Intuition and Artificial Intelligence (AI):

How the Perception of AI influences the Acceptance of AI Advice

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Dissertation submitted in partial fulfilment of requirements for the MSc in International Management with a specialization in Strategy and Consulting, at the Universidade Católica Portuguesa, June 2023

Abstract

Title: Intuition and Artificial Intelligence (AI): How the Perception of AI influences the Acceptance of AI Advice

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With the rapid pace of technological advancements, Artificial Intelligence (AI) is becoming increasingly important in a variety of domains, especially in strategic decision making. The advancements of AI's human-like traits and intuitive abilities have transformed it into a powerful decision tool.

This thesis seeks to find out how individuals perceive AI, and how these perceptions influence their acceptance of advice provided by AI. Therefore, two studies were conducted to test seven hypotheses, which were rooted in the existing literature on human-computer interaction.

The findings suggest a complex relationship between these variables. While both intuitive and rational perceptions of AI contributed to building trust, fostering a sense of closeness did not necessarily translate into advice acceptance. A significant discrepancy between the results of the two studies was found for the influence of perceived intuition on advice acceptance, suggesting the role of additional variables such as personal attitudes or previous experience with technology.

The results present valuable implications for managers aiming to increase acceptance of AI systems, emphasizing a more comprehensive approach that builds trust and enhances both intuitive and rational aspects. Despite certain limitations related to sample diversity and unsuccessful experimental manipulation, the study paves the way for future research in this domain. It emphasizes on the need for AI systems to be not only technologically sophisticated but also intuitively human-like and trusted by users to drive advice acceptance.

Keywords: Artificial Intelligence, AI Advice, Intuition, Rationality, Strategic Decision Making, Acceptance of Advice, Closeness, Trust, Human-Computer Interaction

Sumário

Título: Intuição e Inteligência Artificial (IA): Como a percepção da IA influencia a aceitação de conselhos sobre IA

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Com o ritmo acelerado dos avanços tecnológicos, a Inteligência Artificial (IA) está a tornar-se cada vez mais importante numa variedade de domínios, especialmente na tomada de decisões estratégicas. Os avanços das características semelhantes às humanas e das capacidades intuitivas da IA transformaram-na numa poderosa ferramenta de decisão.

Esta tese procura descobrir como os indivíduos percepcionam a IA e como essas percepções influenciam a sua aceitação dos conselhos fornecidos pela IA. Por conseguinte, foram realizados dois estudos para testar sete hipóteses, que se basearam na literatura existente sobre a interacção homem-computador.

Os resultados sugerem uma relação complexa entre estas variáveis. Embora as percepções intuitivas e racionais da IA tenham contribuído para criar confiança, a promoção de um sentimento de proximidade não se traduziu necessariamente na aceitação de conselhos. Verificou-se uma discrepância significativa entre os resultados dos dois estudos no que respeita à influência da percepção da intuição na aceitação de conselhos, o que sugere o papel de outras variáveis, como as atitudes pessoais ou a experiência anterior com a tecnologia.

Os resultados apresentam implicações valiosas para os gestores que pretendem aumentar a aceitação dos sistemas de IA, sublinhando uma abordagem mais abrangente que crie confiança e realce os aspectos intuitivos e racionais. O estudo abre caminho a futuras investigações neste domínio. Salienta a necessidade de os sistemas de IA serem não só tecnologicamente sofisticados, mas também intuitivamente semelhantes aos humanos e merecerem a confiança dos utilizadores para impulsionar a aceitação dos conselhos.

Palavras-chave: Inteligência Artificial, Conselhos de IA, Intuição, Racionalidade, Tomada de Decisões Estratégicas, Aceitação de Conselhos, Proximidade, Confiança, Interacção Homem-Computador

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List of Abbreviations

Abbreviation	Definition
AI	Artificial intelligence
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
CNN	Convolutional Neural Network
DL	Deep Learning
FFH	Fast and Frugal Heuristics
HCI	Human-Computer Interaction
IOS	Inclusion of Other in the Self
LERNE	Laboratory for Experimental Research iN Economics and management
MC	Manipulation Check
ML	Machine Learning
NLP	Natural Language Processing
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TL	Transfer Learning

1. Introduction

1.1 Topic presentation

Artificial intelligence (AI) has rapidly evolved over the past few years, showing significant advancements in various domains (Enholm et al., 2022). Further, the application of AI in business has transitioned from being a futuristic concept to reality. In the business context, AI has started to play a crucial role in decision-making processes, providing support to managers and organizations in making informed and effective decisions (Davenport & Ronanki, 2018; Enholm et al., 2022; Ransbotham et al., 2022). AI has been increasingly used for strategic decision-making enabling organizations to make informed decisions in various areas (Davenport & Ronanki, 2018). As AI systems become more sophisticated and capable of mimicking human thinking, a shift in the perception ranging from rational to intuitive could be possible. This, in turn, might have an impact on how AI is utilized in decision-making, as the traditional reliance on human intuition and expertise may be complemented or even replaced by AI in certain contexts. The growing acceptance of AI advice in decision-making processes has encouraged researchers to investigate the factors influencing the degree to which decision-makers accept AI advice.

In this context, the present thesis focuses on the degree of perceived intuition in AI as the key independent variable. This perception may influence the extent to which decision-makers accept AI advice, as they may be more inclined to trust AI-generated recommendations if they perceive AI as possessing human-like intuition rather than merely being a rational, data-driven tool. Additionally, several mediating variables may explain the relationship between AI perception and acceptance of AI advice. Trust in AI is a critical factor, as decision-makers strive to have confidence in the system's ability to provide accurate and valuable insights (Bitkina et al., 2020; D. J. Kim et al., 2008; Lankton et al., 2015; Yin et al., 2019). Closeness towards AI, another mediating variable, refers to the emotional connection or affinity that decision-makers may develop with AI systems (Aron et al., 1992; J. Li et al., 2019).

By exploring these mediating variables, this dissertation aims to provide a deeper understanding of the complex relationship between AI perception and the acceptance of AI advice in strategic decision-making. Despite the growing body of literature on AI's role in strategic decision-making and its increasing capabilities, there is a notable research gap in understanding how the perception of AI as more or less intuitive or rational influences individuals' acceptance of AI advice (Keding & Meissner, 2021; Khatri & Ng, 2000; Lindebaum et al., 2020; Simon, 1979).

While existing research has explored factors related to AI adoption, trust, and performance, less attention has been paid to the impact of AI perception on the extent to which decision-makers utilize AI-generated insights in their decision-making processes (J. C. Lee & Chen, 2022; J. D. Lee & See, 2004; X. Li et al., 2008; Wu & Chen, 2005). Furthermore, the mediating roles of trust and closeness towards AI in this relationship have not been thoroughly investigated in this specific context. Addressing this research gap will provide valuable insights into the complex relationship between AI perception, trust, closeness, and acceptance of AI advice, ultimately contributing to a more comprehensive understanding of the effective and responsible integration of AI in strategic decision-making processes.

1.2 Problem statement and research objective

The increasing application of AI in strategic decision-making raises the question of how the degree of perceived intuition of AI influences the acceptance of AI advice. The impact of AI perception on the extent to which decision-makers utilize AI-generated insights in their decision-making processes and the mediating roles of trust and closeness towards AI remain underexplored until today. Therefore, the primary aim of this research is to investigate the influence of the degree of perceived intuition on the acceptance AI advice in decision-making processes. Additionally, the research seeks to understand the mediating roles of trust and closeness towards AI in this relationship. Therefore, this dissertation intends to provide an answer to the following research question:

Which role does the degree of perceived intuition of AI systems play for the acceptance of AI advice?

To investigate the investigated research gap, the research question is divided in four sub-questions, which are investigated by the two studies, being:

1. *How does the degree of perceived intuition of AI systems influence decision-makers' acceptance of AI advice?*
2. *Is the perception of AI influencing the degree of trust and closeness towards AI?*
3. *Is the degree of trust and closeness towards AI impacting the acceptance of AI advice?*
4. *How is the feeling of closeness towards AI impacting the trust towards AI?*

To achieve these objectives, two separate quantitative studies will be conducted to provide a comprehensive understanding of the phenomena.

1.3 Managerial & academic relevance

The findings from this Study contribute to a deeper understanding of the factors influencing decision-makers' acceptance of AI advice, particularly the role of the degree of AI perception as more or less intuitive or rational by exploring the mediating roles of closeness and trust towards AI. From an academic perspective, this research addresses the identified gap in the literature regarding the influence of AI perception on acceptance of AI advice in strategic decision-making. By investigating the mediating variables of trust and closeness, the Study extends the existing knowledge in the fields of AI, strategic decision-making, and human-computer interaction. The results can inform future research on the effective integration of AI in decision-making processes. From a managerial standpoint, the findings of this studies offer valuable insights for organizations and managers that are seeking to integrate AI into their decision-making processes. By understanding the factors influencing decision-makers' acceptance of AI advice, organizations can design and implement AI systems that effectively complement and enhance human decision-making capabilities. Additionally, organizations can leverage the findings to create a culture that encourages the responsible and effective use of AI, promoting trust and collaboration between human decision-makers and AI systems.

1.4 Thesis structure

The thesis is organized into six main chapters, providing a comprehensive understanding of the influence of AI perception on decision-makers' acceptance of AI advice and the mediating roles of closeness and trust towards AI. Following the Introduction chapter presenting the topic, problem statement, research questions, and discussing the managerial and academic relevance of the research, the Literature Review covers the relevant theoretical background, including strategic decision-making, AI in strategic decision-making, factors influencing AI adoption and aversion, perception of AI, and human-computer interaction. Next, the Methodology chapter describes the research design, sample and procedure, measurement of variables, data preparation, and scale reliability for two separate studies. The Results chapter presents the descriptive statistics, hypothesis testing, and findings from both studies, discussing the results in relation to the research questions and hypotheses. In the Discussion chapter, the research findings are analyzed in a broader context, considering the existing literature, theoretical and managerial implications, limitations, and suggestions for future research. Finally, the Conclusion chapter summarizes the main findings, contributions, implications of the research, emphasizing the potential need for further research in this area.

2. Literature review

2.1 Strategic decision-making

The term strategic decision making refers to the act of making long-term decisions that have the potential to shape the direction of an organization, how well it can sustain its competitive advantage and, therefore, the overall success of the organization (Schwenk, 1995). Based on the Rational Decision-Making Model, the systematic process consists of identifying an obstacle or opportunity for the firm, collecting, and analyzing relevant information (Calabretta et al., 2017). In the context of business and management, taking decisions is important for adapting to varying contexts and growth in changing environments. The decision-making process is influenced by the interplay of characteristics of the top management, the nature of the decision, the process characteristics, and the broader context (Papadakish et al., 1998). According to Dean & Sharfman (1996), two constructs play a significant role that explain how managers make their decisions and how they make effective decisions: Procedural rationality and political behavior.

2.1.1 Procedural rationality

The first concept is *procedural rationality*, that describes the importance of following a logical and systematic approach for decision-making (Dean & Sharfman, 1993). Here, the process of decision-making itself is rational in its methods and procedure and is less based on outcome and results (Simon, 1947). Simon (1947) highlights the importance to acknowledge facing constraints such as limited time, resources and cognitive power and refers to the concept of bounded rationality as the underlying principle (Dean & Sharfman, 1996).

Unbounded rationality is based on the idea of the manager acting as a homo economicus, which is characterized by unlimited brain capacity, time, and information to explore all possible alternatives within the context of a decision (Basel & Brühl, 2013). The goal is to optimize for maximum utility when taking a decision. However, for the real world, the concept of unbounded rationality is an unrealistic scenario as there is no single conception of rationality, it disregards the content and context of the decision, and it has unrealistic demands for the human mind (Chase et al., 1998).

Following this, the concept of bounded rationality was introduced by Herbert Simon. The term describes how humans deal with different limitations when making decisions. He argues that this concept fits the real world and the nature of humans better as the demand for the infinite process of gathering information and calculating probabilities would be computationally too high for the human brain (Chase et al., 1998). Besides computational and cognitive limits, Selten (1990) found motivational limits of humans which impose additional limits on rationality. Even though the perfect solution might exist, humans employ different mechanisms to save resources but still tend to find a good solution for all stakeholders.

These ideas are similar to more recent views on human cognition. Specifically, the dual-process theory of cognition posits that reasoning and making decisions can be understood by considering the interplay between two distinct systems of processing (Kahneman, 2003). This theory influenced various fields including psychology, economics, and neuroscience (Evans & Stanovich, 2013). According to this theory, there are two ways of information processing – system 1 and system 2. One part of the dual-process theory is *system 2*, which is a deliberative, analytical, and reflective mode of cognitive processing (Evans, 2010). It contributes to reasoned and logical decision-making outcomes and is often associated with rational thinking. System 2 is especially important for decisions that demand higher cognitive input, such as problem-solving or evaluating complex information (Evans, 2010). Evans & Stanovich (2013), who prefer the term *type 2* over the term *system 2*, describe this slow and sequential mode of cognitive processing closely related with the working memory and general intelligence. Type 2 processing is also responsible for human-unique capabilities such as hypothetical thinking, simulation, and consequential decision-making. Additionally, type 2 thinking is associated with high performance in cognitive tasks and highly correlated with fluid intelligence (Evans & Stanovich, 2013). Important for Stanovich in the context of type 2 reasoning is the concept of cognitive decoupling. It refers to the human ability to separate representations of reality from imaginary situations, which is important for hypothetical reasoning (Evans & Stanovich, 2013). Additionally, *system 2* allows to override decision advice given by the intuitive counterpart called *system 1* reducing bias and error by accurately assessing probabilities, costs, and benefits (Chase et al., 1998; Dane & Pratt, 2007; Kahneman, 2003). *System 1* is a contrasting way of processing information, which will be discussed in the upcoming sections.

