# Artificial Intelligence or the others?
## The Consequences of Social Influence on Reliance on Advice from Artificial Intelligence

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Dissertation written under the supervision of Filipa de Almeida

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## Abstract

**Title**: Artificial Intelligence or the others? The Consequences of Social Influence on Reliance on Advice from Artificial Intelligence

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Organizations are constantly confronted with decisions. The outcome of decisions can have a tremendous impact on the future of the organizations. Thus, organizations are continually investing in different tools that will help them improve the decision making. In this sense, organizations have commonly decided to invest in advice from human experts but lately, due to technological advancements, organizations have started to invest in artificial intelligence (AI; human-AI decision making). Considering that strategic decisions are commonly taken in groups, this thesis aims to research the impact of social influence on advice taking (from humans and AI). Particularly, this thesis investigates how humans react to advice from machine learning algorithms and advice from human experts in a strategic decision about an IPO valuation. Moreover, this dissertation also studies the impact of unanimous majority in team settings and the impact it has on advice taking. The results suggest the robustness of cognitive biases (e.g., anchoring) affecting the decision-making process. Additionally, the findings of this thesis demonstrate the presence of a motivated component (e.g., motivated reasoning) affecting advice taking in strategic decision-making processes. Moreover, the results reveal the importance of the perceived trustworthiness of the advisor, be it an AI tool or human. Nevertheless, the results show no significant effect of the social influence manipulation on advice taking nor of the source of the influence.

**Keywords**: Artificial Intelligence, Strategic Decision Making, Human-AI Decision Making, Social Influence, Advice Taking, WOA, Motivated Reasoning.

## Sumário

**Título:** A Inteligência Artificial ou os outros? As Consequências da influência social na aceitação dos conselhos da Inteligência Artificial

**Autor:** Douglas José Escobar Magaña

As organizações são constantemente confrontadas com decisões. O resultado das decisões pode ter um impacto tremendo no futuro das mesmas. Assim, as organizações estão continuamente a investir em diferentes ferramentas que as ajudem a melhorar a tomada de decisões. Neste sentido, as organizações têm vindo a investir no aconselhamento de peritos humanos mas, ultimamente, devido aos avanços tecnológicos, as organizações começaram a investir na inteligencia artificial (IA; tomada de decisões homem-IA). Considerando que as decisões estratégicas são normalmente tomadas em grupo, esta tese tem como objetivo investigar o impacto da influência social na aceitação de conselhos (de humanos e de IA). Em particular, esta tese investiga como os humanos reagem aos conselhos de algoritmos de aprendizagem automática e aos conselhos de especialistas humanos numa decisão estratégica sobre a avaliação de uma IPO. Além disso, esta dissertação também estuda o impacto da maioria unânime em contextos de equipa e o impacto que tem na aceitação de conselhos. Os resultados sugerem a robustez dos enviesamentos cognitivos (por exemplo, ancoragem) que afectam o processo de tomada de decisão. Além disso, os resultados desta tese demonstram a presença de uma componente motivada (e.g., raciocínio motivado) que afecta a aceitação de conselhos em processos de tomada de decisões estratégicas. Além disso, os resultados revelam a importância da perceção da fiabilidade do conselheiro, seja ele uma ferramenta de IA ou um ser humano. No entanto, os resultados não revelam qualquer efeito significativo da manipulação da influência social na adoção de conselhos ou da fonte da influência.

**Palavras-chave:** Inteligência artificial, tomada de decisões estratégicas, Tomada de decisões homem-IA, influência social, aceitação de conselhos, WOA, raciocínio motivado.

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## Glossary

| | |
|---|---|
| & | And |
| AI | Artificial intelligence |
| ANOVA | Analysis of variance |
| b | Regression coefficient |
| CA | Cronbach´s Alpha |
| df | Degrees of freedom |
| DV | Dependent variable |
| F | F-statistic |
| H1-H5 | Hypothesis 1 (2-6 respectively) |
| IPO | Initial public offering |
| IV | Independent variable |
| JAS | Judge-advisor system |
| M | Mean |
| ML | Machine learning |
| N | Sample size |
| p | p-value |
| RQ | Research question |
| $R^2$ | Multiple correlation squared; measure of strength of association |
| SD | Standard Deviation |
| t | t-statistic |
| WOA | Weight of advice |

**Abbreviations used in Model 14 of Hayes PROCESS macro**

| | |
|---|---|
| M | Mediator |
| W | Moderator |
| X | Independent variable |
| Y | Dependent variable |

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# 1. Introduction

## 1.1. Topic presentation

People make decisions every time. In fact, there are some studies that argue that humans make more than 35,000 decisions every day (Krockow, 2018). Humans are faced with decisions about many different domains of life (e.g., personal life, work, etc.). Many of these decisions are relatively easy to take and rather unimportant for the decision maker but humans are also constantly faced with relevant decisions. Moreover, it can also be argued that the sum of many rather "unimportant decisions" can also have a tremendous impact. Thus, it becomes increasingly important to make the right decisions.

Unfortunately, we don't always make right choices. One of the reasons why we make wrong choices is the existence of biases. Biases can be defined as "distortions in information processing; deviations from optimal reasoning, from rational and logical thinking, and from objective, data-based inference." (Babad et al., 2012, p. 1486). Unfortunately for us, biases are very common, and we are prone to fall prey to them. One of the most robust biases known is the anchoring bias. The anchoring bias refers to the effect initial values have on our judgments and decisions. These values can have a big influence on our decisions, thus, biasing our judgments and decisions (Furnham & Boo, 2011). Different studies have shown the robustness of the anchoring bias to the extent that even random anchors that do not include relevant information for the task at hand can bias our judgments. Research has shown the robustness of anchors regardless the difficulty and importance of the decisions to be made. For instance, Kahneman and Tversky (1974) proved that the results shown by a wheel of fortune served as anchor to questions about general knowledge. Additionally, studies have shown that the sum of 2 dices was an effective anchor for judges choosing the length of an appropriate sentence for criminals (Englich et al., 2006).

