence.

This survey will take approximately 6 minutes. Please read each scenario carefully and answer the questions that follow based on your preferences and instincts. There are no right or wrong answers, so please respond honestly. Your participation is entirely voluntary. All responses will remain anonymous and confidential.

By proceeding with the survey, you confirm that: • You have been informed of the purpose of the study and understand that your participation is voluntary. • You are at least 18 years old. • You consent to participate in this research, and your responses will be used for academic purposes only.

○ I consent to participate in this survey (1)

End of Block: Introductory Information

Start of Block: Intellectual Humility

Q22 When someone disagrees with ideas that are important to me, it feels as though I'm being attacked.

○ Strongly Disagree (1)

○ Disagree (2)

○ Neutral (3)

○ Agree (4)

○ Strongly Agree (5)

Q23 I am open to considering other viewpoints, even when they challenge my own strongly held beliefs.

- Strongly Disagree (1)
- Disagree (2)
- Neutral (3)
- Agree (4)
- Strongly Agree (5)

Q24 This is an attention check, please select "Strongly Disagree".

- Strongly Disagree (1)
- Disagree (2)
- Neutral (3)
- Agree (4)
- Strongly Agree (5)

Q64 I am willing to change my position on an important issue in the face of good reasons.

- Strongly Disagree (1)
- Disagree (2)
- Neutral (3)
- Agree (4)
- Strongly Agree (5)

Q25 I am open to revising my beliefs if I am presented with convincing evidence.

- Strongly Disagree (1)
- Disagree (2)
- Neutral (3)
- Agree (4)
- Strongly Agree (5)

Q26 I respect that there are ways of making important decisions that are different from the way I make decisions.

- Strongly Disagree (1)
- Disagree (2)
- Neutral (3)
- Agree (4)
- Strongly Agree (5)

Q27 I can have great respect for someone even if I disagree with them.

○ Strongly Disagree (1)

○ Disagree (2)

○ Neutral (3)

○ Agree (4)

○ Strongly Agree (5)

Q28 I recognize that I am not as knowledgeable as some other people.

○ Strongly Disagree (1)

○ Disagree (2)

○ Neutral (3)

○ Agree (4)

○ Strongly Agree (5)

Q29 I am willing to admit if I don’t know something.

○ Strongly Disagree (1)

○ Disagree (2)

○ Neutral (3)

○ Agree (4)

○ Strongly Agree (5)

End of Block: Intellectual Humility

Start of Block: Cognitive Reflection Test - Mixed Version (CRT, CRT-V, CRT-L)

Q43 In the next section, you will see a set of questions designed to assess problem-solving and reasoning abilities. Please take your time and answer each question carefully.

Q15 In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half the lake?

____

Q17 If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?

____

Q18 A farmer has 15 sheep, and all but 8 die. How many are left?

____

Q19 You are running a race and you pass the person in second place. What place are you in now?

____

Q20 John's mother has three children. The first is named April, the second is named May. What is the name of the third child?

____

Q21 You're in a dark room with one match. There is a candle, a lamp, and a firewood stove in the room. Which do you light first?

____

End of Block: Cognitive Reflection Test - Mixed Version (CRT, CRT-V, CRT-L)

Start of Block: Experimental Scenario - Intuitive - A

Q45 Imagine you are planning your next summer vacation. You've decided to take two weeks off to treat yourself to something truly special. Two destinations have caught your eye, each offering a unique appeal. You're drawn to both options for different reasons, and they each promise a memorable experience.
If you are on mobile, please swipe to see the full table.

	Destination A - Cala Luna	**Destination B - Sunport Bay**
Location	A secluded coastal area accessible only by boat from the nearest town, known for serene coves and clear waters.	A lively beach town, easily reachable by car, known for sandy beaches, shops, and vibrant nightlife.
Atmosphere	Cala Luna is peaceful and isolated, with unspoiled beaches and minimal tourists, offering a sense of exclusivity. Evenings are quiet, with stunning ocean sunsets and the sounds of nature.	Sunport Bay is bustling, with plenty of tourists, restaurants, and events creating a lively, social scene.
Accommodation	A family-run eco-lodge with rustic charm and limited amenities, ideal for disconnecting. Wi-Fi is available only in the lobby.	A modern hotel with all amenities, including a pool and high-speed internet, close to the beach.
Appeal	This destination promises tranquility, natural beauty, and a chance to fully unplug from daily life.	This destination offers comfort, convenience, and an energetic atmosphere with opportunities to meet people and enjoy various activities.