2.1.2 Political behavior

It is important to consider that the previous chapter about procedural rationality only provides parts of the picture when it comes to understanding the complex human decision-making process. In addition, decision-making is also significantly influenced by personal interests of individuals. Therefore, the following chapter is about the concept of political behavior and its impact on decision-making processes.

Political behavior acknowledges that decisions are influenced by people and their interests, such as functional, hierarchical, professional, and personal (Dean & Sharfman, 1996). Individuals may act according to their own interests to influence the outcome of decisions in their favor and therefore reduce the effectiveness of decisions in the context of organizational objectives, as it may not address the needs of the firm adequately (Dean & Sharfman, 1996). Furthermore, Tversky and Kahneman (1974) demonstrated that people rely on mental shortcuts in decision-making, which have the potential to lead to systematic biases. This highlights the importance of considering both rational and political dimensions when examining the complexities of the human decision-making process. Political behavior can be explained by various cognitive phenomena. The human brain developed several phenomena do deal with the limitations introduced with the concept of bounded rationality, where the first three are: heuristics and biases, satisficing, and fast and frugal heuristics (Akinci & Sadler-Smith, 2012; Basel & Brühl, 2013; Chase et al., 1998; Gigerenzer, 2008; Tversky & Kahneman, 1974).

2.1.3 Heuristics and biases

Decisions are impacted by individual cognitive processes. Additionally, heuristics and biases are influencing factors that also impact the quality of a decision (Tversky & Kahneman, 1974). Tversky and Kahneman introduced the concept of heuristics and biases as a form of mental shortcuts and systematic errors occurring when people make decisions. Heuristics simplify complex decision-making processes for individuals to reach a decision faster with less cognitive effort (Tversky & Kahneman, 1974). This paper identified the first three heuristics that are applied in decision-making and judgement under uncertainty.

The *representativeness* heuristic describes the assumption that the probability of an event or outcome is similar to a stereotypical example and is often used for judgments based on stereotypes. This heuristic often leads to base-rate neglect or the conjunction fallacy (Tversky & Kahneman, 1974, 1981). Base-rate neglect refers to the tendency to ignore the general probability of an event when making a judgement based on specific instances (Kahneman & Tversky, 1973; Y.-Y. Yang & Wu, 2020). The conjunction fallacy occurs when people judge the probability of a conjunction of two events higher than the probability of one of the events (Tversky & Kahneman, 1983).

The *availability* heuristic involves estimating a probability of an event based on how easily instances of that event come to the mind of the person. It can lead to biases when the ease of retrieval is influenced by unrelated vividness, recent exposure, or emotional impact (Tversky & Kahneman, 1983). Lichtenstein explains this heuristic by the example of a plane crash as distributed in the media, which biases the estimated probability of occurrence due to vividness and emotional impact (Lichtenstein et al., 1978).

The *anchoring and adjustment* heuristic refers to the process of making estimations, which is influenced by an initial value (Tversky & Kahneman, 1974). Additionally, when gaining new insights or additional information about the context, the adjustment of the estimation is insufficient. The estimations are significantly influenced by the initial value, which is also called anchor and therefore lead to biased decisions and estimates (Epley & Gilovich, 2001). The adjustment of estimation due to the anchor is influenced by human components such as mood, expertise, motivation, personality, and cognitive ability (Furnham & Boo, 2011).

2.1.4 Satisficing

The blend of sufficing and satisfying is the second phenomena and focuses on finding a solution that is good enough without the need for ultimate optimization. It is a decision-making strategy first introduced by Simon in 1955, where satisficing is defined as the phenomenon that individuals make decisions by seeking only a satisfactory solution for all stakeholders rather than the optimal solution (Simon, 1955). Satisficing is applied in highly complex contexts combined with constraints of resources and cognitive limitations of humans (Gigerenzer & Selten, 2001). The chosen option must meet the minimum threshold or set of criteria predefined by all stakeholders to be satisfied, here it is not the goal to maximize utilization by searching for the best outcome after evaluating all available alternatives (Simon, 1955, 1956).

2.1.5 Fast and Frugal Heuristics

Gigerenzer and his colleagues at the Max Planck Institute for Human Development came up with the concept of Fast and Frugal Heuristics (FFH) as an alternative program to the heuristics and biases program (Czerlinski et al., 1999). FFH are simple decision-making strategies with the aim to reduce the complexity and uncertainty of the environment in the process of decision-making (Gigerenzer, 2008). These heuristics differ from the concept of unbounded rationality, optimization, and satisficing as they follow the concept of ecological rationality, where a decision is ecological rational when it systematically uses structures of the environment of the decision

(Basel & Brühl, 2013). FFH distinguish between fitting to be able to explain past events and predicting future outcomes by generalization of data (Basel & Brühl, 2013).

Political behavior with the usage of heuristics and biases, satisficing and fast and frugal heuristics is associated with the system 1 in the context of the dual-processing model introduced by Kahneman (Kahneman, 2003; Kahneman & Tversky, 1973; Tversky & Kahneman, 1981). *System 1* is characterized by fast, associative, and automatic thinking (Dane & Pratt, 2007). It applies the beforementioned heuristics to simplify the decision-making process but might therefore be subject to biases and systematic errors (Stanovich & West, 2000). Additionally, emotions affect the decision-making process, which can lead to irrational choices when judgement is biased or based on wrong assumptions. Finally, this system is limited in its cognitive capabilities in terms of attention, memory, and speed (Kahneman, 2003).

2.2 AI in strategic decision-making

The Dartmouth Summer Research Project on Artificial Intelligence marks the beginning for AI as a distinct research field. Within this project, AI is defined as “making a machine behave in ways that would be called intelligent if a human were so behaving." (McCarthy et al., 1995, p. 11). In the context of this dissertation, AI can be better defined as “a system’s ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan & Haenlein, 2019, p. 17). AI is increasingly used in strategic decision-making across various domains to enhance the quality of decisions and reduce biases in decisions (Davenport & Ronanki, 2018). AI-generated insights are applied to formulate strategic decisions and help firms to make informed decisions (Agrawal et al., 2019; Blais & Jungdahl, 2019). Also, AI is used to draw conclusions for the future from historical data it analyses. It helps to better detect trends, customer behavior, and potential risks and, therefore, aids decision-makers to make informed choices (Blais & Jungdahl, 2019). This can lead to robust future planning and a competitive advantage in the market (Agrawal et al., 2019). AI-assisted resource planning, process optimization, and automation can additionally contribute to this effect (Davenport & Ronanki, 2018). AI is not only applied cross-functional but is also applied in various industries, such as manufacturing (Ying et al., 2018), health care (Auloge et al., 2020), legal (du Plessis & du Toit, 2006), military (Heller, 2019), governments (Heller, 2019), construction (Sabeti et al., 2021), logistics and supply chain management (Gunasekaran & Ngai, 2014), human resources management (Pereira et al., 2021), marketing (Mariani et al., 2022) and real estate (Baur et al., 2023).

2.3 Understanding adoption and aversion of AI

AI continues to become increasingly knowledgeable and capable, making it more and more important for decision-making processes (Davenport & Ronanki, 2018; Duan et al., 2019; Langer & Landers, 2021). Therefore, it is crucial to understand the factors that either contribute to the adoption or the aversion towards AI. Thus, this section aims to provide an overview behind the two concepts of AI adoption, which refers to the willingness of individuals and organizations to adopt AI technologies and incorporate them into their decision-making processes (Venkatesh et al., 2003) and AI aversion, which characterizes factors that explain resistance towards using AI within the decision-making process (Dietvorst et al., 2015).

2.3.1 Individual factors

When psychological factors are considered in the context of AI, an interesting interplay between aversion and adoption can be found. On one hand, factors such as a negative perception about AI, exaggerated expectations, or a lack of emotional trust in AI hinder individuals from using algorithms (Dietvorst et al., 2015; Logg et al., 2019). Also, people tend to overestimate their abilities and trust their own judgement over AI augmented by a resistance to change (Dzindolet et al., 2002; Prahl & Van Swol, 2017; Promberger & Baron, 2006). On the other hand, personal motivation can lead to the adaption of AI (Dietvorst et al., 2015).

Furthermore, personality traits can both steer individuals towards embracing AI and also prompt them to avoid it. High self-esteem and domain-specific expertise can lead to an over-reliance on personal knowledge and abilities, reducing reliance on AI (Dietvorst et al., 2015; Logg et al., 2019). This is intensified by an individual's locus of control – if one believes in their actions shaping outcomes, aversion to AI increases (Ajzen, 2002; Duttweiler, 1984; Shaffer et al., 2013). Contrarily, traits like online self-efficacy can enhance AI adoption, with individuals confident in their tech-use abilities more likely to embrace AI (Compeau et al., 1999; Davis et al., 1992; Del Giudice et al., 2023; Gursoy et al., 2019; McBride et al., 2012).

Familiarity is another important factor of this dynamic. In the context of AI aversion, a lack of familiarity or a negative prior experience can increase AI skepticism (Z. Li et al., 2020; P. Liu et al., 2019; Slovic et al., 2007). However, an increased openness to new experiences, time spent with AI technologies, and understanding of AI's capabilities can promote AI adoption (Chua et al., 2023; Gönül et al., 2006; J. D. Lee & See, 2004; Venkatesh et al., 2003; Workman, 2005; Y. Zhang et al., 2020)

Demographics add another layer to this complex interplay. With AI aversion, age is often, but not always (Logg et al., 2019), seen as a barrier with older individuals less likely to incorporate AI into their decision-making process (Araujo et al., 2020; Thurman et al., 2019). In contrast, the AI adoption narrative showcases differences in technology readiness, perceived usefulness, and ease of use between genders and varying educational backgrounds (Araujo et al., 2020; Hargittai, 2010; Nouraldeen, 2022; Venkatesh & Morris, 2000).

2.3.2 Algorithm factors

Complex algorithms can cause hesitation among individuals, especially when they struggle to understand the decision logic or quality measurements (Chenoweth et al., 2004; Kayande et al., 2009). A dissonance between their own reasoning and the algorithm's decision advice strengthens this aversion (Aronson & Texas, 1969). Furthermore, AI systems that lack iterative decision-making or only provide performance feedback on the taken decision can fuel aversion, especially when the outcomes are negative (Van Dongen & Van Maanen, 2013). On the other side, effective AI design emphasizing accessibility, integration, and explainability foster user acceptance (Laato et al., 2021; Shin, 2021; Y. Zhang et al., 2020). Also, individuals value AI systems that provide performance feedback, adapt, and learn, responding quickly (Baumeister et al., 2007; Czerwinski et al., 2021; Dayan & Niv, 2008; Kayande et al., 2009; J. C. Lee & Chen, 2022; Pelau et al., 2021).

The characteristics of AI's decision-making also influence adoption. The accuracy of an AI system's decisions is essential for user acceptance as it builds trust and confidence (Y. Zhang et al., 2020; Zhu et al., 2022). Further, the valuation of an AI decision increases when costs, either time or money, are associated with its accessibility (Boutilier et al., 1999). Moreover, positive outcomes encourage individuals to follow AI advice contributing to AI adoption (Drnevich & Croson, 2013; Toma et al., 2020). Furthermore, individuals who perceive themselves superior to AI systems and incorporate AI advice into their final decisions are more likely to adopt AI advice (Bigman & Gray, 2018; Logg et al., 2019).

Finally, the algorithm's delivery style significantly impacts its adoption. Presenting advice orally rather than only on a screen enhances acceptance (Kelly et al., 2023; Nass et al., 1999; Nass & Moon, 2000). Similarly, users appreciate concise yet informative explanations, further influencing user satisfaction and adoption (Gönül et al., 2006; Mahmud et al., 2022).

2.3.3 Task factors

The nature and complexity of tasks also shape individuals' attitudes towards AI. Moral tasks, characterized by ethical considerations with significant implications for others, often inhibit hesitation to rely on AI, which stems from the perception that AI might fail to understand and evaluate ethical considerations adequately (Bonnefon et al., 2016; Greene et al., 2009). This is especially relevant for subjective tasks, where personal judgement, interpretation, or intuition play a pivotal role (Dietvorst et al., 2015). People tend to view AI systems as rational entities, potentially lacking the human attributes of intuition, creativity, or emotional understanding, thereby increasing AI aversion (Bigman & Gray, 2018; Castelo et al., 2019; M. K. Lee, 2018). Furthermore, task complexity can drive AI adoption. As tasks grow more complicated, demanding heightened cognitive effort, individuals are more inclined to consult AI systems for assistance (Gino & Moore, 2007; Önkal et al., 2019)

2.4 Perception of AI

Especially in the context of subjectivity, the perception of AI is an important factor when researching how individuals interact with and accept AI systems and their advice. This chapter explores different facets of AI perception starting with perceiving it as a rational agent. Then, it investigates the technological enhancements of AI systems and how they can change the perception of AI. Finally, the chapter explores the evolution of AI towards intuition and the impact on the perception and acceptance of AI.