## 1.2. Relevance of the topic

Considering the robustness of biases like anchoring and the negative effects they have on our judgments and decisions, it is important to find new ways to improve decision making. In a managerial context, in which humans are constantly faced with strategic decisions that have a big influence on the future of companies, biased judgments and decisions can be very expensive (Borrero& Henao, 2017). Therefore, many companies are investing in different tools and state-of-the-art technologies to help their employees take better decisions. This is where AI comes

into place. In this new era of Big Data, AI based algorithms have risen as an important advice tool with high potential of improving decision making processes (Duan et al., 2019; Wang, 2021). Moreover, AI has proven to be a quite successful tool that can outperform human judgment and help overcome biases (Logg et al., 2019).

Thus, many companies have decided to implement an AI-assisted decision-making approach with the goal of helping their employees overcome biases and make better decisions. Many companies already use AI algorithms as help for taking decisions in many different business activities such as human resources, forecasting, logistics, etc. (Dietvorst et al., 2015). Even though AI systems are known to outperform humans (even experts) in a comprehensive number of tasks, humans are still responsible for making the definitive decisions in an AI-assisted decision making approach (Castelo et al., 2019; Logg et al., 2019). Thus, the role of AI is merely to support humans take better decisions by providing advice. After receiving the advice humans decide if they want to rely on the advice of AI or not. Humans have the power of rejecting or accepting the advice of AI (Chong et al., 2022). Research has shown that incorporating AI advice has positive effects on decisions´ outcomes (Doreswamy & Horstmanshof, 2022). Despite the proven benefits of AI advice, many people still prefer to disregard AI advice, which leads to poorer choices (Chong et al., 2022; Meissner & Keding, 2021). Thus, it becomes increasingly important to understand the reasons why humans tend to either reject or accept AI advice and incorporate it in their decisions.

## 1.3. Problem statement & research questions

Research has shown that different factors influence our decision to rely or not on the advice of AI. For instance, these factors include lack of trust in the AI tools, a sense of human experts being considered more trustworthy even though the effectiveness of different AI tools has already been proven, high levels of confidence in our own judgments and decisions, etc. (Bailey et al., 2022; Bonaccio & Dalal, 2006; Fortuin, 2022). Additionally, one important aspect that influences judgments and decisions is social influence. Social influence plays a big role in decision making, especially when decisions are taken in teams. Thus, social influence can directly affect the way in which we deal with help from AI during AI-assisted decision-making processes. Moreover, this dissertation investigates if under social influence (presented via unanimous majority), participants are motivated to stick with the same answer as the majority.

Based on past research (Fortuin, 2022), this master thesis aims at investigating the effectiveness of AI at helping humans take better and unbiased decisions at the workplace. Moreover, this

study focuses on researching how social influence can have an impact on advice taking. Thus, this thesis aims at answering the following research questions:

*RQ1: Do humans rely more on advice from AI tools or human experts?*
*RQ2: What role does trust in the advisor play in advice taking and in the effect of advice as a form of debiasing?*
*RQ3: What role does confidence in own (pre-advice) judgments and decisions play in advice taking and how does it affect advice effectiveness as form of debiasing?*
*RQ4: To what extent does social influence affect individuals´ advice taking?*
*RQ5: Is there a motivated component that affects advice taking in situations of social influence?*

## 1.4. Overview of the dissertation´s structure

This dissertation´s structure consists of five different chapters. In order to be able to answer the just mentioned research questions, I conducted an experimental study through a questionnaire made with Qualtrics. Thus, this dissertation has been structured as an empirical research paper, but also includes a chapter dedicated to a literature review on relevant topics. The first chapter of this dissertation is an introduction which includes the presentation of the topic, highlights the relevance of the topic, and describes the research questions which will be addressed. The next section comprises a literature review on relevant topics to answer the research questions. The literature review focuses on summarizing existing research on decision making (covering important topics such as strategic decision making and human´s decision making process), the presence of heuristic and biases and their effect on strategic decision making, the role of artificial intelligence (AI) in the workplace (with a special focus on human-AI strategic decision making and the role of AI to improve decision making processes), human´s reliance on advice and the role social influence can play on advice taking as part of group decisions. This chapter also includes the hypotheses generation based on the existing literature.

The third chapter goes through the methodology. This section focuses on the experiment design and procedure, the composition of the sample and the measurement of variables. Chapter four includes the presentation of the conducted analysis and the results of the hypotheses. The fifth chapter comprises a discussion of the results of the hypotheses, the academical and managerial implications and the limitations. Finally, the last chapter is the conclusion of the dissertation.

# 2. Literature Review

## 2.1. Decision making

### 2.1.1. General decision making

What should I eat today for lunch? Where and what do I want to study? What should I wear today? Those are just a few examples of questions humans are faced with every day. Humans, as decision makers have to decide between many different choices throughout their lifetime (Banks & Gamblin, 2022; Del Maschio et al., 2022). Even though there is no clear answer on how many decisions humans make every day, the number of daily decisions can definitely be very high (Deloitte, 2022; Krockow, 2018). For instance, just in the food domain, research has shown that in average, humans take more than 220 decisions every day (Wansink & Sobal, 2007).

Some of these decisions human make are rather easy to make, whereas some of them are rather difficult to make (Banks & Gamblin, 2022). Regardless of the difficulty of the decisions, the decision maker aims to take good choices. Humans aim to take good choices, because their decisions, indifferently of being big difficult decisions like where or what to study or rather smaller but repeated decisions like food-related decisions, can have a big impact on their life (Banks & Gamblin, 2022; Galotti et al., 2006; Wansink & Sobal, 2007).

### 2.1.2. Strategic decision making

Similarly, as in personal life, humans are also constantly confronted with having to take decisions on a business environment. For example, employees from the HR department need to take decisions on how to evaluate the performance of other employees, sales people need to decide how to estimate the number of sales of the next period, managers need to decide who they are going to promote, etc. (Dalal et al., 2010). Humans need to make decisions every day on the workplace, and these decisions have an effect on the future of the organization (Dalal et al., 2010). Certainly, there are some decisions which have a bigger effect on the organization. For instance, there are strategic decisions that are commonly of high importance for organizations. These strategic decisions in organizations generally fall under the concept known as strategic decision making. Strategic decision making refers to a process in which top management deals with making fundamental decisions that have an important effect on the future of an organization (Ceschi et al., 2017; Das & Teng, 1999; Eisenhardt & Zbaracki, 1992).