Q34 Take a moment to reflect on each option and make a choice based on your initial feeling. Think about which destination aligns more closely with the experience you want from this vacation.

○ Destination A - Cala Luna (1)

○ Destination B - Sunport Bay (2)

Q38 Please rate how confident you feel about your decision.

○ 1 = Not at all confident (1)

○ 2 (2)

○ 3 (3)

○ 4 = Moderately confident (4)

○ 5 (5)

○ 6 (6)

○ 7 = Extremely confident (7)

Q35 After making your initial decision, you consult an AI travel advisor. The AI analyzes your preferences and recommends **Destination A - Cala Luna**, explaining that this option aligns with your desire for an exclusive, peaceful getaway that allows you to reconnect with nature.

Q36 Reflect on the AI's recommendation. Does this advice influence your choice? Please indicate your final decision:

○ After receiving the AI's advice, I would choose Destination A - Cala Luna (1)

○ After receiving the AI's advice, I would choose Destination B - Sunport Bay (2)

Q47 Please rate how confident you feel about your decision.

- ◯ 1 = Not at all confident (1)
- ◯ 2 (2)
- ◯ 3 (3)
- ◯ 4 = Moderately confident (4)
- ◯ 5 (5)
- ◯ 6 (6)
- ◯ 7 = Extremely confident (7)

End of Block: Experimental Scenario - Intuitive - A

Start of Block: Experimental Scenario - Deliberate - C

Q46 Imagine you have recently received a large sum of money, and you are looking to invest it wisely to secure your financial future. You've narrowed down your options to two investment opportunities, each with its own level of risk and potential return.
If you are on mobile, please swipe to see the full table.

	Option A - Stable Fund	**Option B - High-Growth Fund**
Type	A low-risk investment fund that focuses on stable, established companies.	A high-risk investment fund targeting emerging markets and innovative sectors.
Expected Return	A steady annual return, likely around 4-5%.	Potential for high returns, possibly 10% or more, but with greater volatility.
Risk Level	Minimal fluctuations; considered a safe choice with limited chance of loss.	Significant ups and downs; risk of loss is higher, especially in unstable market conditions.
Appeal	This option is designed for those looking for reliable, long-term growth without major risks.	This option appeals to those willing to take risks for the possibility of high rewards in a shorter timeframe.

Q41 Consider each option carefully and make a choice based on your investment goals and risk tolerance. Think about which option aligns better with your financial strategy.

- ○ Option A - Stable Fund (1)
- ○ Option B - High-Growth Fund (2)

Q48 Please rate how confident you feel about your decision.

- ○ 1 = Not at all confident (1)
- ○ 2 (2)
- ○ 3 (3)
- ○ 4 = Moderately confident (4)
- ○ 5 (5)
- ○ 6 (6)
- ○ 7 = Extremely confident (7)

Q43 After making your initial decision, you consult an AI investment advisor. The AI reviews market data and trends and recommends **Option A - Stable Fund**, emphasizing that it offers more security and steady growth, especially in uncertain economic times.

Q44 Reflect on the AI's recommendation. Does this advice influence your choice? Please indicate your final decision.

○ After receiving the AI's advice, I would choose Option A. (1)

○ After receiving the AI's advice, I would choose Option B (2)

Q49 Please rate how confident you feel about your decision.