2.4.1 AI perceived as rational

In the context of strategic decision-making, procedural rationality, as discussed in section 2.1.1, refers to a systematic and rule-based decision-making approach arriving at an optimal decision leveraging available information and alternatives (Frantz, 2003; Simon, 1955, 1979). AI systems often apply the concepts of procedural rationality to reach an optimal decision using algorithmic calculations aiming for optimization (Cormen et al., 2009, p. 414). These algorithms are programmed to find the best solution given an explicit context, specific constraints, and objectives (Cormen et al., 2009, p. 414). Therefore, the perception of AI as rational can be attributed to the way AI systems work in terms of processing information and making decisions (Dietvorst et al., 2015). Indeed, Y. Li and colleagues (2022) found that AI handles large datasets better than humans and is therefore perceived better for producing analytical reports based on data applying rational thinking and calculus.

Furthermore, Lindebaum et al. (2020) argue that AI systems are the ideal of rationality as they are programmed to reach a specific goal through optimization and therefore eliminate influences of individuals or situational biases and error (Gigerenzer & Selten, 2001; Lindebaum et al., 2020). They also noted that unbounded rationality can be reached again through the computational power of AI-powered algorithms (Lindebaum et al., 2020). Also, AI systems leverage elements of game theory to make informed and rational decisions by analyzing and predicting the behavior of other agents (Sandholm, 2010). In addition, AI systems have demonstrated solving complex problems and achieved high performance successfully in various domains (e.g., game-playing) outperforming their human counterparts reinforcing the perception of AI systems to be rational as they highlight their ability to make optimized decisions based on calculated probabilities (Silver et al., 2016).

Moreover, to understand how the self attributes mental capabilities such as thoughts and emotions towards other agents (e.g., AI systems), the mind perception theory is used as the psychological framework. The theory consists of two dimensions: agency and experience (Gray et al., 2007), which originates from the ideal that humans have the tendency to attribute minds to their counterpart to help them understand their behavior (Gray et al., 2007; Waytz et al., 2010). The agency dimension includes attributes such as the capacity to execute a task, emotion recognition, communication, and thought ultimately associated with responsibility. The experience dimension incorporates consciousness, personality, and pleasure, which is related to rights or privileges (Gray et al., 2007; Waytz et al., 2010). The perception of AI is based on these two dimensions and according to this paper, AI is perceived to be high in agency while categorized low in experience and is therefore perceived as a utilitarian decision-maker applying rational thinking (Gogoll & Uhl, 2018; Z. Zhang et al., 2022). Ongoing technological advances in AI systems further strengthen the perception of AI to be rational by improving their efficiency, accuracy, and overall performance in decision-making.

2.4.2 Technologic advances in AI systems

Technological advances contribute significantly to the improvement of decision-making by AI across many industries and functions (Davenport & Ronanki, 2018; Gill et al., 2019; Gogoll & Uhl, 2018; Sandholm, 2010; Silver et al., 2016).

For example, the advances in Natural Language Processing (NLP) enabled the technology to better understand, interpret and generate text more efficiently (Joshi, 1991). NLP is a field within artificial intelligence and a subfield of machine learning that deals with the interaction between computers and human languages (Joshi, 1991). It applies algorithms and techniques to enable computers to analyze and understand language including several tasks including syntactic and semantic analysis, discourse processing and language generation (Joshi, 1991). NLP can be applied to a variety of use cases, including voice recognition for IoT devices in many fields in the healthcare industry (Li et al., 2022; Rani et al., 2017).

Furthermore, advancements in Machine Learning (ML) and Deep Learning (DL) contribute to the development of more efficient and accurate AI systems (LeCun et al., 2015). Improvements of model architectures and new approaches such as Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) achieve higher levels of accuracy in a wide range of tasks including image recognition and pattern recognition (Hayes, 2014; LeCun et al., 2015). Also, reinforcement learning models enable AI systems to learn from their own experience, which allows them to make more informed decisions in new and uncertain environments (Dayan & Niv, 2008). Especially deep neural networks can capture contextual information and understand underlying structures of data (Kirkpatrick et al., 2017).

Advanced learning techniques such as Transfer Learning (TL) and Meta-Learning allow AI systems to generalize knowledge from one topic and apply it to another topic, which enables more efficient learning as these AI systems become more adaptable, versatile, and capable (Pan & Yang, 2010; Zhuang et al., 2019). For the application of these pre-trained AI systems on new domains, only limited data on that new specific domain is needed to be able to create a high performing systems (Pan & Yang, 2010; Zhuang et al., 2019). Meta-Learning algorithms learn how to learn by themselves, which enables them to quickly adapt to unknown tasks and domains (Finn et al., 2017; Vanschoren, 2018). Both techniques enable AI systems to facilitate cross-domain decision-making, transforming them to an even stronger advisor for individuals using them (Finn et al., 2017; Pan & Yang, 2010; Vanschoren, 2018).

In conclusion, AI technology is simultaneously getting better at rational decision-making and evolving towards more intuitive decision-making capabilities by recognizing underlying structures and is therefore better able to assist individuals with human-like thinking and advanced reasoning.

2.4.3 Evolution of AI towards intuition

NLP allows AI systems to better understand the nuances of human communication and thinking, leading to the ability to engage with individuals in more intuitive ways. These advances, especially in sentiment analysis and context-aware language understanding, enable AI systems to comprehend subjective information such as emotion and context. By leveraging these improvements, AI systems are perceived as more human-like and capable of human-like decision-making, bridging the gap between AI and human intuition (Cambria et al., 2020).

DL and ML improvements enable AI systems to process and analyze contextual information effectively (LeCun et al., 2015). Reinforcement learning allows them to learn from experience, much like humans. Quick learning based on limited data, rapid adaptation capabilities, and the ability to generalize knowledge across different domains demonstrate the flexibility and adaptability of modern AI systems, contributing to the decision-making process of individuals (Dayan & Niv, 2008; Denil et al., 2017). These technological advancements in AI systems contribute to the perception of AI as intuitive.

The rapidly increasing development of AI towards intuitive capabilities indicates a significant paradigm shift in AI perception. Traditional studies on AI have primarily examined reactions to AI without exploring how it's perceived, indicating that the widespread notion is that AI is perceived as rational. The emerging intuitive qualities of AI systems may change this perception. Thus, there is a need to understand these changing perceptions.

In conclusion, the evolution of AI systems towards intuitive decision-making capabilities, combined with a potential shift in perception, could redefine the dynamics between humans and AI (Nass & Moon, 2000). AI systems perceived as intuitive may reshape the dynamics between humans and AI, leading to differences from previously designed studies. Based on these insights, the first three hypotheses are proposed:

H1: *Individuals who perceive AI systems as more intuitive accept AI advice more than individuals perceiving them as less intuitive.*

H2: *Individuals who perceive AI systems as more intuitive feel closer towards AI systems than individuals perceiving them as less intuitive.*

H3*: Individuals who perceive AI systems as more intuitive trust AI systems more than individuals perceiving them as less intuitive.*

2.5 Human-Computer Interaction

To understand the implications of the shift in the perception of AI towards an intuitive system, it is important to understand how humans interact with computers, which is researched in the field of Human-Computer Interaction (HCI). HCI focuses on understanding how humans interact with computers in an efficient and effective way (Anzai et al., 1995; Nass & Moon, 2000). The field integrates knowledge from computer science, psychology, and cognitive science (Anzai et al., 1995; Carroll, 1997). In the context of this paper, the aspects of closeness, trust, and reliance on AI systems are explored within HCI. The beforementioned technological advancements make AI systems able to understand and respond to humans even better and therefore enhance the interaction between the two agents (Pelau et al., 2021; Rani et al., 2017).

2.5.1 Closeness towards AI

In HCI research, the feeling of closeness towards AI systems is an essential aspect (Glikson & Woolley, 2018). Closeness refers to the degree of emotional attachment, intimacy, and identification that individuals feel towards AI systems (Aron et al., 1992; J. Li et al., 2019; Uleman et al., 2000). This is a critical factor in determining the acceptance of AI advice, as users who feel closer to AI systems are more likely to trust and rely on them within the decision-making process (Glikson & Woolley, 2018). When discussing closeness towards AI, it is essential to also consider contributing factors like perceived similarity between the individual and the AI system. Research suggests that individuals are more likely to feel closer to others who share their values, beliefs, and interests (Aron et al., 1992). Additionally, based on the similarity-attraction effect (Montoya & Horton, 2013) and the assumption that AI systems can be perceived as intuitive and therefore more human-like, the next hypothesis is the following:

> ***H4:*** *The closer individuals feel towards AI systems the more they are more likely to accept AI advice.*

2.5.2 Trust in AI

Closeness towards AI, as discussed in the previous section, has a significant impact on the way users interact with AI systems. Trust is another crucial factor in the human-machine interaction domain that influences the acceptance of AI advice (Araujo et al., 2020; J. D. Lee & See, 2004; Merritt & Ilgen, 2008). Trust in AI can be defined as the user's belief in the competence, reliability, and dependability of an AI system to perform a specific task (Choung et al., 2022; Mcknight et al., 2011; Tschannen-Moran & Hoy, 2000). This belief plays an important role in users' willingness to accept and act upon the AI system's feedback, especially as AI is perceived to be difficult to understand in terms of how decisions are made for the end user (Gulati et al., 2019). Trust in AI systems can be classified into three main types: dispositional, situational, and learned (Mayer et al., 1995; Mcknight et al., 2011; Merritt & Ilgen, 2008).

Dispositional trust is related to the trust initially given to the other person or technology and reflects a general tendency to trust others. Situational trust is influenced by the specific context or environment in which the interaction takes place, such as culture, norms, and task influence. This type of trust plays a role in shaping initial trust towards someone. Learned trust develops through repeated interaction with the other and positive experiences (behavior, competencies, and reliability) with it, aligning with knowledge-based trust. Komiak & Benbasat (2006) further differentiate trust into cognitive trust and emotional trust. Cognitive trust is the rational component of trust, based on the assessment of competence, reliability, and integrity (comparable to knowledge-based trust). Emotional trust incorporates feelings of security and comfort when relying on technology or AI, including beliefs, gut feeling, and faith, which can be rational or irrational.

Various factors influence trust in AI systems, one of which is the closeness established between the user and the AI system. As individuals feel closer to AI systems, they are more likely to identify with them and perceive them as dependable and reliable (Glikson & Woolley, 2018). This notion is also supported by the Social Identity Theory, which suggests that individuals are more likely to trust others who they perceive as similar to themselves (Edwards et al., 2019). Consequently, when individuals feel emotionally closer to AI systems, they develop trust in these systems, leading to the following hypothesis:

H5: *The closer individuals feel towards AI systems the more they tend to trust them.*

The relationship between trust and acceptance of AI advice is closely intertwined. As users develop trust in AI systems, they are more likely to perceive the system as competent, reliable, and dependable, which in turn increases their willingness to accept AI-generated advice (Bickmore & Picard, 2005). According to Choung et al. (2022) , trust in AI systems ultimately leads to the acceptance and reliance on AI systems and their advice and is therefore an important factor when explaining the usage of AI. This is particularly true in situations where decision-making is complex, uncertain, or risky, as individuals tend to seek guidance from sources they consider trustworthy (Mcknight et al., 2011). Moreover, users who have developed a strong emotional trust in AI systems may feel more secure and comfortable relying on the system's recommendations, even when facing challenging decisions (J. D. Lee & See, 2004; Mcknight et al., 2011). Therefore, based on the aforementioned factors and the importance of trust in AI systems, the following hypothesis is proposed:

H6: *The more individuals trust AI systems the more they are likely to accept AI advice.*

Having established the connection between trust in AI and reliance on AI advice, the next section will investigate how these factors, along with closeness towards AI systems, influence users' acceptance and utilization of AI-generated feedback in strategic decision-making.

2.5.3 Acceptance of AI advice

Closeness and trust in AI systems serve as key determinants for the acceptance of AI advice. As users feel emotionally closer to AI systems and develop trust in their competence, reliability, and dependability, they are more willing to accept and act upon the AI-generated feedback (Choung et al., 2022; Glikson & Woolley, 2018). The acceptance of AI advice is highly influenced by various factors that were mentioned in the chapters about AI aversion and adoption. Therefore, the next hypothesis reads:

H7: *The degree of perception of AI as more intuitive directly impacts the acceptance of AI advice mediated by closeness towards and trust in the AI system.*

This concludes the discussion on human-machine interaction in the context of strategic decision-making. The next chapter will explore the methodology employed in this research to investigate the hypotheses derived from the literature review.

3. Methodology

3.1 Study 1

3.1.1 Research design

The aim of the first Study was to investigate how the perception of AI as rational or intuitive correlates with the likelihood of considering AI's feedback, and the potential mediating roles of closeness and trust towards AI in this relationship. A correlational Study is used to explore the relationship between the variables in terms of strength and direction without manipulating any of the variables involved (Charness et al., 2012). It is important to note that correlational studies can only identify associations between variables and cannot establish causality (Charness et al., 2012). Nevertheless, findings from the first correlational Study can serve as a basis for further studies using an experimental design. Other studies in the field of reliance on AI advice in the decision-making process and the perception towards technology mainly applied a quantitative approach.