Similarly as in decisions of personal matters, humans need to take good decisions at the workplace, especially when it comes to strategic decisions because those decisions are the ones that shape the future of the organization where they work (Eisenhardt & Zbaracki, 1992; Schwenk, 1988).

### 2.1.3. Human´s decision making process

But how do humans deal with having to make many decisions every day? In order to understand the human decision-making process, there are many aspects that need to be taken into consideration. It is important to understand that there are different types of tasks, different types of decisions, and different types of information processing systems (Phillips et al., 2016).

#### 2.1.3.1. Different types of decisions or tasks

Research on different types of decisions or different types of tasks has shown that different aspects or features of the task or the decision to be made have an impact on the decision maker. For example, some tasks are distinguished by characteristics related to an intuitive processing, whereas other tasks are rather distinguished by features closely connected to a rational information processing (Inbar et al., 2010). Thus, depending on how the tasks or decisions are formulated and/or perceived by the decision maker, decision makers can be rather inclined to make a decision based on their intuition, based on rational thinking, or even a compromise of the two just mentioned (Hammond et al., 1987; Inbar et al., 2010).

According to Inbar et al. (2010) and Phillips et al. (2016) key features that influence whether the decision maker employs rather a rational or an intuitive approach to a decision or task include the following: the complexity of the task, whether it is a one-shot task or a sequential one, the importance of the decision, and how precisely the success of the decision can be evaluated. On one hand research has shown that decision makers tend to apply a rational approach when they perceive the task or the decision making process to be rather complex, when the decision is presented as part of a sequential evaluation (e.g., the decision maker has to make many choices step by step), when they consider the decision and its outcomes to be important for them, and when the decision can be deemed as correct or successful based on objective measures (Inbar et al., 2010; McElroy & Seta, 2003; Phillips et al., 2016). On the other hand, decision makers tend to approach the task or the decision process with intuition when the task is perceived to be rather easy, when the task is framed as a one-shot task, when the outcomes of the decision are irrelevant, and when the decision can be deemed correct or

successful based rather on personal, subjective factors (Inbar et al., 2010; McElroy & Seta, 2003; Phillips et al., 2016).

The reason why different characteristics and features of decisions and tasks tend to lead to decision makers favoring intuition or rationality can be explained by the fact that those characteristics and features of decisions and tasks (Inbar et al., 2010; Phillips et al., 2016) represent a resemblance with the two types of information processing that humans have (Kahneman, 2011; Phillips et al., 2016; Sanders & McHugh, 2021). One system represents rather an intuitive approach, and the other system represents rather a reflective, rational, and analytical approach. These two types of information processing are commonly known as System 1 and System 2 (Gronchi & Giovannelli, 2018; Kahneman, 2011; Sanders & McHugh, 2021). The next subchapter will give a more detailed explanation of the role of System 1 and System 2 in decision making.

#### 2.3.1.2. Two different types of information processing – System 1 and System 2

According to dual process and dual system theories, human beings have two different information processing and reasoning types. As before mentioned, these two types are commonly known as System 1 and System 2 (Kahneman, 2011; Sanders & McHugh, 2021). Other researchers have also called these two systems differently. For instance, Sloman (1996) talks about an associative system and a rules-based system, Evans (2006) makes reference to a heuristic system and to an analytic system, Evans and Stanovich (2013) discuss about Type 1 of reasoning and Type 2 of reasoning, and Phillips et al. (2016) mention an intuitive processing and a reflective processing. Even though there are different name tags for these two systems, the reasoning behind them is quite alike. Meaning that on one hand, “System 1”, the “heuristic system”, the “Type 1 of reasoning”, and the “intuitive processing” represent a single type of information processing and reasoning. On the other hand, “System 2”, the “analytic system”, “Type 2 of reasoning”, and the “reflective processing” represent the other single type of information processing and reasoning (Thompson, 2014). For purposes of this study, the terminology System 1 and System 2 will be used.

The System 1, as a type of information processing and reasoning, is characterized as fast, heuristic thinking (Evans, 2006), intuitive, automatic (Kahneman, 2011), associative (Sloman, 1996), autonomous, preconscious (Phillips et al., 2016), effortless (Sanders & McHugh, 2021),

and producing default responses (Evans & Stanovich, 2013). The System 2 is rather known for being slow, deliberative (Kahneman, 2011; Sanders & McHugh, 2021), effortful, conscious, (Phillips et al., 2016), analytical, reflective, rational, and producing structured responses (Evans & Stanovich, 2013). The following image depicts a comparison between both systems.

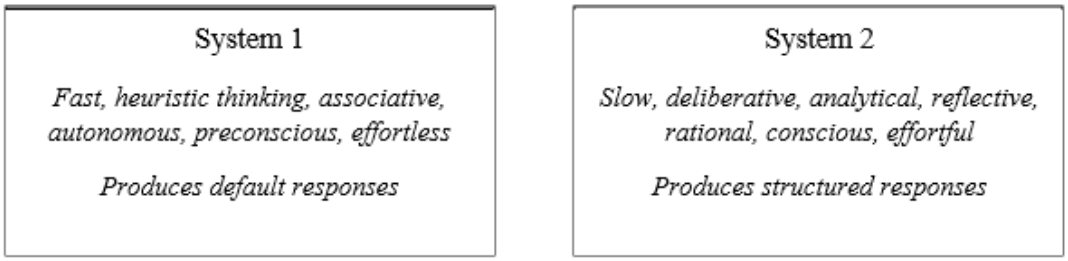


*Figure 1: Comparison between System 1 and 2, adapted from Sanders and McHugh (2021)*

Due to the fact that System 1 is known for its fast thinking, requires almost no effort, and works unconsciously (e.g., by mental pattern recognitions), it is mostly selected when decisions are either considered easy to take, the possible outcomes are rather irrelevant for the decision maker, and/or when there is time pressure for the decision maker (Kahneman, 2011; Phillips et al., 2016; Sanders & McHugh, 2021). System 2 is rather used for tasks and decisions that require more attention from the decision maker. For instance, tasks or decisions that demand higher levels of attention, involve data to process carefully or important data is missing, and don't involve time-pressure concerns for the decision maker, are normally approached via System 2 (Kahneman, 2011; Phillips et al., 2016; Sanders & McHugh, 2021). Moreover, McElroy and Seta (2003) argue that there are two relevant factors that determine to which degree System 1 or System 2 is favored. Those two factors are the decision maker´s capability and the decision maker´s motivation. Decision maker´s capability implies how capable or able is the decision maker to solve a certain task, and decision maker´s motivation refers to how motivated is the decision maker to solve a certain task (McElroy & Seta, 2003).