○ 1 = Not at all confident (1)

○ 2 (2)

○ 3 (3)

○ 4 = Moderately confident (4)

○ 5 (5)

○ 6 (6)

○ 7 = Extremely confident (7)

End of Block: Experimental Scenario - Deliberate - C

Start of Block: Experimental Scenario - Intuitive - B

Q59 Imagine you are planning your next summer vacation. You've decided to take two weeks off to treat yourself to something truly special. Two destinations have caught your eye, each

offering a unique appeal. You're drawn to both options for different reasons, and they each promise a memorable experience.
If you are on mobile, please swipe to see the full table.

	Destination A - Cala Luna	Destination B - Sunport Bay
Location	A secluded coastal area accessible only by boat from the nearest town, known for serene coves and clear waters.	A lively beach town, easily reachable by car, known for sandy beaches, shops, and vibrant nightlife.
Atmosphere	Cala Luna is peaceful and isolated, with unspoiled beaches and minimal tourists, offering a sense of exclusivity. Evenings are quiet, with stunning ocean sunsets and the sounds of nature.	Sunport Bay is bustling, with plenty of tourists, restaurants, and events creating a lively, social scene.
Accommodation	A family-run eco-lodge with rustic charm and limited amenities, ideal for disconnecting. Wi-Fi is available only in the lobby.	A modern hotel with all amenities, including a pool and high-speed internet, close to the beach.
Appeal	This destination promises tranquility, natural beauty, and a chance to fully unplug from daily life.	This destination offers comfort, convenience, and an energetic atmosphere with opportunities to meet people and enjoy various activities.

Q60 Take a moment to reflect on each option and make a choice based on your initial feeling. Think about which destination aligns more closely with the experience you want from this vacation.

- ◯ Destination A - Cala Luna (1)
- ◯ Destination B - Sunport Bay (2)

Q61 Please rate how confident you feel about your decision.

- ◯ 1 = Not at all confident (1)
- ◯ 2 (2)
- ◯ 3 (3)
- ◯ 4 = Moderately confident (4)
- ◯ 5 (5)
- ◯ 6 (6)
- ◯ 7 = Extremely confident (7)

Q62 Based on your preferences and travel data, the AI recommends **Option B - Sunport Bay**. This destination offers convenience, accessibility, and a lively atmosphere with numerous amenities. It’s a practical choice that ensures comfort and social opportunities.

Q63 Reflect on the AI’s recommendation. Does this advice influence your choice? Please indicate your final decision:

- ◯ After receiving the AI’s advice, I would choose Destination A - Cala Luna (1)
- ◯ After receiving the AI’s advice, I would choose Destination B - Sunport Bay (2)

Q64 Please rate how confident you feel about your decision.

- ◯ 1 = Not at all confident (1)
- ◯ 2 (2)
- ◯ 3 (3)
- ◯ 4 = Moderately confident (4)
- ◯ 5 (5)
- ◯ 6 (6)
- ◯ 7 = Extremely confident (7)

End of Block: Experimental Scenario - Intuitive - B

Start of Block: Experimental Scenario - Deliberate – D

Q66 Imagine you have recently received a large sum of money, and you are looking to invest it wisely to secure your financial future. You've narrowed down your options to two investment opportunities, each with its own level of risk and potential return.

If you are on mobile, please swipe to see the full table.

	Option A - Stable Fund	Option B - High-Growth Fund
Type	A low-risk investment fund that focuses on stable, established companies.	A high-risk investment fund targeting emerging markets and innovative sectors.
Expected Return	A steady annual return, likely around 4-5%.	Potential for high returns, possibly 10% or more, but with greater volatility.
Risk Level	Minimal fluctuations; considered a safe choice with limited chance of loss.	Significant ups and downs; risk of loss is higher, especially in unstable market conditions.
Appeal	This option is designed for those looking for reliable, long-term growth without major risks.	This option appeals to those willing to take risks for the possibility of high rewards in a shorter timeframe.

Q67 Consider each option carefully and make a choice based on your investment goals and risk tolerance. Think about which option aligns better with your financial strategy.

○ Option A - Stable Fund (1)

○ Option B - High-Growth Fund (2)

Q68 Please rate how confident you feel about your decision.