Therefore, such an approach is also used in this Study to test the beforementioned hypotheses. The data was collected with an online survey using Qualtrics. In this Study, a within-subject design was employed, wherein all participants were presented with an identical survey consisting of a set of questions (Charness et al., 2012). To minimize response-order effects, which could potentially bias the results, the order of questions concerning the perception of AI (intuitive/rational) and those assessing closeness, trust, and reliance were randomized, which ensures a robust and reliable assessment of the relationships among the variables under investigation (Krosnick & Alwin, 1987).

3.1.2 Sample and procedure

The online survey was distributed among graduate students enrolled in the NOVA Information Management School, specifically those pursuing a master's degree in data science and advanced Analytics. Thus, a convenience sampling method was applied, which is supported by the literature (Etikan et al., 2016). The participation in the survey was voluntary, allowing students the freedom to engage without any obligation. Thereby, a potential bias arising from forced participation was mitigated.

First, the participants were presented with an introduction to the survey giving an overview of the Study and the context of the upcoming questions. After emphasizing on the confidentiality and anonymity of participants' responses, the participants were asked for their consent to participate. Next, the participants were asked about their perception of AI in a randomized way using a 7-point Likert scale, with one question being if they perceive AI to be rational, the other question being if they perceive AI to be intuitive, followed by a scale where participants had to decide if they perceive AI as rather intuitive or rational using a 7-point scale. Following this, the participants are asked about how likely they would consider feedback from AI. In the next step, trust towards AI is evaluated by the agreement with a series of statements related to trust in AI. Additionally, participants are presented with a variety of Venn diagrams representing different levels of closeness towards and are asked to select the diagram that best represents how close they feel to AI. In the debriefing section, the purpose of the Study is disclosed, and participants are asked to provide demographic information, such as gender, age, and country of origin. Finally, participants are asked to indicate their attentiveness during the Study to ensure the quality of the data collected and are given the opportunity to provide any comments or feedback regarding the Study.

During the time the survey was accessible to the students, a total number of 98 responses were received. However, upon further examination of the received data, some participants were excluded from the final sample due to failing the attention check or providing incomplete answers. Thus, the final sample size was reduced to 72 valid participants, ensuring the reliability of the dataset used for the subsequent analysis. In terms of gender, 51.4% of participants identified themselves as male, 44.4% as female and 4.2% chose not to disclose their gender. The age distribution of participants ranged from 21 to 50 years, with a mean age of 27.3 years and a standard deviation of 7.05 years and most participants in the years of 21, 22 and 25. Furthermore, participants represented a diverse array of nationalities, where most respondents (61.1%) were from Portugal, followed by 5.6% from the Russian Federation, 4.2% from Brazil and 4.2% for Italy. For more information on the characterization of the sample, please see Appendix 3.

3.1.3 Measurement of variables

3.1.3.1 Independent Variable

The *Perception of AI systems* is operationalized as to which extent AI is perceived as either rational or intuitive by the participants on a 7-point Likert scale (1 = *Strongly disagree*; 7 = *Strongly agree*) utilizing two questions. The participants are asked the following question for measuring the degree of an intuitive perception of AI: “To what extent do you agree with the following statement? I perceive AI to be intuitive”. Further, for measuring the perception of AI as rational, participants are asked the question: “To what extent do you agree with the following statement? I perceive AI to be rational”. Both questions are essential to measure the degree of cognitive alignment between humans and AI systems, as well as to evaluate how it affects the acceptance of AI's advice.

3.1.3.2 Dependent Variable

As the dependent variable in this Study, *Reliance on AI advice* is used as the degree to which participants choose to accept or reject AI-generated advice in general. It was measured on a 7-point Likert scale (1 = *Very unlikely*; 7 = *Very likely*) asking the following question: “How likely would you be to consider AI's feedback?”.

3.1.3.3 Mediator variables

Closeness is measured through the single-item measure introduced by Aron et al. (1992). The Inclusion of Other in the Self (IOS) was first used to assess the closeness between individuals in the context of romantic relationships (Aron et al., 1992). A series of Venn diagram-like images represent the varying levels of closeness between the two agents (Aron et al., 1992).

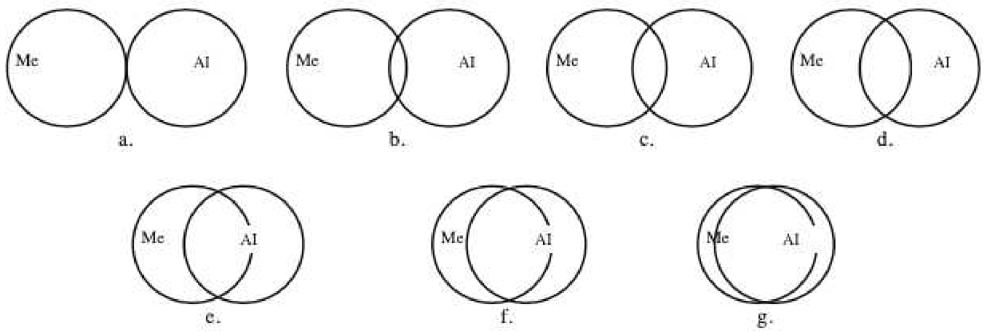

Figure 1: Modified IOS diagram

According to (Woosnam, 2010), the IOS scale can also be applied to research non-romantical interpersonal relations. The scale is widely used in research and has demonstrated strong reliability and validity in measuring closeness (Dalsky et al., 2008; Uleman et al., 2000). Stenzel et al. (2013) applied the IOS in the context of measuring closeness in human-robot interactions. In the context of this Study, the IOS scale is used to measure closeness between the individual and the AI system.

As *Trust* is an essential component in human-computer interactions, particularly in the context of AI systems (Glikson & Woolley, 2018; Gulati et al., 2019; Kelly et al., 2023b), it is utilized as a second mediator variable potentially affecting the relationship between the perception of AI and reliance on AI advice. For measurement, I utilized the Human-Computer Trust scale developed by Gulati et al. (2019), which has demonstrated robust psychometric properties, such as reliability (high internal consistency and test-retest reliability) and validity (convergent and discriminant validity), making it suitable for use in various contexts involving human-AI. The scale consists of 12 items capturing several dimensions of trust including benevolence, competence, and perceived risk. The total score is calculated as the average of the respective scores of the 12 single items. An example item from the Human-Computer Trust Scale used in the survey is: "I believe that the AI system is reliable in providing accurate advice." Participants were asked to rate their agreement with this statement on a 7-point Likert scale (1 = *Strongly disagree*; 7 = *Strongly agree*). By utilizing this renowned scale, I aim to provide a comprehensive assessment of participants' trust in the AI system, which may influence their likelihood of considering AI feedback in their decision-making process.

3.1.3.4 Control variables

In line with prior research, this Study includes demographics such as *Age, Gender, and Country of origin* as control variables to minimize the impact of individual differences and to be able to better isolate the effects of the key variables of interest and provide a more rigorous assessment of the hypothesized relationships in the Study (Ahn et al., 2022; Bernerth & Aguinis, 2016; Chua et al., 2023). *Age* was captured in years, for *Gender*, participants could select between "*Male*", "*Female*", "*Non-binary / third gender*" and "*Prefer not to say*". For *Country of Origin*, a list of all countries was provided for the participants to choose from.

3.2 Study 2

3.2.1 Research design

The second Study aims to investigate the causal relation between the perception of AI as rational or intuitive and the likelihood of considering the feedback of AI, as well as the mediating role of closeness and trust towards AI. In contrast to Study 1, this Study employs an experimental design to be able to further examine the relationships between the variables. The introduction of a manipulation aimed to explore whether framing AI in a specific way would have a causal impact on participants' perception of, closeness to, and trust towards AI and, consequently, the likelihood of considering the feedback of AI systems. Study 2 applied a between-subjects design with each participant being exposed to one of the three experimental conditions, which therefore allowed a direct effect comparison. For the manipulation checks and the questions regarding closeness, trust, and reliance, randomization was employed to minimize potential response-order effects and ensure a robust assessment of the causal relationships under investigation. Again, a quantitative approach was utilized in Study 2, with the data being collected through an online survey using Qualtrics. Additionally, Study 2 incorporated the context of strategy development as information technology is integral to business strategy (Drnevich & Croson, 2013; Seemann, 2007). Also, the insights gained from studying the perception of AI in this context could potentially be generalized to other decision-making contexts. Furthermore, strategy development often involves intuitive or rational thinking or the combination of both (Agor, 1986; Akinci & Sadler-Smith, 2012; Calabretta et al., 2017b; Hodgkinson et al., 2008; Luoma & Martela, 2021; Thanos, 2022; Vincent, 2021). By focusing on strategy development as the context, Study 2 can explore how individuals perceive AI's capabilities in both intuitive and rational aspects of decision-making, providing valuable insights into how AI can best support decision-makers.

3.2.2 Sample and procedure

The survey was distributed in the Laboratory for Experimental Research in Economics and Management (LERNE) at Católica Lisbon School of Business and Economics, where students participate in behavioral studies and their decision processes. Here, bachelor and master students were able to participate from various backgrounds (e.g., management or marketing studies).

The procedure of Study 2 was mainly the same as in Study 1, therefore, only the differences are emphasized here. The introductory text was tailored to the new context of the LERNE environment. Also, before participants were asked about their perception of AI, one of three different manipulations is shown to the participants consisting of a description of AI, the explanation of the context of strategy development and either a description of intuition, rationality, or no description for the control group (for reference see Appendix 2). Following that, the participants are asked about their perception of AI, as a manipulation check. Additionally, after emphasizing the context and that the development of strategy can be done by rational and intuitive reasoning, participants are asked about their reliance on, closeness to, and trust towards AI.

During the time slots the study was available at LERNE, a total number of 248 responses were collected. Some participants were removed from the final sample due to the lack of attention detected by the attention check. Therefore, a final number of 219 responses was achieved as a basis for the upcoming analysis.

53% of the sample identified themselves as male, while 46.1% identified as female. The remaining is evenly distributed between "*Non-binary*" and "*Prefer not to say*". In terms of age, the mean was 24.25 years with a standard deviation of 5.17 years. The majority of participants were 24 years old (26%), which is also the median of the sample. For more information on the characterization of the sample, please see Appendix 4.

Moreover, the sample consisted of students from diverse countries of origin. While the majority was from Germany (44.3%) and Portugal (21.5%), there were also participants from Italy (4.1%), Norway (3.7%), and Hungary (2.7%). For a more detailed overview of the sample, please refer to Appendix 4.

3.2.3 Measurement of variables

The control, mediator, and dependent variables are the same as in Study 1. Therefore, refer to the respective chapter for an in-depth understanding of the measurement of these variables.

Study 2 intends to investigate a causal relationship between variables using three manipulation levels, these are intended to be employed as the independent variable. This, however, is contingent on the successful outcome of the manipulation checks.

3.2.4 Manipulation check

To utilize the 3 manipulation levels as the independent variable, a manipulation check is needed utilizing a mean comparison performing a one-way ANOVA. In detail, this allows to investigate if the manipulations have a significant effect on the two manipulation check variables ("I perceive the described AI to be intuitive" and "I perceive the described AI to be rational"). The manipulation checks are measured on a 7-point Likert scale (1 = *Strongly disagree*; 7 = *Strongly agree*).

3.3 Data preparation

For both studies, several steps were undertaken to carefully prepare the data for conducting the statistical analysis. First, test runs were identified and removed from the dataset to ensure the data consisted only of valid participants. Furthermore, only participants who reached a 100% completion rate were included in the analysis to ensure complete data. Additionally, participants were asked about their level of attention during the survey. Those who were non-attentive, were filtered out from the final dataset, as their responses could potentially compromise the data quality and validity of the findings. Thus, the remaining sample for each Study consisted of participants wo provided complete and attentive responses, ensuring a reliable dataset for the subsequent analysis.

3.4 Scale reliability

To evaluate the reliability of the trust scale in both studies, Cronbach's alpha coefficients were calculated (Cronbach, 1951; Peterson, 1994). The values were assessed against the commonly accepted threshold of 0.7 (Peterson, 1994) indicating internal consistency and scale reliability (Study 1: Cronbach's $\alpha = .736$; Study 2: Cronbach's $\alpha = .779$). Therefore, the trust score is a reliable measure and suitable for further investigations of the research question.

4. Results

4.1 Study 1

4.1.1 Descriptive statistics

In this section, the descriptive statistics for Study 1 are presented. For deriving the statistics, no data cleaning, or data transformation apart from what was described in the Methodology section was undertaken.

For the perception of AI systems, participants' responses to questions about both the perceived degree of intuition and rationality of AI systems were gathered. The mean score for participants' degree of perceiving AI as intuitive was 4.72 with a standard deviation of 1.376, while the mean score for the degree of perceiving AI as rational was 5.01 with a standard deviation of 1.506. As for the feeling of closeness towards AI systems, participants exhibited an average score of 3.58 with a standard deviation of 1.33. The mean score for trust in AI systems was 4.4329, accompanied by a standard deviation of 0.6746. Finally, participants' reliance on AI systems showed a mean score of 5.49 with a standard deviation of 0.872. These statistics provide a basis for understanding the overall trends and patterns of the sample, allowing for further analysis of the relationships between the main variables in the subsequent hypotheses testing.