As explained in the previous paragraph, System 1 and System are quite different. Nevertheless, according to Kahneman (2011), when humans are awake, System 1 and System 2 are both active simultaneously. Moreover, it has been proven that both reasoning types (System 1 and System 2) are important for decision making. The reason behind this is that both systems (System 1 and System 2) generate important and unique inputs that help humans in the decision making process (Goel et al., 2000; Phillips et al., 2016).

Considering that System 1 and System 2 are able to produce relevant inputs that help humans take decisions, it is also important to further analyze the way in which these two systems function. As before stated, Kahneman (2011) argues that System 1 and System 2 are working at the same time. On one hand, System 1 is continuously fully running. It can be argued that System 1 is working via automatic and quick processes all the time (Inbar et al., 2010; Kahneman, 2011; Phillips et al., 2016). Thus, System 1 is responsible for constantly processing information, fabricating suggested decisions, and forwarding the suggested decisions to the System 2 (Kahneman, 2011). On the other hand, System 2 is generally rather just working at a minimized effort. In other words, System 2 is usually operating in battery-saving mode. System 2 normally operates like this, because its use at higher capacity requires bigger effort and higher mental energy investment. Therefore System 2 is used at an increased capacity only when it is necessary (Kahneman, 2011; Sanders & McHugh, 2021). In the majority of the time the suggested decisions from System 1 are well received by System 2, meaning that System 2 embraces those suggested decisions and puts them into action (Kahneman, 2011).

Therefore, if System 2 approves the suggested decisions of System 1, then System 2 continues working in low-battery mode. But there are situations in which System 2 has to take fully over. For instance, in situations in which System 2 does not consider that the suggested decisions of System 1 are good enough, or in situations in which System 1 is facing difficulties (e.g., a complex decision requiring analytical, reflective, rational thinking), or in situations in which System 1 is susceptible to make mistakes (e.g., unusual, or ambiguous situations), the System 2 decides to fully take over the decision making process (Kahneman, 2011; Kahneman & Frederick, 2002; Sanders & McHugh, 2021).

This process, in which System 2 decides to override the suggested recommendations from System 1 takes place to make humans less prone to making wrong decisions. For example, System 1, due to its nature (e.g., fast, heuristic, associative, intuitive thinking) is highly susceptible to heuristic thinking (J. E. Korteling et al., 2018; Tversky & Kahneman, 1974). Heuristic thinking is commonly employed by System 1 to reduce the complexity of a decision, but it is important to consider that heuristic thinking makes humans prone to systematic errors (e.g., biases) (Tversky & Kahneman, 1974). Thus, in those situations in which the intuitive reasoning of System 1 can lead to errors, System 2 comes into play with a correcting role. Unfortunately, System 2 does not always completely correct or override the biased suggested

decisions from System 1. That leads to humans being more prone to errors in their decisions (Kahneman, 2011; Phillips et al., 2016).

The next chapter will focus on heuristics and different biases and the effect that they can have on decision making.

## 2.2. Heuristic thinking and biases

### 2.2.1. Heuristic thinking

As explained in the previous chapter, humans tend to appeal to heuristic thinking to reduce the complexity of certain tasks or decisions (Tversky & Kahneman, 1974). Humans, as decision makers are quite susceptible to heuristic thinking and other strategies that make taking decisions an easier activity for them (Borrero & Henao, 2017). But what does exactly heuristic thinking mean? Heuristic thinking refers to the fact that humans tend to apply a limited set of heuristic principles (e.g., availability, representativeness, adjustment, and anchoring) when dealing with difficult tasks or decisions. By applying this limited set of heuristics, humans manage to turn a rather difficult task or decision into a situation of simpler judgmental operations (Tversky & Kahneman, 1974). In this sense, heuristics can be defined as simple rule of thumbs or shortcuts humans use for decision making processes (Albar & Jetter, 2009; Dale, 2015). It is important to mention, that heuristics follow an approach to problem solving that is "quite different from consequential logic" (Albar & Jetter, 2009, p. 578).

Research has shown that on one hand heuristic thinking can be a quite useful tool for approaching certain tasks or decisions (e.g., deciding to take a look at both sides of the road before crossing a street). But on the other hand, heuristic thinking is closely associated to negative effects on critical rational thinking. Therefore, heuristic thinking is known for commonly leading to poor judgments and to making wrong decisions (Dale, 2015; Tversky & Kahneman, 1974; West et al., 2008). Heuristics can lead to poor judgments and to making wrong decisions, because in "some contexts they can lead to systematic errors" (Bojke et al., 2021, p. 43). These systematic errors are commonly known as biases (Durkee, 2006; West et al., 2008).

### 2.2.2. Biases

Biases are "distortions in information processing; deviations from optimal reasoning, from rational and logical thinking, and from objective, data-based inference." (Babad et al., 2012,

p. 1486). There are many different biases that can affect humans´ decision making processes. For instance, there are motivational and cognitive biases (Montibeller & Winterfeldt, 2015). On one hand, motivational biases are those biases that appear consciously or unconsciously when the judgment or the decision is affected by an specific interest, motivation, or desire of the decision maker (Montibeller & Winterfeldt, 2015; Winterfeldt, 1999). Motivational biases include for example the confirmation bias (Borrero & Henao, 2017), desirability of choice (Montibeller & Winterfeldt, 2015), and the false uniqueness effect (Wilson et al., 2008). On the other hand, cognitive biases represent "a systematic discrepancy between the "correct" answer in a judgmental task, given by a formal normative rule, and the decisionmaker's or expert's actual answer to such a task" (Montibeller & Winterfeldt, 2015, p. 1231). Examples of cognitive biases include anchoring, the overconfidence bias, and the certainty effect (Montibeller & Winterfeldt, 2015; Tversky & Kahneman, 1974; Yasseri & Reher, 2022). For purposes of this master thesis, this study is going to focus on cognitive biases. Therefore, the next subchapter will discuss the effect of cognitive biases on decision making.