○ 1 = Not at all confident (1)

○ 2 (2)

○ 3 (3)

○ 4 = Moderately confident (4)

○ 5 (5)

○ 6 (6)

○ 7 = Extremely confident (7)

Q69 Based on emerging market data and growth potential, the AI recommends **Option B - High-Growth Fund**. This option aligns with higher risk-tolerance and the potential for substantial returns, ideal for those willing to take calculated risks for greater rewards.

Q70 Reflect on the AI's recommendation. Does this advice influence your choice? Please indicate your final decision.

○ After receiving the AI's advice, I would choose Option A. (1)

○ After receiving the AI's advice, I would choose Option B (2)

Q71 Please rate how confident you feel about your decision.

- ◯ 1 = Not at all confident (1)
- ◯ 2 (2)
- ◯ 3 (3)
- ◯ 4 = Moderately confident (4)
- ◯ 5 (5)
- ◯ 6 (6)
- ◯ 7 = Extremely confident (7)

End of Block: Experimental Scenario - Deliberate - D

Start of Block: Demographics

Q10 Please answer the following questions about yourself.

What is your age?

____

Q11 What is your gender?

- ◯ Male (1)
- ◯ Female (2)
- ◯ Non-binary / Third gender (3)
- ◯ Prefer not to say (4)

Q12 What is the highest level of education you have completed?

- ◯ Less than High School (1)
- ◯ High School (2)
- ◯ Vocational Training / Trade Degree (3)
- ◯ Bachelor's Degree (4)
- ◯ Master's Degree (5)
- ◯ Doctoral Degree (6)
- ◯ Other (please specify) (7) ____

Q13 What is your employment status?

- ◯ Full-time (1)
- ◯ Part-Time (2)
- ◯ Self-employed (3)
- ◯ Unemployed (4)
- ◯ Student (5)
- ◯ Retired (6)
- ◯ Other (please specify) (7) ____

Q14 Have you ever used AI-based systems (such as virtual assistants, chatbots, or decision-making tools (e.g. ChatGPT))?

○ Yes (1)

○ No (2)

○ I don't know (3)

End of Block: Demographics

Start of Block: Block 8

Q65 Please leave any additional comments that you might have here.

____

End of Block: Block 8

Appendix 2: Data Analysis

Frequency table for Attention Check

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Fail	15	5.2	5.2	5.2
	Pass	275	94.8	94.8	100.0
	Total	290	100.0	100.0	

Frequency table for Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	141	62.9	62.9	62.9
	Female	77	34.4	34.4	97.3
	Non-binary / Third gender	5	2.2	2.2	99.6
	Prefer not to say	1	.4	.4	100.0
	Total	224	100.0	100.0	

Descriptive Statistics for Age

	N	Minimum	Maximum	Mean	Std. Deviation
What is your age?	224	18	59	28.84	7.763
Valid N (listwise)	224				

Frequency table for Education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than High School	2	.9	.9	.9
	High School	19	8.5	8.5	9.4
	Vocational Training / Trade Degree	3	1.3	1.3	10.7
	Bachelor's Degree	161	71.9	71.9	82.6
	Master's Degree	37	16.5	16.5	99.1
	Doctoral Degree	1	.4	.4	99.6
	Other (please specify)	1	.4	.4	100.0
	Total	224	100.0	100.0	

Frequency table for Employment

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Full-time	150	67.0	67.0	67.0
	Part-Time	13	5.8	5.8	72.8
	Self-employed	7	3.1	3.1	75.9
	Unemployed	4	1.8	1.8	77.7
	Student	45	20.1	20.1	97.8
	Retired	2	.9	.9	98.7
	Other (please specify)	3	1.3	1.3	100.0
	Total	224	100.0	100.0	

Frequency table for prior AI use

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	161	71.9	71.9	71.9
	No	63	28.1	28.1	100.0
	Total	224	100.0	100.0	

Appendix 3: Data Preparation and Scale Reliability

IH Scale Reliability with all 8 items

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Intellectual Humility	.543	.558	8

IH Scale Reliability after removal of the reverse coded item: "When someone disagrees with ideas that are important to me, it feels as though I am being attacked."