4.1.2 Hypothesis testing

In this section, the results of the mediation analysis conducted using the PROCESS macro in SPSS (version 4.2 beta) are presented to examine the relationships between different variables. The mediation model tested was Model 6 with the respective variables introduced in section 3, with X representing both the degree of perceived intuition of AI systems and the degree of perceived rationality of AI systems, acknowledging the possibility of different interpretations along the intuition-rationality continuum. Further, M_1 symbolizes the degree of closeness towards AI, while M_2 embodies trust towards AI. Finally, Y stands for the acceptance of AI advice.

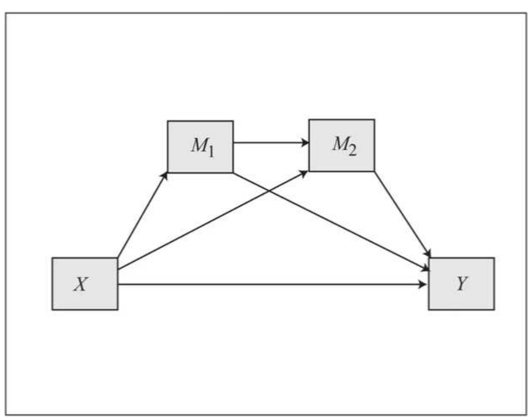

Figure 2: Model 6 of Hayes PROCESS macro for IBM SPSS

The model tests for the direct effect of X on Y, and the indirect effects through the two mediator variables. As using a bootstrap method makes the sample not to be obliged to the regression assumptions, 5,000 bootstrap replications and a significance level of .05 were chosen for testing the hypotheses (Wehrens et al., 2000).

Regarding H1, the results do not support the idea that the degree of perceiving AI as more or less intuitive has a significant influence on the acceptance on AI advice ($t(6, 63) = -.15$, $b = -.01$, $p = .88$). Thus, H1 is not supported. To ensure the robustness of this (and H2 and H3's) result, a similar measure was taken regarding the degree of perceiving AI as more or less rational. Again, no significant influence on the acceptance of AI advice was found ($t(6, 63) = -.31$, $b = -.02$, $p = .76$). This suggests that the degree of perceived nature of AI systems in terms of intuition and rationality does not significantly influence an individual's acceptance of AI advice.

For H2, when asked about the perception of AI systems as more or less intuitive, the higher the degree of perceived intuition of AI systems, the closer the AI system is perceived to be to the individual ($t(4, 65) = 2.01$, $b = .24$, $p = .05$). The hypothesis is therefore supported and implies that intuitive AI systems might foster a greater sense of connection and feeling of closeness. Furthermore, for the degree of perceiving AI systems as more or less rational, no significant influence is found ($t(4, 65) = 1.65$, $b = .18$, $p = .10$).

In terms of H3, I find significant support for the influence of the degree of perceived intuition in AI systems on trust ($t(5, 64) = 2.76$, $b = .16$, $p = .01$) meaning that the more intuitive an AI system is perceived, the more trust is built towards this system. Surprisingly, also for the degree of perceived rationality in AI systems, a significant effect, in the same direction, was found ($t(5, 64) = 2.99$, $b = .15$, $p = .004$) for building trust in those systems. This suggests that more trust in AI systems can be established the more these AI systems are perceived as intuitive and as rational by the individual.

With respect to H4, the results do not support the idea that individuals are more likely to accept AI advice when feeling a greater degree of closeness towards the AI system ($t(6, 63) = 1.38$, $b = .10$, $p = .17$), which implies that the feeling of closeness towards an AI system does not necessarily translate to an increased acceptance of its advice.

Regarding H5, the data do not show a significant relationship between feeling close towards AI systems and developing trust towards them ($t(5, 64) = .52$, $b = .03$, $p = .60$). Consequently, H5 is not supported, indicating that the sense of closeness towards an AI system does not imply the development of trust towards it.

Furthermore, H6 is supported, as the results indicate that individuals are more likely to accept AI advice the higher the trust in the AI system ($t(6, 63) = 2.04$, $b = .32$, $p = .05$). This finding underlines the importance of trust as a key factor in shaping individuals' acceptance of AI advice.

For testing H7, the sequential mediation model was applied. Results do not support the idea that the degree of perceived intuition of AI systems indirectly influences the acceptance of AI advice through a sequence of closeness and trust as the confidence intervals include zero ($b = .0024$, BootLLCI = -.0077, BootULCI = .0161). Also, the results indicate that closeness ($b = .0253$, BootLLCI = -.0060, BootULCI = .0832) and trust ($b = .0529$, BootLLCI = -.0019, BootULCI = .1176) separately do not significantly mediate the relationship between the degree of perceived intuition of AI systems and the acceptance of AI advice.

4.2 Study 2

4.1.1 Descriptive statistics

The main variables for Study 2 are the same as in Study 1. For the descriptive statistics, no additional data cleaning or data transformation was carried out apart from what was described in the Methodology section.

For the perception of AI systems, participants provided their assessment for both the degree of intuitive and rational characteristics of the described AI. The mean score for the perceived intuitiveness of the AI system was 4.59, with a standard deviation of 1.198. Further, the mean score for the perceived rationality of the same AI system was 4.89, with a standard deviation of 1.162. Regarding the likelihood of participants considering AI's feedback for strategy development, the mean score was 5.05 with a standard deviation of 1.096. The trust score in AI systems had a mean value of 4.3968 and a standard deviation of 0.66291. Lastly, the mean score for the feeling of closeness towards the described AI was 3.46 with a standard deviation of 1.297.

4.1.2 Hypothesis testing

Before testing the hypotheses, the outcomes of the manipulation check (MC) are presented. The results suggest that the manipulation did not have a significant effect on the two manipulation check variables (intuition MC: $p = .592$; rational MC: $p = .793$). Thus, the manipulations were not effective in creating distinct levels of intuitive and rational perceptions of AI. Therefore, I will consider the manipulation checks answers directly as the independent variable, as they provide insights as to what degree participants consider the AI system as intuitive and rational. Thus, data from Study 2 is correlational and not experimental, as initially intended.

For H1, the analysis revealed that the more intuitive the AI system is perceived to be, the more likely it is that the individuals accept the advice given by the AI system ($t(6, 141) = 3.48$, $b = .25$, $p = .001$). Thus, hypothesis H1 is supported. Again, to ensure the robustness of this (and H2 and H3) result, a similar measure was taken regarding the degree of perceiving AI as more or less rational. Here. the effect on the acceptance on AI advice was also observed the more the AI system was perceived as rational ($t(6, 141) = 4.28$, $b = .32$, $p = .00$). This outcome contrasts with Study 1, where no significant relationship was observed.

Regarding H2, the findings indicated a positive and significant effect for the relationship between the degree of perceiving AI systems as more intuitive and the feeling of greater closeness towards these systems ($t(4, 143) = 3.03$, $b = .25$, $p = .003$). Surprisingly, this effect was also observed for the degree of perceived rationality of AI systems, indicating that when the individual perceived the AI system as more rational, a greater feeling of closeness was established ($t(4, 143) = 2.44$, $b = .21$, $p = .016$). This relationship deviates from Study 1, in which only the degree of intuitive perception showed a significant effect.

Furthermore, the results for H3 presented a significant positive effect meaning that the more the AI system was perceived as intuitive, the greater trust was built in the system ($t(5, 142) = 3.39$, $b = .15$, $p = .001$). Thus, the hypothesis is supported. In line with Study 1, the same result was observed for perceiving the AI system as more rational ($t(5, 142) = 3.55$, $b = .16$, $p = .001$) and the effect of building greater trust in the described system.

Additionally. the analysis of H4 displayed no significant effects ($t(6, 141) = .01$, $b = .00$, $p = .99$) on the relationship between the feeling of closeness and the acceptance of AI advice. Therefore, the hypothesis is not supported, which is in line with the findings from Study 1.

In H5, it was hypothesized that a feeling of closeness towards AI systems would develop trust in those systems. The results showed a significant effect ($t(5, 142) = 2.23$, $b = .10$, $p < .027$) and therefore, the hypothesis is supported suggesting that closeness is an important prerequisite for building trust in AI systems. This outcome is different from Study 1, where no significant relationship was found.

Moreover, the result for testing H6 supported the hypothesis ($t(6, 141) = 4.02$, $b = .53$, $p < .00$), which is congruent with the results from Study 1indicating that trust is an important factor positively influencing the acceptance of AI advice by individuals.

Finally, results suggest that the indirect effect of closeness and trust on the relationship between the degree of perceived intuition of AI systems and the acceptance of AI advice is not significant. Therefore, H7 is not supported ($b = .0130$, BootLLCI = -.0003, BootULCI = .0325). This outcome is congruent with Study 1.

Interestingly, results indicate that trust alone (($b = .0800$, BootLLCI = .0294, BootULCI = .1403)) significantly mediates the relationship between the degree of perceived intuition of AI systems and the acceptance of AI advice, which is contrary to the results from Study 1.

5. Discussion

5.1 Main research findings

5.1.1 Study 1

The results from Study 1 support H2, showing that individuals who perceive AI systems as more intuitive feel significantly closer towards them.

Also, H3 was supported indicating that a higher degree of perceived intuition in AI systems is associated with higher levels of trust towards these systems. Further, hypothesis H6 was supported, suggesting that trust has a positive influence on the acceptance of AI advice. Surprisingly, for H3 and H6, this was also true for higher degrees of perceived rationality of AI systems.

Moreover, data did not support hypotheses H1, suggesting that a more intuitive perception of AI does not significantly impact the feeling of closeness towards AI. Also, H4 and H5 are not supported by the data, indicating that closeness has no significant impact on building trust and on the acceptance of AI advice. Finally, when applying the sequential mediation model for H7, results did not indicate a significant relationship between the perceived degree of intuition of AI systems and the acceptance of AI advice mediated by closeness and trust.

5.1.2 Study 2

In line with Study 1, H3 and H6 were supported by the results. Again, the results were also significant for higher degrees of perceived rationality of AI systems, not only for higher degrees of perceived intuition.

Furthermore, H2 was also supported by the results, which is congruent with Study 1. Here, the degree of perceived rationality of AI systems also had a significant positive influence on feeling close to AI systems, which is different to Study 1.

Also, in line with Study 1, H4 and H7 were not supported indicating that the feeling of closeness does not significantly influence the acceptance of AI advice and also that the degree of perceived intuition in AI systems does not significantly influence the acceptance of AI advice mediated by closeness and trust.

For H1 and H5, Study 2 offered different results from Study 1. Contrarily, Study 2 showed a positive and significant relationship between the degree of perceived intuition in AI systems and the acceptance of AI advice. Also, Study 2 revealed a positive impact of the feeling of closeness towards AI systems on building trust in those systems.

5.2 Theoretical and managerial implications

For the first hypothesis, the contradictory results between Study 1 and Study 2 suggest that the relationship between the degree of perceived intuition in AI systems and the acceptance of AI advice might be influenced by other factors. The discrepancy underlines the possible influence of additional contextual or individual factors on the relationship between the perceived intuition of AI and acceptance of its advice. This might include user's attitudes, previous experience with technology, or perceived usefulness and ease of use, as outlined in the Technology Acceptance Model (Davis, 1989; Venkatesh et al., 2003). For managers aiming to increase individuals' acceptance of AI systems, the findings suggest that focusing on the intuition aspect alone might not be sufficient. Instead, taking a more holistic approach that considers different facets of AI perception could yield better results. This way, organizations can navigate the nuanced role of perceived intuition in influencing the acceptance of AI advice more effectively.

The second hypothesis was supported in both studies, suggesting that users who perceive AI as more intuitive are more likely to feel a personal connection or closeness to the system. This could be because intuitive systems, which seemingly understand and respond to human needs and emotions, appear more human-like and familiar. Interestingly, Study 2 also found a significant positive relationship between the degree of perceived rationality and closeness, differing from Study 1. It suggests that a rational AI system, perhaps due to its reliable and consistent functioning, can also engender feelings of closeness. These findings suggest that different qualities (intuition and rationality) in AI systems can create a sense of closeness in individuals. This aligns with theories suggesting that human-like characteristics, such as the ability to mimic intuition, can foster a more intimate connection with AI systems. Similarly, the predictability and dependability of a rational system can also create feelings of familiarity and closeness (Edwards et al., 2019).

Both studies supported H3, indicating that intuitive AI systems are more likely to be trusted by individuals. Surprisingly, both studies also found that a higher degree of perceived rationality in AI systems was associated with higher trust levels. This suggests that whether AI is seen as intuitive or rational, it can generate trust. This aligns with existing research suggesting that both intuition and rationality in AI systems can contribute to user trust (Muir & Moray, 1996; Schepman & Rodway, 2022). Therefore, the perceived degree of intuition and rationality can be viewed as significant attributes of AI systems that influence individuals' trust. Managers should therefore aim to implement AI systems that are both highly intuitive and highly rational, as these characteristics can foster trust, which is crucial for AI acceptance.

The results from the fourth hypothesis indicate that the sense of closeness to AI systems does not have a significant impact on the acceptance of AI advice. Since both studies did not support H4, it challenges the traditional understanding of affective responses towards technology and their influence on technology acceptance. As this finding is contradictory to existing literature, the current models in HCI and technology acceptance literature may need to be revisited to account for such findings (Glikson & Woolley, 2018). From a managerial perspective, the results imply that efforts to make users feel closer to AI systems might not necessarily lead to increased acceptance of AI advice. This suggests that organizations investing in AI technologies may want to focus less on trying to foster a sense of closeness and more on other aspects that could influence acceptance, such as improving performance, reliability, and transparency of AI.