### 2.2.3. Effect of cognitive biases on decision making

As explained before, biases are those systematic errors that originate from heuristic thinking (Bojke et al., 2021). Thus, it can be argued that heuristic thinking and the resulting cognitive biases can have a negative impact on both, decision making on a personal level and strategic decision making (Borrero & Henao, 2017; Das & Teng, 1999; Franco & Hämäläinen, 2016). According to the heuristic-analytic theory of reasoning, heuristic thinking and the resulting cognitive biases can have a negative effect on the correctness of human´s judgments (Evans, 2006). The following figure is a simplified representation of the heuristic-analytic theory.

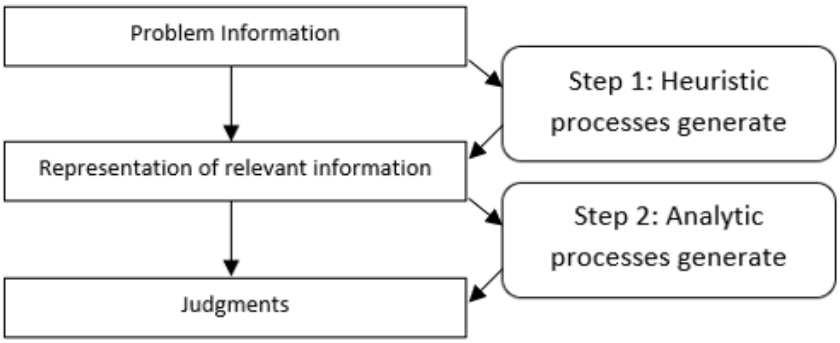


*Figure 2: Visual representation of the heuristic-analytic theory, adapted from Evans (2006)*

The explanation behind the heuristic-analytic theory is that reasoning is a two-steps cognitive sequential process. The first step is known as the heuristic step, and it is in charge of generating a representation of important information and passing this on to the second step. In the heuristic step, heuristics can lead to important information not being considered or to unimportant information being wrongfully considered. In the second step, analytical processes are in charge of generating judgments based on the information received from the heuristic step. If the representation of information is altered by heuristics, then biases can result, leading to poor judgment (Evans, 2006). Considering that human´s judgments are needed for personal decisions and for strategic decisions in the workplace, and also taking into consideration that biases negatively affect human´s judgments, it can be concluded that biases certainly have a damaging effect on decision making on a personal level and on strategic decision making.

After having proved that cognitive biases have a negative effect on the correctness of human´s judgments and decisions, this study will further analyze anchoring and its effects on decision making. This study will focus on anchoring because it is one of the most studied and robust cognitive biases (Cen et al., 2013; Yoon et al., 2019).

### 2.2.4. Anchoring bias

Tversky and Kahneman (1974) were the first researchers to mention the anchoring bias. Anchoring refers to the fact that humans, when dealing with uncertain estimates and numerical judgments, tend to start their estimations with an initial value and then decide to adjust it to arrive to a final value (Yik et al., 2018; Yoon et al., 2019). The initial value "may be suggested by the formulation of the problem, or it may be the result of a partial computation" (Tversky & Kahneman, 1974, p. 1128) or may originate from simply relying too much on the first information humans are given as part of the decision making process (Yasseri & Reher, 2022). The problem with this, is that the initial value can be completely irrelevant and that generally the adjustments that humans make to arrive to the final value are not sufficient (Tversky & Kahneman, 1974).

Many researchers have studied the effects of anchoring. By using approaches like the standard anchoring paradigm researchers follow a two-step process. In the first step, researchers provide participants with an anchor or a question that will lead to an anchor and ask them to compare it with the target value. After doing this, researchers ask participants to make a final judgment about the target value (Bahník et al., 2019). For example, in a first step researchers could ask

participants if the average summer temperature in Lisbon is higher or lower than 25 (low anchor condition) or higher or lower than 35 degrees (high anchor condition). In the second step researchers could ask participants to make a final judgment and estimate the average summer temperature in Lisbon. In this case 25 degrees and 35 degrees serve as either the low anchor or the high anchor respectively. If the anchor has an effect, researchers could expect participants in the low anchor condition to provide final answers to the question about the average summer temperature Lisbon with lower values than participants in the high anchor condition (Bahník et al., 2019; Lalot et al., 2019).

The above-mentioned approach is an example in which the anchor is consider quite relevant for the final judgment. This is so because both temperatures (25 degrees for the low anchor and 35 degrees for the high anchor) provide relevant information and are actually plausible answers for the question about the average summer temperature in Lisbon (Furnham & Boo, 2011). But interestingly, other researchers have also proven that the anchor does not necessarily need to be relevant or a plausible value for the target judgment. For example, Englich et al. (2006) showed that judges can give either shorter or longer sentences for the same crime depending on the results of throwing a pair of dices. Judges which were in the low anchor condition, threw two dices and the sum of both dices was "3", whereas judges in the high anchor condition threw two dices and the sum of both dices was "9". Even though the sum of two dices did not provide any relevant information for the sentencing, judges were clearly affected by the anchor and judges in the low anchor condition gave significantly shorter sentences that judges in the high anchor condition (Englich et al., 2006). Moreover, Crichter and Gilovich (2008) have also shown that incidental irrelevant anchor values can also have a tremendous effect on judgments and decisions. Crichter and Gilovich (2008) showed that the jersey number of an American football player can serve as an anchor for people estimating the player´s performance. This findings are extremely important because they reveal how robust the anchoring effect can be, even when the anchor value is considered to be incidental, random, and/or irrelevant (Belle et al., 2017; Kahneman, 2011).