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Intellectual Humility	.568	.569	7

Frequency table for Recruitment_Platform_Dummy

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	106	47.3	47.3	47.3
	1	118	52.7	52.7	100.0
	Total	224	100.0	100.0	

Frequency table for Employment_Status_Dummy

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	54	24.1	24.1	24.1
	1	170	75.9	75.9	100.0
	Total	224	100.0	100.0	

Frequency table for Employment_Student_Dummy

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	179	79.9	79.9	79.9
	1	45	20.1	20.1	100.0
	Total	224	100.0	100.0	

Frequency table for Education_High_Dummy

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	25	11.2	11.2	11.2
	1	199	88.8	88.8	100.0
	Total	224	100.0	100.0	

Frequency table for Prior_AI_Use_Dummy

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	63	28.1	28.1	28.1
	1	161	71.9	71.9	100.0
	Total	224	100.0	100.0	

Frequency table for AI_Recommendation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	116	51.8	51.8	51.8
	1	108	48.2	48.2	100.0
	Total	224	100.0	100.0	

Frequency table for Decision_Travel

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	-1	22	9.8	9.8	9.8
	0	169	75.4	75.4	85.3
	1	33	14.7	14.7	100.0

	Total	224	100.0	100.0	

Frequency table for Decision Changes in Travel Scenario – Option A

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	29	64.4	64.4	64.4
	1	16	35.6	35.6	100.0
	Total	45	100.0	100.0	

Frequency table for Decision Changes in Travel Scenario – Option B

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	17	27.4	27.4	27.4
	1	45	72.6	72.6	100.0
	Total	62	100.0	100.0	

Frequency table for Decision Changes in Investment Scenario – Option A

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	18	48.6	48.6	48.6
	1	19	51.4	51.4	100.0
	Total	37	100.0	100.0	

Frequency table for Decision Changes in Investment Scenario – Option B

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	21	28.4	28.4	28.4
	1	53	71.6	71.6	100.0
	Total	74	100.0	100.0	

Frequency table for Decision_Investment

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	-1	26	11.6	11.6	11.6
	0	158	70.5	70.5	82.1
	1	40	17.9	17.9	100.0
	Total	224	100.0	100.0	

Frequency table for Confidence_Travel_Change

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	-4	3	1.3	1.3	1.3
	-3	4	1.8	1.8	3.1

	-2	7	3.1	3.1	6.3
	-1	26	11.6	11.6	17.9
	0	129	57.6	57.6	75.4
	1	42	18.8	18.8	94.2
	2	10	4.5	4.5	98.7
	3	1	.4	.4	99.1
	4	2	.9	.9	100.0
	Total	224	100.0	100.0	

Frequency table for Confidence_Investment_Change

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	-4	1	.4	.4	.4
	-3	5	2.2	2.2	2.7
	-2	15	6.7	6.7	9.4
	-1	39	17.4	17.4	26.8
	0	122	54.5	54.5	81.3
	1	31	13.8	13.8	95.1
	2	7	3.1	3.1	98.2
	3	4	1.8	1.8	100.0
	Total	224	100.0	100.0	

Descriptive Statistics table for Confidence_Travel_Change and Confidence_Investment_Change

Descriptives

	Confidence_Travel_Change	Confidence_Investment_Change
N	224	224
Missing	0	0
Mean	0.0402	−0.138
Median	0.00	0.00
Standard deviation	1.08	1.06
Minimum	−4.00	−4.00
Maximum	4.00	3.00

Descriptive Statistics table for confidence levels before and after receiving advice from AI

Descriptives

	Confidence_Travel_Pre	Confidence_Travel_Post	Confidence_Investment_Pre	Confidence_Investment_Post
N	224	224	224	224
Missing	0	0	0	0
Mean	5.58	5.62	5.59	5.45
Median	6.00	6.00	6.00	6.00
Standard deviation	1.28	1.41	1.28	1.32
Minimum	1	1	1	1
Maximum	7	7	7	7