The inconsistency in the support for H5 between the two studies suggests that the relationship between emotional closeness and trust towards AI systems is not straightforward and is likely influenced by other factors, which reflects the current literature. Some studies suggest that increasing closeness positively affects trust formation, while other studies indicate that closeness may not necessarily lead to increased trust (Firmansyah et al., 2021; S. H. Liu, 2014; Ng, 2013; Sánchez Pérez & Mollá Descals, 1999; L. Yang et al., 2021). Given this discrepancy, it becomes relevant to question the robustness of the relationship, which could be context-dependent and therefore requires further investigation. For managers in the business context, the inconsistent findings suggest that simply cultivating a sense of closeness may not always translate into higher levels of trust in AI systems.

The consistent findings in both studies supporting H6 align with the existing literature on the central role of trust as an important prerequisite for the acceptance of AI advice and the established link between trust and the acceptance of advice in HCI literature (Araujo et al., 2020; Bitkina et al., 2020; Choung et al., 2022; Dzindolet et al., 2003; Glikson & Woolley, 2018). From a managerial perspective, the robust support for H6 underscores the importance of fostering trust in AI systems. If individuals trust an AI system, they are more likely to accept its advice, which could lead to improved efficiency, effectiveness, and satisfaction in various AI-assisted tasks and decision-making contexts. Therefore, managers should consider incorporating feedback mechanisms into AI systems to facilitate understanding and create opportunities for trust to be established and strengthened over time. As trust promotes advice acceptance, it could ultimately lead to greater AI adoption.

The result for H7 contribute to the understanding of the complex interplay between the perceived degree of intuition of AI, closeness towards AI, trust in AI, and acceptance of AI advice, suggesting that the hypothesized mediating roles of closeness and trust may not exist in the way theorized. Here, studies suggest that factors influencing the acceptance of AI advice include interest in technology, performance expectancy, openness, perceived complexity, technology competence, perceived behavioral control, personal attitudes, task complexity, beliefs about human vs. AI performance, and perceived usefulness (Gursoy et al., 2019; J. Kim et al., 2021; Kocielnik et al., 2019; Lin et al., 2020; Sohn & Kwon, 2020; Z. Zhang et al., 2021).

On a managerial level, the non-support of H7 indicates that simply enhancing the intuitive aspect of AI systems may not directly lead to increased acceptance of AI advice through closeness and trust. This implies that managers should focus on a more comprehensive strategy when aiming to improve acceptance of AI advice. For example, organizations should seek to build trust in their AI systems beyond merely making them more intuitive. This could involve improving transparency, providing clear communication about how the AI system works, demonstrating its competency and reliability, and incorporating user-friendly design features.

5.3 Limitation and future research

While the findings from the two studies have provided valuable insights and advances in the understanding of human perception and interaction with AI systems, there are several limitations that should be noted, which simultaneously present opportunities for future research.

One limitation is the inconsistency in the results between Study 1 and Study 2 for hypotheses H1 and H5. These might stem from variations in context or sample characteristics between the two studies. It may also be due to unmeasured variables or contextual factors that were not accounted for in our studies. Future research should try to replicate these studies using different methodologies, for example employing longitudinal or experimental designs to minimize potential variations and provide a more robust test of these hypotheses. This will help clarify the relationships and their directions, providing further insights into the role of perceived intuition on the acceptance of AI advice and the influence of closeness on trust.

The research primarily focused on perceived intuition and rationality as the key attributes of AI systems. While these are important, they do not include all potential factors. Future studies should consider expanding the scope of AI attributes, such as AI transparency, dependability, and user-friendliness. A more holistic assessment of AI attributes could lead to a more comprehensive understanding of their collective influence on the interaction with AI systems.

Another limitation was the lack of consideration for individual differences among the participants. Aspects such as technological literacy, prior experience with AI, or personality traits may affect how they perceive and interact with AI systems (Etikan et al., 2016). Future research should consider incorporating these factors into their study design. For example, a future study could include a pre-study survey to assess participants' prior experience with AI and their level of technological literacy. Additionally, personality traits could be measured using established scales, and these factors could be controlled for or examined as potential moderators in the analyses.

Also, findings indicated a lack of support for H4 and H7. This suggests that the proposed mediating roles of closeness and trust might not operate as initially theorized. To address this, future research should consider other potential mediating variables. For instance, perceived usefulness or perceived ease of use, as proposed in the TAM (Davis, 1989; Venkatesh et al., 2003; Wu & Chen, 2005), could be included in future studies. A study could be designed to test a more comprehensive sequential mediation model including these variables, which would provide a better understanding of the complex relationship among these factors.

Furthermore, the sample sizes of both studies were relatively small due to time and resource constraints, and the convenience sampling method used may have excluded relevant subgroups, including diverse age groups and educational backgrounds. These limitations may limit the generalizability of our findings, and future research would benefit from larger and more diverse samples. Moreover, the experimental manipulation in Study 2 was not successful, subsequently changing the nature of the study to correlational. This limits the conclusions that can be drawn regarding causal relationships. The issues with the manipulation could originate from the complexity of the concepts described or the length of these descriptions. It's also possible that the participants found the concepts challenging to understand or interpret. Therefore, future research should ensure that the experimental manipulation is clear and easily understandable for the participants. This could involve pre-testing the manipulation on a smaller sample to assess its effectiveness and comprehensibility and incorporating the feedback from this pre-test to refine the manipulation before it is used in the main study.

6. Conclusion

This research aimed to explore the relationship between human perceptions of AI, their trust in AI systems, the feeling of closeness towards AI, and their reliance on AI advice. Two studies were conducted, and seven hypotheses were tested. Findings revealed that both higher degrees of intuitive and rational perceptions of AI foster trust, which is crucial for advice acceptance. This finding aligns with the previous literature and highlights the critical role of trust in human-computer interaction. Yet, cultivating a sense of closeness may not necessarily translate into trust or advice acceptance. Contradictions between the studies suggest the influence of other variables like personal attitudes or prior experience with technology. While this research has shed light on some aspects of the relationship between perception, trust, closeness, and reliance on AI advice, there is still much to explore in this fascinating field. The findings presented here provide a steppingstone for further explorations, with the ultimate goal of improving our understanding of human-computer interaction in the era of artificial intelligence.

Appendix

Appendix 1: Survey 1

Q14 Welcome and thank you for participating in this experiment on artificial intelligence.
This experiment is of the responsibility of Prof. Ian Scott
It consists of reading a description of artificial intelligence (AI) and answering a couple of questions about it. It will take about 3 minutes to complete. Please answer as honestly as possible.
All answers will be kept strictly confidentially and are anonymous. This means that there will be no way to link your responses to your identity. The data collected will be used for research purposes only. There are no expected side effects of participating in this study. You may drop out at any point.
If you have any questions about this study, please email Ian Scott (iscott@novaims.unl.pt). By continuing you agree to participate.

MC1 To what extent do you agree with the following statement?
I perceive AI to be intuitive.
Strongly disagree (13)
Disagree (14)
Somewhat disagree (15)
Neither agree nor disagree (16)
Somewhat agree (17)
Agree (18)
Strongly agree (19)

MC2 To what extent do you agree with the following statement?
I perceive AI to be rational.
Strongly disagree (13)
Disagree (14)
Somewhat disagree (15)
Neither agree nor disagree (16)
Somewhat agree (17)
Agree (18)
Strongly agree (19) Q34 How rational/intuitive do you perceive AI to be?
Strongly intuitive (13)
Intuitive (14)
Somewhat intuitive (15)
Equally intuitive and rational (16)
Somewhat rational (17)
Rational (18)
Strongly rational (19)

Q30 How likely would you be to consider AI's feedback?
Very unlikely (1)
Unlikely (2)
Slightly unlikely (3)
Neither likely nor unlikely (4)
Slightly likely (5)
Likely (6)
Very likely (7)

Please read the following statements and state your agreement/disagreement about them considering an AI assisting you.	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe that there could be negative consequences when using AI. (1)	○	○	○	○	○	○	○
I feel I must be cautious when using AI. (4)	○	○	○	○	○	○	○
It is risky to interact with AI. (5)	○	○	○	○	○	○	○
I believe that AI will act in my best interest. (6)	○	○	○	○	○	○	○
I believe that AI will do its best to help me if I need help. (7)	○	○	○	○	○	○	○
I believe that AI is interested in understanding my needs and preferences. (8)	○	○	○	○	○	○	○
I think that AI is competent and effective. (10)	○	○	○	○	○	○	○
I think that AI performs its role very well. (11)	○	○	○	○	○	○	○
I believe that AI has all the functionalities I would expect. (12)	○	○	○	○	○	○	○
If I use AI, I think i would be able to depend on it completely. (14)	○	○	○	○	○	○	○
I can always rely on AI. (16)	○	○	○	○	○	○	○
I can trust the information presented to me by AI. (17)	○	○	○	○	○	○	○

Input Thank you!

Now, we would like to know how you feel towards AI.

Please look at the picture provided below and indicate how close you feel to AI.

Closeness question: Which diagram best represents how close you feel to AI?

a. (1)

b. (2)

c. (3)

d. (4)

e. (5)

f. (6)
g. (7)

Q41 Now, please let us know more about your perception of AI for different domains by answering the questions below using the scales provided.

Q35 I would trust data from an on premises database.
Very unlikely (1)
Unlikely (2)
Slightly unlikely (3)
Neither likely nor unlikely (4)
Slightly likely (5)
Likely (6)
Very likely (7)

Q36 I would rely on data from an on premises database.
Very unlikely (1)
Unlikely (2)
Slightly unlikely (3)
Neither likely nor unlikely (4)
Slightly likely (5)
Likely (6)
Very likely (7)

Q37 I would trust data from the cloud.
Very unlikely (1)
Unlikely (2)
Slightly unlikely (3)
Neither likely nor unlikely (4)
Slightly likely (5)
Likely (6)
Very likely (7)

Q38 I would rely on data from the cloud.
Very unlikely (1)
Unlikely (2)
Slightly unlikely (3)
Neither likely nor unlikely (4)
Slightly likely (5)
Likely (6)
Very likely (7)

Q39 I would trust data from a blockchain.
Very unlikely (1)
Unlikely (2)
Slightly unlikely (3)
Neither likely nor unlikely (4)
Slightly likely (5)

Likely (6)
Very likely (7)

Q40 I would rely on data from a blockchain.
Very unlikely (1)
Unlikely (2)
Slightly unlikely (3)
Neither likely nor unlikely (4)
Slightly likely (5)
Likely (6)
Very likely (7)

Q24 Thank you for your participation in this study. In this study we actually want to study how AI is perceived (intuitive or rational) and how that perception affects reliance, trust and closeness towards it.

Gender How do you identify yourself?
Male (1)
Female (2)
Non-binary / third gender (3)
Prefer not to say (4)

Age How old are you?

Country of origin Where are you from?
Afghanistan (1) ... Zimbabwe (1357)

Q35 Did you pay attention to the study? If you were distracted, please let us know, so we don't use your data, which would invalidate the conclusions. Thank you very much!
I was attentive (1)
I was mostly attentive (2)
I was mostly inattentive (3)
I was inattentive (4)

Q34 If you have any comment for the researchers (e.g., was something unclear?) feel free to share it below. Thank you.

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Appendix 2: Survey 2

ParticipantID What is your participant ID?

Q14 Welcome and thank you for participating in this experiment on artificial intelligence. This experiment is of the responsibility of Prof. Filipa de Almeida. It consists of reading a description of artificial intelligence (AI) and answering a couple of questions about it. It will take about 3 minutes to complete. Please answer as honestly as possible. All answers will be kept strictly confidentially and are anonymous. This means that there will be no way to link your responses to your identity. The data collected will be used for research purposes only. There are no expected side effects of participating in this study. You may drop out at any point. If you have any questions about this study, please email Filipa de Almeida (filipadealmeida@ucp.pt). By continuing you agree to participate.
Again, thank you in advance for your valuable time answering our questions.

Q20 Please, take your time to read the following text from beginning to end. Then, you will be able to answer the follow-up questions accordingly.

AI description AI is a technological advancement that combines reasoning with learning capabilities to solve problems and make decisions.

AI systems are designed to analyze vast amounts of data and recognize patterns, making it easier for them to draw conclusions and make predictions.
One of the key strengths of AI is its ability to understand and interpret complex information in a way that is similar to human thinking. This enables AI systems to identify correlations and make predictions based on previous experiences and data, similar to how humans draw upon past experiences to make decisions.

AI has advantages over human thinking in a number of ways, firstly AI systems can be highly consistent, as they are able to apply the same logic and reasoning to similar problems, without being influenced by emotions or biases.

In addition, they can be trained over vast quantities of data, encompassing most of existing human knowledge and artistic expression, and freely learn connections over vastly different topics and sources.

A growing area of AI application is generative AI where AI systems generate new text, images, or videos creatively combining from their vast source material.

AI in diff domains AI can be applied in various domains. For example, it can be used for predictive analytics, where it analyzes data to identify patterns and predict future outcomes.
It can also be used for natural language processing, where it interprets human language and responds accordingly.

In the business world, AI can be used to enhance efficiency, reduce costs, and increase productivity. It can be used to optimize supply chain management, automate routine tasks, and improve customer service.
AI can also be used for fraud detection, risk assessment, and portfolio management.