Many researchers have tested the effect of anchoring on many different domains of life. For instance, researchers have found a strong effect of anchors in domains such as general knowledge, physical and temporal lengths estimations, and political decisions (Furnham & Boo, 2011; Yoon et al., 2019). Epley and Gilovich (2001, 2005) have shown the effect of anchors when dealing with uncertainty in decisions or judgments about general knowledge

such as the freezing point of vodka or the year in which George Washington became president. Other researchers have shown the effect of anchors on decisions and judgments about political topics such as how many migrants should a country be open to welcome (Lalot et al., 2019). LeBoeuf and Shafir (2006) have even shown that physical stimuli (and not only abstract numerical values) can serve as an anchor in estimations about physical and temporal lengths.

Taking into consideration the way in which anchors work and the robustness of how they affect judgments and decisions in many different domains, it is also important to reflect on the effect anchors can have on strategic decision making.

### 2.2.5. The effect of anchoring on strategic decision making

Many researchers have analyzed the role of anchoring on strategic decisions taken in different business contexts. For example, Galinsky and Mussweiler (2001), Schweinsberg et al. (2012) and Zeckhauser et al. (2020) studied the effect of anchors on negotiations, Critcher and Gilovich (2008) and Cen et al. (2013) the anchoring effect on sales forecasting and equity market forecasting respectively, Wansik et al. (1998) measured the effect of anchors on marketing related topics that deal with purchasing decisions Zong and Guo researched the effect anchoring can have on experience marketing (2022), Ariely et al. (2003) and Alevy et al. (2015) researched how anchoring can affect economic valuations, Bellé et al. (2017) analyzed the influence of anchors on employee performance evaluation, Elaad et al. (2010) focused their research on the impact of anchors on price evaluation tasks and decisions, and Thorsteinson (2011) examined anchoring´s effect on salary offers. The following table provides a list of the just mentioned papers that study the anchoring effect on strategic decisions in their respective business contexts.

| Business context/domain | Research |
|---|---|
| Employee performance evaluation | Bellé et al. (2017) |
| Economic valuations | Ariely et al. (2003) and Alevy et al. (2015) |
| Experience marketing | Zong and Guo (2022) |
| Negotiations | Galinsky and Mussweiler (2001), Schweinsberg et al. (2012) and Zeckhauser et al. (2020) |
| Price evaluation tasks | Elaad et al. (2010) |
| Purchasing decisions | Wansik et al. (1998) |
| Salary offers | Thorsteinson (2011) |
| Forecasting | Critcher and Gilovich (2008), Cen et al. (2013) |

*Table 1: Examples of research on the effect of anchoring on strategic decisions across different business domains*

Table 1 clearly shows that anchoring is present on strategic decisions in many different business domains. Since the anchoring effect is very robust, it can be argued that anchoring has a high potential to cloud objectivity and lead to wrong judgments and strategic decisions (Montibeller & Winterfeldt, 2015). Considering that in a strategic decision making context, decisions can determine the future of an organization, biased judgments and decisions can be extremely damaging because they can undermine organizational value (Borrero & Henao, 2017). Thus, it is important to find ways to overcome biases like anchoring and help management make better judgments to take better strategic decisions. In this sense, artificial intelligence (from now on also referred to as AI) is a relatively new tool which is being increasingly applied in the workplace to help managers take better strategic decisions (Del Pero et al., 2022; Deranty & Corbin, 2022). Therefore, the next chapter will discuss AI, its importance, and its role in improving decision making in the workplace.

## 2.3. The role of Artificial Intelligence in the workplace

Artificial Intelligence refers to a "system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein & Kaplan, 2019, p. 5). Furthermore, AI is able to recognize different patterns in data and learn from those patterns to take better decisions (Hassani et al., 2020). Moreover, Wang (2021, p. 3) argues that AI "refers to a type of algorithms or computerized systems that resemble human mental processes of decision-making".

### 2.3.1. Brief history of AI

The roots of AI can be traced back to more than 70 years ago. In 1950 Alan Turing, a British mathematician that had developed a machine that helped the British government break the Enigma code used by Germany during World War 2, decided to publish an article about "*Computing Machinery and Intelligence*" (Collins et al., 2021; Haenlein & Kaplan, 2019). Shortly after that, the word "Artificial Intelligence" was first created and used during the "*Dartmouth Summer Research Project on Artificial Intelligence*" (also referred to as DSRPAI) in 1956. Thus, AI was established as an academic discipline at the end of the 1950s (Collins et al., 2021; Haenlein & Kaplan, 2019; Wang, 2021). But AI was considered, for the next almost 50 years an academic discipline, to have reduced practical interest (Haenlein & Kaplan, 2019).

As before mentioned, despite its potential, AI remained an uninteresting academic discipline for a very long time. But lately, many different factors such as the rise of Big Data, the internet,

technological devices, and further development of computer sciences, have contributed to drastically increase the importance of AI (Duan et al., 2019; Haenlein & Kaplan, 2019; Wang, 2021). Thus, AI is now consider to be a quite important interdisciplinary academic discipline and a key player in many domains of life, including the workplace (Hassani et al., 2020; Louisiana State University, 2023).

### 2.3.2. Current state of AI

AI has become extremely important in day to day activities because it is able to deliver a very high performance in many different domains of life (Hassani et al., 2020; Park & Woo, 2022). According to Vemuri (2020) there are seven different AI technological approaches that are responsible for AI´s exceptional performance. These are neural networks, natural language programming, physical robots, robotics process automation, rules-based expert systems, and deep learning and machine learning (Vemuri, 2020; Wang, 2021). This study has a specific focus on machine learning and the use and impact of machine learning algorithms.

Machine learning is one of the hottest subfields of AI (Edgar & Manz, 2017; Subasi, 2020), especially because many AI intelligent systems rely on it (Janiesch et al., 2021). Janiesch et al. (2021, p. 685) define machine learning as "the capacity of systems to learn from problem-specific training data to automate the process of analytical model building and solve associated tasks". Machine learning algorithms are frequently used to analyze and simplify huge amounts of data because they are very accurate, cost effective, and are able to generate and draw relevant inferences from vast amounts of data (Basha & Rajput, 2019; Edgar & Manz, 2017; Srivastava et al., 2023).