Descriptive Statistics table for total CRT score (CRT_Total)

N	Valid	224
	Missing	0
Mean		4.26
Median		5.00
Std. Deviation		1.803
Minimum		0
Maximum		6

Frequency table for total CRT score (CRT_Total)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	13	5.8	5.8	5.8
	1	9	4.0	4.0	9.8
	2	24	10.7	10.7	20.5
	3	19	8.5	8.5	29.0
	4	21	9.4	9.4	38.4
	5	72	32.1	32.1	70.5
	6	66	29.5	29.5	100.0
	Total	224	100.0	100.0	

Descriptive Statistics for the t-test

	Recruitment_Plattform_Dummy	N	Mean	Std. Deviation	Std. Error Mean
CRT_Total	0	106	4.46	1.758	.171
	1	118	4.08	1.831	.169

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means		
		F	Sig.	t	df	Significance One-Sided p
CRT_Total	Equal variances assumed	1.077	.300	1.605	222	.055
	Equal variances not assumed			1.609	221.015	.055

		t-test for Equality of Means				
		Significance Two-Sided p	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
CRT_Total	Equal variances assumed	.110	.386	.240	-.088	.860

	Equal variances not assumed	.109	.386	.240	-.087	.859

Independent Samples Effect Sizes

		Standardizer (a.)	Point Estimate	95% Confidence Interval	
				Lower	Upper
CRT_Total	Cohen's d	1.797	.215	-.048	.478
	Hedges' correction	1.803	.214	-.048	.476
	Glass's delta	1.831	.211	-.053	.474

a. The denominator used in estimating the effect sizes. Cohen's d uses the pooled standard deviation. Hedges' correction uses the pooled standard deviation, plus a correction factor. Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Bivariate Correlations Table