AI has the potential to transform many industries and business processes by creating new opportunities for innovation, improving decision-making, and increasing efficiency.

Q27 Please, take your time to read the following text from beginning to end. Then, you will be able to answer the follow-up questions accordingly.

Q28 AI is a technological advancement that combines reasoning with learning capabilities to solve problems and make decisions.

AI systems are designed to analyze vast amounts of data and recognize patterns, making it easier for them to draw conclusions and make predictions.
One of the key strengths of AI is its ability to understand and interpret complex information in a way that is similar to human thinking. This enables AI systems to identify correlations and make predictions based on previous experiences and data, similar to how humans draw upon past experiences to make decisions.

AI has advantages over human thinking in a number of ways, firstly AI systems can be highly consistent, as they are able to apply the same logic and reasoning to similar problems, without being influenced by emotions or biases.

In addition, they can be trained over vast quantities of data, encompassing most of existing human knowledge and artistic expression, and freely learn connections over vastly different topics and sources.

A growing area of AI application is generative AI where AI systems generate new text, images, or videos creatively combining from their vast source material.

Q28 AI can be applied in various domains. For example, it can be used for predictive analytics, where it analyzes data to identify patterns and predict future outcomes.
It can also be used for natural language processing, where it interprets human language and responds accordingly.

In the business world, AI can be used to enhance efficiency, reduce costs, and increase productivity. It can be used to optimize supply chain management, automate routine tasks, and improve customer service.
AI can also be used for fraud detection, risk assessment, and portfolio management.

AI has the potential to transform many industries and business processes by creating new opportunities for innovation, improving decision-making, and increasing efficiency.

Def. Intuition Intuition can be defined as a subconscious or automatic thought process that enables individuals to quickly understand or recognize something without the need for conscious reasoning or analysis.

Intuition can be influenced by a variety of factors, including past experiences.

It is often associated with creativity and innovation, as it allows individuals to make connections and identify patterns that may not be immediately apparent through rational analysis alone.

In the context of AI, intuition is a fundamental characteristic of many AI systems. AI systems rely on pattern recognition, learn from experiences, adapt to new situations, and generate creative output quickly and, therefore, can be considered intuitive decision makers.

Q29 Please, take your time to read the following text from beginning to end. Then, you will be able to answer the follow-up questions accordingly.

Q30 AI is a technological advancement that combines reasoning with learning capabilities to solve problems and make decisions.

AI systems are designed to analyze vast amounts of data and recognize patterns, making it easier for them to draw conclusions and make predictions.
One of the key strengths of AI is its ability to understand and interpret complex information in a way that is similar to human thinking. This

enables AI systems to identify correlations and make predictions based on previous experiences and data, similar to how humans draw upon past experiences to make decisions.

AI has advantages over human thinking in a number of ways, firstly AI systems can be highly consistent, as they are able to apply the same logic and reasoning to similar problems, without being influenced by emotions or biases.

In addition, they can be trained over vast quantities of data, encompassing most of existing human knowledge and artistic expression, and freely learn connections over vastly different topics and sources.

A growing area of AI application is generative AI where AI systems generate new text, images, or videos creatively combining from their vast source material.

Q29 AI can be applied in various domains. For example, it can be used for predictive analytics, where it analyzes data to identify patterns and predict future outcomes.
It can also be used for natural language processing, where it interprets human language and responds accordingly.

In the business world, AI can be used to enhance efficiency, reduce costs, and increase productivity. It can be used to optimize supply chain management, automate routine tasks, and improve customer service.
AI can also be used for fraud detection, risk assessment, and portfolio management.

AI has the potential to transform many industries and business processes by creating new opportunities for innovation, improving decision-making, and increasing efficiency.

Def. Rationality: Rationality can be defined as the ability to think logically and make decisions based on reason, rather than emotions or biases.

It involves the use of systematic, structured reasoning to analyze information and draw conclusions.

It is often associated with objectivity and impartiality, as it involves making decisions based on evidence and facts, rather than personal opinions or beliefs. It also involves the ability to weigh the costs and benefits of different options and make decisions based on a rational assessment of the situation.

In the context of AI, rationality is a fundamental characteristic of many AI systems. AI systems rely on algorithms and logical reasoning processes, the analysis of empirical data, and exclude emotion and biases and, therefore, can be considered rational decision makers.

Intro Thank you. Now, please answer the questions below and keep in mind what you just read.

MC1 To what extent do you agree with the following statement?
I perceive the described AI to be intuitive.
Strongly disagree (13)
Disagree (14)
Somewhat disagree (15)
Neither agree nor disagree (16)
Somewhat agree (17)
Agree (18)
Strongly agree (19)

Q41 To what extent do you agree with the following statement?
I perceive the described AI to be rational.
Strongly disagree (13)
Disagree (14)
Somewhat disagree (15)
Neither agree nor disagree (16)
Somewhat agree (17)
Agree (18)
Strongly agree (19)

Strategy dev: Now, please imagine that AI would assist you in strategy development.
Developing effective business strategies requires both rational analysis of market trends and opportunities, and intuitive creativity to find unique and successful solutions.

Q30 How likely would you be to consider AI's feedback for strategy development?
Very unlikely (1)
Unlikely (2)
Slightly unlikely (3)
Neither likely nor unlikely (4)
Slightly likely (5)
Likely (6)
Very likely (7)

Please read the following statements and state your agreement/disagreement about them considering an AI assisting you in strategy development.	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe that there could be negative consequences when using AI. (1)	○	○	○	○	○	○	○
I feel I must be cautious when using AI. (4)	○	○	○	○	○	○	○
It is risky to interact with AI. (5)	○	○	○	○	○	○	○
I believe that AI will act in my best interest. (6)	○	○	○	○	○	○	○
I believe that AI will do its best to help me if I need help. (7)	○	○	○	○	○	○	○
I believe that AI is interested in understanding my needs and preferences. (8)	○	○	○	○	○	○	○
I think that AI is competent and effective in strategy development. (10)	○	○	○	○	○	○	○
I think that AI performs its role in strategy development very well. (11)	○	○	○	○	○	○	○
I believe that AI has all the functionalities I would expect for strategy development. (12)	○	○	○	○	○	○	○
If I use AI, I think i would be able to depend on it completely. (14)	○	○	○	○	○	○	○
I can always rely on AI for strategy development. (16)	○	○	○	○	○	○	○
I can trust the information presented to me by AI. (17)	○	○	○	○	○	○	○

Input Thank you!

Now, we would like to know how you feel about the previously described AI.

Please look at the picture provided below and indicate how close you feel to the AI.

Closeness question: Which diagram best represents how close you feel to the described AI?

a. (1)
b. (2)
c. (3)
d. (4)
e. (5)
f. (6)
g. (7)

Q24 Thank you for your participation in this study.

In this study we actually want to study how AI is perceived and therefore tested for attitude, trust and closeness towards AI.

For that, we manipulated providing a definition of intuition, rationality or no definition at all by assigning one third of participants to each condition.

Gender How do you identify yourself?

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

Age How old are you?

Country of origin Where are you from?
▼ Afghanistan (1) ... Zimbabwe (1357)

Q35 Did you pay attention to the study? If you were distracted, please let us know, so we don't use your data, which would invalidate the conclusions. Thank you very much!
I was attentive (1)
I was mostly attentive (2)
I was mostly inattentive (3)
I was inattentive (4)

Q34 If you have any comment for the researchers (e.g., was something unclear?) feel free to share it below. Thank you.
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Appendix 3: Data Analysis Study 1

Statistics

		How do you identify yourself?	How old are you?	List of Countries
N	Valid	72	72	70
	Missing	0	0	2
Mean		1,49	27,2361	118,66
Median		1,00	25,0000	138,00
Mode		1	21,00[a]	138
Std. Deviation		,581	6,95760	41,074
Variance		,338	48,408	1687,098
Minimum		1	21,00	5
Maximum		4	50,00	179
Sum		107	1961,00	8306

a. Multiple modes exist. The smallest value is shown

How do you identify yourself?

	N	%
Male	39	54,2%
Female	32	44,4%
Prefer not to say	1	1,4%

How old are you?

	N	%
21,00	12	16,7%
22,00	10	13,9%
23,00	5	6,9%
24,00	3	4,2%
25,00	12	16,7%
26,00	3	4,2%
27,00	4	5,6%
28,00	2	2,8%
29,00	2	2,8%
30,00	3	4,2%
32,00	2	2,8%
33,00	3	4,2%
34,00	1	1,4%
35,00	2	2,8%
36,00	1	1,4%
38,00	1	1,4%
41,00	1	1,4%
44,00	2	2,8%

45,00	1	1,4%
47,00	1	1,4%
50,00	1	1,4%

List of Countries

		N	%
Angola		1	1,4%
Argentina		1	1,4%
Bangladesh		1	1,4%
Brazil		3	4,2%
China		1	1,4%
Croatia		1	1,4%
Ecuador		1	1,4%
Germany		1	1,4%
Ghana		1	1,4%
Iran		1	1,4%
Italy		3	4,2%
Mexico		1	1,4%
Mozambique		1	1,4%
Niger		1	1,4%
Portugal		46	63,9%
Russian Federation		4	5,6%
Spain		1	1,4%
Turkey		1	1,4%
Missing	System	2	2,8%

		To what extent do you agree with the following statement? I perceive AI to be intuitive.	To what extent do you agree with the following statement? I perceive AI to be rational.
N	Valid	72	72
	Missing	0	0
Mean		4,72	5,01
Median		5,00	5,00
Std. Deviation		1,376	1,506
Range		6	6
Minimum		1	1
Maximum		7	7

Which diagram best represents how close you feel to AI?

N	Valid	72
	Missing	0
Mean		3,58

Median	3,00
Std. Deviation	1,330
Range	6
Minimum	1
Maximum	7

Trust_Score

N	Valid	72
	Missing	0
Mean		4,4329
Median		4,4583
Std. Deviation		,67464
Range		3,50
Minimum		2,33
Maximum		5,83

How likely would you be to consider AI's feedback?

N	Valid	72
	Missing	0
Mean		5,49
Median		6,00
Std. Deviation		,872
Range		4
Minimum		3
Maximum		7

Reliability Statistics

Cronbach's Alpha	N of Items
,736	12

Model : 6 (Intuition)
Y : Q30
X : MC1
M1 : Closenes
M2 : Trust_Sc

Covariates:
Gender Age_ Country_

Sample
Size: 72
****
OUTCOME VARIABLE:
Closenes

Model Summary
R R-sq MSE F df1 df2 p

,3090	,0955	1,7136	1,7155	4,0000	65,0000	,1572

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,7041	1,2388	2,9902	,0039	1,2301	6,1781
MC1	,2423	,1202	2,0164	,0479	,0023	,4823
Gender	-,0862	,2851	-,3024	,7633	-,6557	,4832
Age_	-,0247	,0234	-1,0572	,2943	-,0714	,0220
Country_	-,0040	,0040	-,9968	,3226	-,0119	,0040

****

OUTCOME VARIABLE:

Trust_Sc

Model Summary

R	R-sq	MSE	F	df1	df2	p
,4717	,2225	,3895	3,6633	5,0000	64,0000	,0056

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,1470	,6299	4,9960	,0000	1,8886	4,4054
MC1	,1628	,0591	2,7570	,0076	,0448	,2808
Closenes	,0309	,0591	,5221	,6034	-,0873	,1490
Gender	-,0628	,1360	-,4615	,6460	-,3345	,2090
Age_	-,0005	,0112	-,0478	,9620	-,0230	,0219
Country_	,0045	,0019	2,3380	,0225	,0006	,0083

****

OUTCOME VARIABLE:

Q30

Model Summary

R	R-sq	MSE	F	df1	df2	p
,3559	,1266	,6308	1,5224	6,0000	63,0000	,1854

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,3784	,9451	3,5748	,0007	1,4898	5,2670
MC1	-,0122	,0795	-,1534	,8786	-,1710	,1466
Closenes	,1042	,0754	1,3824	,1717	-,0465	,2550
Trust_Sc	,3247	,1591	2,0414	,0454	,0068	,6426
Gender	,1913	,1734	1,1030	,2742	-,1553	,5378
Age_	-,0011	,0143	-,0800	,9365	-,0297	,0274
Country_	,0009	,0025	,3704	,7123	-,0041	,0060

************************** TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:

Q30

Model Summary

R	R-sq	MSE	F	df1	df2	p
,1921	,0369	,6742	,6225	4,0000	65,0000	,6481

Model

	coeff	se	t	p	LLCI	ULCI
constant	4,8236	,7770	6,2079	,0000	3,2718	6,3754
MC1	,0684	,0754	,9070	,3677	-,0822	,2189
Gender	,1610	,1788	,9004	,3712	-,1962	,5182
Age_	-,0041	,0147	-,2825	,7785	-,0334	,0251
Country_	,0019	,0025	,7760	,4406	-,0030	,0069

************** INDIRECT EFFECTS OF X ON Y **************

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	,0806	,0381	,0139	,1611
Ind1	,0253	,0232	-,0060	,0832
Ind2	,0529	,0307	-,0019	,1176
Ind3	,0024	,0055	-,0077	,0161
(C1)	-,0276	,0395	-,1000	,0576
(C2)	,0228	,0236	-,0109	,0814
(C3)	,0504	,0309	-,0022	,1180

Specific indirect effect contrast definition(s):

(C1) Ind1 minus Ind2
(C2) Ind1 minus Ind3
(C3) Ind2 minus Ind3

Indirect effect key:

Ind1 MC1 -> Closenes -> Q30
Ind2 MC1 -> Trust_Sc -> Q30
Ind3 MC1 -> Closenes -> Trust_Sc -> Q30

Model : 6 (Rationality)
Y : Q30
X : MC2
M1 : Closenes
M2 : Trust_Sc

Covariates:
Gender Age_ Country_

Sample
Size: 72

****

OUTCOME VARIABLE:
Closenes

Model Summary

R	R-sq	MSE	F	df1	df2	p
,2791	,0779	1,7469	1,3730	4,0000	65,0000	,2530

Model

	coeff	se	t	p	LLCI	ULCI
constant	4,7781	1,0347	4,6177	,0000	2,7116	6,8446
MC2	,1827	,1102	1,6580	,1021	-,0374	,4029
Gender	-,3101	,2762	-1,1229	,2656	-,8617	,2415
Age_	-,0404	,0241	-1,6763	,0985	-,0886	,0077
Country_	-,0047	,0041	-1,1461	,2560	-,0128	,0035

****

OUTCOME VARIABLE:

Trust_Sc

Model Summary

R	R-sq	MSE	F	df1	df2	p
,4870	,2372	,3822	3,9803	5,0000	64,0000	,0033

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,7656	,5577	6,7518	,0000	2,6514	4,8798
MC2	,1577	,0526	2,9966	,0039	,0526	,2629
Closenes	,0354	,0580	,6104	,5437	-,0805	,1513
Gender	-,2217	,1304	-1,7001	,0940	-,4823	,0388
Age_	-,0128	,0115	-1,1122	,2702	-,0358	,0102
Country_	,0037	,0019	1,9454	,0561	-,0001	,0076

****

OUTCOME VARIABLE:

Q30

Model Summary

R	R-sq	MSE	F	df1	df2	p
,3573	,1277	,6300	1,5366	6,0000	63,0000	,1809

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,3060	,9371	3,5281	,0008	1,4335	5,1786
MC2	-,0226	,0722	-,3130	,7553	-,1668	,1216
Closenes	,1056	,0747	1,4138	,1623	-,0437	,2549
Trust_Sc	,3344	,1605	2,0835	,0413	,0137	,6551
Gender	,2084	,1712	1,2173	,2280	-,1337	,5505
Age_	,0005	,0149	,0303	,9759	-,0294	,0303
Country_	,0010	,0025	,4038	,6877	-,0041	,0061

************************* TOTAL EFFECT MODEL ***************************

OUTCOME VARIABLE:

Q30

Model Summary

R	R-sq	MSE	F	df1	df2	p
,1820	,0331	,6768	,5567	4,0000	65,0000	,6949

Model

	coeff	se	t	p	LLCI	ULCI
constant	5,1265	,6441	7,9595	,0000	3,8402	6,4128
MC2	,0516	,0686	,7524	,4545	-,0854	,1886
Gender	,0978	,1719	,5691	,5713	-,2455	,4412
Age_	-,0086	,0150	-,5716	,5696	-,0386	,0214
Country_	,0017	,0025	,6824	,4974	-,0033	,0068

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI	c_cs
,0516	,0686	,7524	,4545	-,0854	,1886	,0959

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI	c'_cs
-,0226	,0722	-,3130	,7553	-,1668	,1216	-,0420

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	,0742	,0413	,0080	,1675
Ind1	,0193	,0223	-,0083	,0765
Ind2	,0527	,0366	-,0040	,1360
Ind3	,0022	,0050	-,0042	,0160
(C1)	-,0334	,0451	-,1247	,0572
(C2)	,0171	,0221	-,0117	,0745
(C3)	,0506	,0367	-,0063	,1349

Specific indirect effect contrast definition(s):

(C1)	Ind1	minus	Ind2
(C2)	Ind1	minus	Ind3
(C3)	Ind2	minus	Ind3

Indirect effect key:

Ind1 MC2	->	Closenes	->	Q30			
Ind2 MC2	->	Trust_Sc	->	Q30			
Ind3 MC2	->	Closenes	->	Trust_Sc	->	Q30	

Appendix 4: Data Analysis Study 2

How do you identify yourself?

N	Valid	219
	Missing	0
Mean		1,48
Median		1,00
Std. Deviation		,536
Minimum		1
Maximum		4

How do you identify yourself?	N	%
Male	116	53,0%
Female	101	46,1%
Non-binary / third gender	1	0,5%
Prefer not to say	1	0,5%

How old are you?

N	Valid	219
	Missing	0
Mean		24,2466
Median		24,0000
Std. Deviation		5,17434
Minimum		21,00
Maximum		89,00

How old are you?	N	%
21,00	28	12,8%
22,00	26	11,9%
23,00	33	15,1%
24,00	57	26,0%
25,00	36	16,4%
26,00	23	10,5%
27,00	11	5,0%
28,00	3	1,4%
55,00	1	0,5%
89,00	1	0,5%

List of Countries

	N	%
Andorra	2	0,9%
Angola	1	0,5%
Argentina	2	0,9%
Austria	5	2,3%

Belarus		1	0,5%
Belgium		5	2,3%
Belize		2	0,9%
Brazil		2	0,9%
Canada		1	0,5%
Croatia		1	0,5%
France		5	2,3%
Germany		97	44,3%
Hungary		6	2,7%
Italy		9	4,1%
Lebanon		1	0,5%
Mexico		1	0,5%
Morocco		2	0,9%
Mozambique		2	0,9%
Netherlands		1	0,5%
Norway		8	3,7%
Peru		1	0,5%
Poland		2	0,9%
Portugal		47	21,5%
Russian Federation		1	0,5%
Spain		1	0,5%
Sweden		3	1,4%
Switzerland		2	0,9%
Tunisia		4	1,8%
Turkey		1	0,5%
Missing	System	3	1,4%

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
To what extent do you agree with the following statement? I perceive the described AI to be intuitive.	Between Groups	1,516	2	,758	,526	,592
	Within Groups	311,497	216	1,442		
	Total	313,014	218			
To what extent do you agree with the following statement? I perceive the described AI to be rational.	Between Groups	,630	2	,315	,232	,793
	Within Groups	293,516	216	1,359		
	Total	294,146	218			

Statistics

		To what extent do you agree with the following statement? I perceive the described AI to be intuitive.	To what extent do you agree with the following statement? I perceive the described AI to be rational.	How likely would you be to consider AI's feedback for strategy development?	Trust_Score	Which diagram best represents how close you feel to the described AI?
N	Valid	219	219	218	185	184
	Missing	0	0	1	34	35
Mean		4,59	4,89	5,05	4,3968	3,46
Median		5,00	5,00	5,00	4,3333	3,00
Std. Deviation		1,198	1,162	1,096	,66291	1,297
Range		6	6	6	3,92	6
Minimum		1	1	1	2,50	1
Maximum		7	7	7	6,42	7

Reliability Statistics

Cronbach's Alpha	N of Items
,779	12

Model : 6 (Intuition)
Y : Q30
X : MC1
M1 : Closenes
M2 : Trust_Sc

Covariates:
Gender Age_ Country_

Sample
Size: 148
****
OUTCOME VARIABLE:
Closenes

Model Summary

R	R-sq	MSE	F	df1	df2	p
,3162	,1000	1,4664	3,9719	4,0000	143,0000	,0044

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,2348	,7292	4,4362	,0000	1,7934	4,6762

MC1	,2501	,0826	3,0289	,0029	,0869	,4134
Gender	-,3220	,1940	-1,6601	,0991	-,7054	,0614
Age_	-,0017	,0169	-,1024	,9186	-,0351	,0316
Country_	-,0041	,0024	-1,7454	,0831	-,0088	,0005

****

OUTCOME VARIABLE:

Trust_Sc

Model Summary

R	R-sq	MSE	F	df1	df2	p
,3706	,1374	,4024	4,5224	5,0000	142,0000	,0007

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,4621	,4074	8,4974	,0000	2,6567	4,2676
MC1	,1514	,0446	3,3916	,0009	,0631	,2396
Closenes	,0980	,0438	2,2371	,0268	,0114	,1846
Gender	,0151	,1026	,1477	,8828	-,1877	,2179
Age_	-,0064	,0088	-,7267	,4686	-,0239	,0110
Country_	,0005	,0012	,3686	,7130	-,0020	,0029

****

OUTCOME VARIABLE:

Q30

Model Summary

R	R-sq	MSE	F	df1	df2	p
,5001	,2501	,9891	7,8363	6,0000	141,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1,8627	,7845	2,3743	,0189	,3117	3,4137
MC1	,2533	,0727	3,4819	,0007	,1095	,3971
Closenes	,0008	,0699	,0117	,9907	-,1373	,1390
Trust_Sc	,5285	,1316	4,0172	,0001	,2684	,7886
Gender	,1164	,1608	,7236	,4705	-,2016	,4344
Age_	-,0118	,0139	-,8475	,3981	-,0392	,0157
Country_	-,0025	,0020	-1,2657	,2077	-,0063	,0014

************************** TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:

Q30

Model Summary

R	R-sq	MSE	F	df1	df2	p
,4014	,1611	1,0910	6,8661	4,0000	143,0000	,0000

Model

coeff	se	t	p	LLCI	ULCI

constant	3,8627	,6290	6,1415	,0000	2,6195	5,1060
MC1	,3464	,0712	4,8637	,0000	,2056	,4872
Gender	,1075	,1673	,6423	,5217	-,2233	,4382
Age_	-,0152	,0145	-1,0480	,2964	-,0440	,0135
Country_	-,0024	,0020	-1,2055	,2300	-,0065	,0016

************** INDIRECT EFFECTS OF X ON Y **************

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	,0932	,0331	,0339	,1639
Ind1	,0002	,0220	-,0405	,0483
Ind2	,0800	,0284	,0294	,1403
Ind3	,0130	,0085	-,0003	,0325
(C1)	-,0798	,0405	-,1610	,0004
(C2)	-,0128	,0232	-,0590	,0341
(C3)	,0670	,0284	,0157	,1271

Specific indirect effect contrast definition(s):

(C1) Ind1 minus Ind2
(C2) Ind1 minus Ind3
(C3) Ind2 minus Ind3

Indirect effect key:

Ind1 MC1 -> Closenes -> Q30
Ind2 MC1 -> Trust_Sc -> Q30
Ind3 MC1 -> Closenes -> Trust_Sc -> Q30

Model : 6 (Rationality)
Y : Q30
X : Q41
M1 : Closenes
M2 : Trust_Sc

Covariates:
Gender Age_ Country_

Sample
Size: 148

****

OUTCOME VARIABLE:
Closenes

Model Summary

R	R-sq	MSE	F	df1	df2	p
,2837	,0805	1,4982	3,1290	4,0000	143,0000	,0168

Model

	coeff	se	t	p	LLCI	ULCI

constant	3,4947	,7318	4,7752	,0000	2,0481	4,9413
Q41	,2143	,0879	2,4383	,0160	,0406	,3880
Gender	-,3813	,1972	-1,9333	,0552	-,7711	,0086
Age_	-,0033	,0170	-,1941	,8464	-,0370	,0304
Country_	-,0045	,0024	-1,8866	,0612	-,0092	,0002

****

OUTCOME VARIABLE:

Trust_Sc

Model Summary

R	R-sq	MSE	F	df1	df2	p
,3788	,1435	,3996	4,7593	5,0000	142,0000	,0005

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,4281	,4070	8,4238	,0000	2,6236	4,2326
Q41	,1644	,0463	3,5507	,0005	,0729	,2560
Closenes	,1038	,0432	2,4047	,0175	,0185	,1892
Gender	-,0272	,1032	-,2638	,7923	-,2311	,1767
Age_	-,0071	,0088	-,8020	,4239	-,0244	,0103
Country_	,0003	,0012	,2337	,8155	-,0022	,0027

****

OUTCOME VARIABLE:

Q30

Model Summary

R	R-sq	MSE	F	df1	df2	p
,5285	,2793	,9505	9,1091	6,0000	141,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1,7678	,7687	2,2998	,0229	,2482	3,2874
Q41	,3192	,0745	4,2829	,0000	,1719	,4666
Closenes	,0068	,0680	,1004	,9202	-,1275	,1412
Trust_Sc	,4956	,1294	3,8292	,0002	,2397	,7515
Gender	,0329	,1592	,2066	,8366	-,2818	,3475
Age_	-,0128	,0136	-,9388	,3495	-,0396	,0141
Country_	-,0028	,0019	-1,4372	,1529	-,0065	,0010

************** INDIRECT EFFECTS OF X ON Y **************

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	,0940	,0321	,0343	,1629
Ind1	,0015	,0192	-,0369	,0426
Ind2	,0815	,0286	,0302	,1428
Ind3	,0110	,0083	,0000	,0312
(C1)	-,0800	,0383	-,1563	-,0061
(C2)	-,0096	,0212	-,0560	,0308

(C3)	,0705	,0286	,0183	,1314

Specific indirect effect contrast definition(s):

(C1)	Ind1	minus	Ind2
(C2)	Ind1	minus	Ind3
(C3)	Ind2	minus	Ind3

Indirect effect key:

Ind1	Q41	->	Closenes	->	Q30		
Ind2	Q41	->	Trust_Sc	->	Q30		
Ind3	Q41	->	Closenes	->	Trust_Sc	->	Q30

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