Based on the just mentioned advantages and capabilities of machine learning algorithms and the increasing importance of the use of Big Data in the workplace, many organizations have decided to invest in AI to enhance business processes and decision making (Haenlein & Kaplan, 2019; Logg et al., 2019). Thus, the next subchapter will discuss the role of AI (e.g., machine learning algorithms) in the business domain.

### 2.3.3. AI in business domain

In the long term, it is expected that AI will be part of every company (Haleem et al., 2022). The use of AI to enhance business (processes) has proven to be very promising. Indeed, more than 80% of companies recognize that the use of AI is a strategic opportunity that will help

them increase and sustain their competitiveness in the market (Ransbotham et al., 2017). Some of the reasons why companies consider that the use of AI is quite beneficial for them include an easier detection of patterns and trends from existing data, an enhanced design process for products and services, access to more comprehensive analytics tools (Soni et al., 2020), task-automation, the chance to collect relevant data about its customers, its products and services through smart devices (Kaličanin Bojić et al., 2019), a better software management (Haleem et al., 2022), etc. Furthermore, the use of AI has many advantages for companies and organizations. For example, with increasing use of AI, companies can enhance decision making processes, improve the efficiency of day to day operations, increase productivity, and reduce total costs, which in turn leads to bigger profits for the firm (Cockburn et al., 2018; Doreswamy & Horstmanshof, 2022; Miller et al., 2020). Moreover, Collins et al. (2021) have shown that the advantages of AI in the business context are so powerful that they apply across many different industries and sectors.

### 2.3.4. AI as a tool to enhance strategic decision making (Human-AI strategic decision making)

As before demonstrated, humans are prone to many different biases that can negatively affect their judgments and decisions. Due to the importance of certain strategic decisions, many companies decide to make considerable investments into improving decision making processes. Over the last years, AI has established itself as a favored debiasing mechanism and valuable tool employed by companies to help its employees in their decision making (Logg et al., 2019). Companies rely on different machine learning algorithms because they are able to transform and improve decision making processes around strategic decisions (Haenlein & Kaplan, 2019; Johnson et al., 2022). Moreover, machine learning algorithms have proven to be superior to humans in many domains. For instance, machine learning algorithms are quite efficient in drawing helpful inferences from Big Data (Chong et al., 2022; Logg et al., 2019). Machine learning algorithms, being able to work more effectively and more time-efficiently than humans with data-driven activities, are increasingly taking over important tasks. For instance, even in the healthcare industry, a crucial industry of utmost importance, AI is increasingly being used for diagnosis and selection of treatments (Davenport & Kalakota, 2019; Kumar et al., 2023). Moreover, experts predict that AI will soon outperform humans in many different daily activities such as writing an essay or driving a truck as well as in many rather more complicated activities such as operating as a surgeon (Grace et al., 2018).

This has given rise to a new reality on the workplace. Nowadays, in many companies, most strategic decisions are taken with an AI-assisted decision-making approach. As part of AI-assisted decision-making humans and AI systems work as a team. The AI-based systems generate suggestions (based on data). These suggestions are recommended to humans with the goal of debiasing and helping them make better judgments and strategic decisions (Meissner & Keding, 2021). In this sense, the role of the AI systems is to support humans take better strategic decisions. Even though AI systems like machine learning algorithms have proven to be superior to humans, the generated insights from the AI systems serve only as a second opinion or a recommendation and the final decision is still in hands of humans (Chong et al., 2022; Haenlein & Kaplan, 2019).

In many cases, AI-assisted decision making has proven to be very successful, as in the case of Salesforce. Salesforce has developed its own AI program. This AI program is being used during important meetings to help Salesforce´s decision makers take better decisions. The use of its own AI program during strategic meetings has allowed Salesforce to improve its decision making processes and diminish biases (Meissner & Keding, 2021). But it is important to notice, that, as before mentioned, even though AI-assisted decision making has proven to be very promising in helping humans take strategic decisions, reducing costs and times, humans still have the final say. This means that humans, as final decision makers, can choose whether they want to accept the suggestion of AI-systems or not (Chong et al., 2022; Logg et al., 2019). This indeed, ends up being a limitation of AI-assisted decision making, because humans are prone to error. Furthermore, even though the superiority of AI systems and algorithms has been proven (Hassani et al., 2020), many humans still prefer not to rely on the recommendation of their AI-counterpart (Chong et al., 2022). Therefore, the next chapter will discuss the extent to which humans rely on advice and different factors that can affect it.

## 2.4. Reliance on advice

Humans tend to look for advice when confronted with important decisions (Bonaccio & Dalal, 2006). This applies both for personal decisions and for strategic decisions on the workplace. For example, people tend to ask for advice when dealing with life-changing decisions such as changing job, getting married, etc. Similarly, managers tend to seek advice before taking strategic decisions like choosing a new strategic partner or expanding to another country.

There are many reasons for humans to seek advice when dealing with important strategic decisions. The most common measure for advice-taking is the judge-advisor system (also

known as JAS) paradigm (Bailey et al., 2022; Bonaccio & Dalal, 2006). The JAS paradigm is used to determine the extent to which the decision maker (referred to as judge) incorporates external advice in its decision. A few decades ago, advice tended to come only from other persons, but nowadays, due to technological advances, there are other relevant sources of advice such as AI systems (e.g., machine learning algorithms). Thus, a broadly accepted definition of the term advice in the JAS paradigm is that advice is provided by another person or system that "does not require any particular advocacy by the advice giver" (Rader et al., 2017, p. 3).

Research has shown that there are many reasons that lead humans to seek advice when dealing with important decisions. For instance, humans tend to look for advice in situations in which they want to share accountability for the final decision. For example, if a decision is quite challenging or important (which is the case of strategic decisions in the workplace), humans like to seek advice because in that way, they can share responsibility over the final decision (Yaniv, 2004a). Another advantage of seeking advice is getting access to new information or alternatives (Bonaccio & Dalal, 2006). Brooks et al. (2015) argue that looking for advice also helps decision makers acquire new skills. But maybe the most important reason for seeking advice is to improve the decision making process to increase the chances of making an optimal and accurate decision in order to achieve better outcomes (Bonaccio & Dalal, 2006; Brooks et al., 2015; Önkal et al., 2009; Yaniv, 2004b).