Correlations

			Gender_Dummy	Age	Recruitment_Plattform_Dummy	Education_High_Dummy	Employment_Status_Dummy	Employment_Student_Dummy	CRT_Total	Decision_Travel	Decision_Investment	Confidence_Travel_Change	Confidence_Investment_Change	AI_Recommendation	Prior_AI_Use_Dummy
Spearman's rho	Gender_Dummy	Correlation Coefficient	1.000	-.003	.243**	.245**	.220**	-.196**	.108	.062	.025	.021	-.001	.013	-.375**
		Sig. (2-tailed)	.	.966	<.001	<.001	<.001	.003	.108	.358	.712	.755	.989	.844	<.001
		N	223	223	223	223	223	223	223	223	223	223	223	223	223
	Age	Correlation Coefficient	-.003	1.000	.222**	.258**	.395**	-.434**	-.015	.093	.022	.019	.054	.055	-.059
		Sig. (2-tailed)	.966	.	<.001	<.001	<.001	<.001	.823	.164	.740	.775	.423	.409	.382
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	Recruitment_Plattform_Dummy	Correlation Coefficient	.243**	.222**	1.000	.232**	.574**	-.507**	-.122	.030	-.061	.018	.069	.002	-.474**
		Sig. (2-tailed)	<.001	<.001	.	<.001	<.001	<.001	.068	.657	.363	.787	.306	.977	<.001
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	Education_High_Dummy	Correlation Coefficient	.245**	.258**	.232**	1.000	.364**	-.247**	.135*	.068	-.008	.032	-.041	-.055	-.222**
		Sig. (2-tailed)	<.001	<.001	<.001	.	<.001	<.001	.044	.312	.903	.634	.542	.411	<.001
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	Employment_Status_Dummy	Correlation Coefficient	.220**	.395**	.574**	.364**	1.000	-.890**	.026	.061	-.024	.024	-.011	.084	-.353**
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	.	<.001	.694	.361	.726	.726	.867	.209	<.001
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	Employment_Student_Dummy	Correlation Coefficient	-.196**	-.434**	-.507**	-.247**	-.890**	1.000	-.024	-.054	.017	-.062	.032	-.105	.314**
		Sig. (2-tailed)	.003	<.001	<.001	<.001	<.001	.	.718	.420	.795	.359	.631	.118	<.001
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	CRT_Total	Correlation Coefficient	.108	-.015	-.122	.135*	.026	-.024	1.000	.049	.015	.029	.039	.139*	.012
		Sig. (2-tailed)	.108	.823	.068	.044	.694	.718	.	.466	.819	.665	.564	.038	.862
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	Decision_Travel	Correlation Coefficient	.062	.093	.030	.068	.061	-.054	.049	1.000	.103	.008	-.037	-.040	-.104
		Sig. (2-tailed)	.358	.164	.657	.312	.361	.420	.466	.	.125	.910	.578	.549	.120
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	Decision_Investment	Correlation Coefficient	.025	.022	-.061	-.008	-.024	.017	.015	.103	1.000	.028	.010	.004	.047
		Sig. (2-tailed)	.712	.740	.363	.903	.726	.795	.819	.125	.	.677	.880	.957	.486
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	Confidence_Travel_Change	Correlation Coefficient	.021	.019	.018	.032	.024	-.062	.029	.008	.028	1.000	.069	-.066	.091
		Sig. (2-tailed)	.755	.775	.787	.634	.726	.359	.665	.910	.677	.	.305	.322	.177
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	Confidence_Investment_Change	Correlation Coefficient	-.001	.054	.069	-.041	-.011	.032	.039	-.037	.010	.069	1.000	.092	.057
		Sig. (2-tailed)	.989	.423	.306	.542	.867	.631	.564	.578	.880	.305	.	.171	.398
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	AI_Recommendation	Correlation Coefficient	.013	.055	.002	-.055	.084	-.105	.139*	-.040	.004	-.066	.092	1.000	.007
		Sig. (2-tailed)	.844	.409	.977	.411	.209	.118	.038	.549	.957	.322	.171	.	.912
		N	223	224	224	224	224	224	224	224	224	224	224	224	224
	Prior_AI_Use_Dummy	Correlation Coefficient	-.375**	-.059	-.474**	-.222**	-.353**	.314**	.012	-.104	.047	.091	.057	.007	1.000
		Sig. (2-tailed)	<.001	.382	<.001	<.001	<.001	<.001	.862	.120	.486	.177	.398	.912	.
		N	223	224	224	224	224	224	224	224	224	224	224	224	224

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix 4: Hypothesis testing

Parameter estimates for ordinal regression (hypothesis test H1 & H3)

Model Fit Measures

							Overall Model Test		
Model	**Deviance**	**AIC**	**BIC**	**R^2_{McF}**	**R^2_{CS}**	**R^2_N**	**χ^2**	**df**	**p**
1	680	704	753	0.00592	0.00302	0.00755	4.05	10	0.945

Note. The dependent variable 'Decision' has the following order: -1 | 0 | 1

Note. Models estimated using sample size of N=446

Model Coefficients - Decision

		95% Confidence Interval				
Predictor	**Estimate**	**Lower**	**Upper**	**SE**	**Z**	**p**
Age	0.0211	-0.00773	0.0495	0.0146	1.4429	0.149
Gender_Dummy	0.1763	-0.29592	0.6510	0.2413	0.7307	0.465
Education_High_Dummy	0.0270	-0.70457	0.7615	0.3743	0.0720	0.943
Employment_Student_Dummy	0.1129	-0.98648	1.2285	0.5672	0.1991	0.842
Employment_Status_Dummy	0.1102	-0.98287	1.2219	0.5646	0.1952	0.845
Recruitment_Plattform_Dummy	-0.2443	-0.78746	0.2993	0.2770	-0.8819	0.378
Prior_AI_Use_Dummy	-0.1763	-0.74994	0.3991	0.2928	-0.6021	0.547
CRT_Total	0.0396	-0.12352	0.2040	0.0836	0.4742	0.635
Decision_Context_Dummy	0.2045	-0.85592	1.2648	0.5409	0.3780	0.705
Interaction_CRT_Context	-0.0341	-0.26209	0.1939	0.1162	-0.2931	0.769

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