### 2.4.1. Factors that influence the reliance on advice

#### 2.4.1.1. Trust in the advisor

According to the JAS paradigm, trust in the advisor is one of the most important factors that can influence the degree to which humans rely on advice. Different studies have shown that humans tend to rely more on advice if they consider that the advisor is trustworthy (Bailey et al., 2022; Burton et al., 2019; Tauchert & Mesbah, 2019). If a decision maker considers an advisor to be trustworthy, then this decision maker is expected to rely more on the provided advice and accordingly adjust more from its pre-advice judgment (Bonaccio & Dalal, 2006; Brooks et al., 2015).

According to Yaniv (2004a) the question if a human considers the advisor trustworthy or not depends on the decision maker´s assessment of the advisor. The more accurate the decision

maker assesses the advisor to be, the more trustworthy this advisor will be perceived (Chong et al., 2022). Thus, the following hypothesis is proposed:

> **H1:** *Higher trust in the advisor increases the level of adjustment from the pre advice decision towards the advice.*

Moreover, research has shown that trust in advisors is quite difficult to maintain, because "negative experiences with a source have proportionally greater influence than positive ones" (Yaniv, 2004a, p. 76). This applies for human advisors and for AI advisors such as machine learning algorithms (Burton et al., 2019). For instance, different studies have shown that mistakes from the advisor lead to humans losing trust in them. Even though AI systems are known to outperform human experts in many different tasks, AI mistakes have a more negative effect on trust when compared to human experts´ mistakes, meaning that humans tend to lose trust in AI advisors much faster than on human advisors (Chong et al., 2022; Dietvorst et al., 2015). Furthermore, when people are presented with advice from humans and advice from AI, and both sources are assessed as equally trustworthy, some people still tend to opt for the human advice (Dietvorst et al., 2015).

This is a serious problem for the adoption of human-AI decision making processes, because humans need to trust AI to an extent in which they feel comfortable enough to rely on its advice (Enholm et al., 2021). Thus, trust in AI is a factor that companies should consider when introducing AI to business decisions. According to Chong et al. (2022), another factor that should be considered to achieve successful human-AI assisted decision making processes is the confidence people have on their own judgments and decisions, because this plays an important role on how much humans rely on AI advice. Therefore, the next subchapter will discuss how the confidence humans have on their own judgment and decisions affect their advice taking processes.

#### 2.4.1.2. Confidence in own judgment and decisions

As before mentioned, the degree of confidence that humans have on their own judgments and decisions is a factor that influences how much people decides to rely on advice. The more people trust their own judgments and answers (taken in a pre-advice stage), the less people tend to rely on advice because high levels of self-confidence are a known factor to lead to advice discounting (Bonaccio & Dalal, 2006; Chong et al., 2022).

Research on the JAS paradigm has shown that humans tend to overweigh their own judgment and decisions in comparison to advice (Yaniv, 2004b). The reason behind this is because humans tend to feel that their opinions are better than the advice. Sometimes humans tend to consider that their opinions are superior because they have little knowledge about the reasoning and justification of the advice (Bonaccio & Dalal, 2006). Other times, humans simply display extremely high levels of overconfidence, which in turn decreases their trust in the advisor and thus also their reliance on advice (Burton et al., 2019). Based on this information, the following hypothesis reads as follows:

> **H2**: *Confidence in one´s own decisions moderates the relationship between trust in the source and reliance on advice, such that higher levels of confidence on own decisions (in a pre-advice stage) decrease the effect of trust on reliance on advice*.

### 2.4.1.3. Advisor´s expertise

According to the JAS paradigm, another important factor that influences the extent to which people tend to utilize or discount advice, is the degree of expertise or knowledge that the advisor has (Bailey et al., 2022; Bonaccio & Dalal, 2006). Bailey et al. (2022) argue that advice from experts is highly valued because people perceive it as high quality information that can lead to an optimal (or at least more accurate) decision. Bonaccio and Dalal (2006) demonstrated that humans tend to utilize advice more, when the source of advice is consider to have high task-relevant expertise. Moreover, humans tend to rely more on advice from experts when they are confronted with complex tasks because this allows them to better justify their decisions based on the fact that they listened to the expert advice (Jungermann & Fischer, 2005; Yaniv, 2004b).

In this sense, the use of human experts´ advice and state-of-the-art machine learning algorithms´ advice can be used by companies as form of a debiasing technique that will help decision makers take better unbiased choices.

### 2.4.1.4. Task type

Besides expertise of the advisor, the type of task can also influence human´s reliance on advice. For instance, people tend to rely more on human advice for some types of tasks and rely more on AI advice for other types of tasks. The reason behind this is that humans perceive some tasks to be more algorithmically appropriate than others (Logg et al., 2019).

On one hand, this highly depends on how common the use of algorithms is for certain tasks. For example, it is quite common to use AI for weather forecasting. This has led to people considering that a task of weather forecasting is algorithmically appropriate. On the other hand, people also tend to consider a task more algorithmically appropriate when there is an external standard of accuracy or correctness. In other words, humans tend to consider a task algorithmically appropriate when the task is rather objective (Castelo et al., 2019; Logg et al., 2019). This means that humans tend to rely more on AI advice than human advice when the task can have an objectively correct answer (such as investment decisions, numerical tasks, forecasting, etc.). Consequently, humans prefer to rely on human advice for tasks that are rather perceived as subjective (e.g., tasks in which answers are mostly affected by personal taste or intuition). (Castelo et al., 2019; Yeomans et al., 2019). Considering that the study conducted as part of this master thesis involves advice taking on a rather objective task (e.g., numerical task, with a measurable answer), the third and fourth hypotheses of this study read as follows:

> **H3**: *The effect of the AI advice on the revision of the pre-advice answer will be higher than the effect of the human advice.*
>
> **H4**: *Considering that the task at hand is rather an objective task, participants will trust more the AI advisor than the human advisor.*

Considering that many strategic decisions are taken in teams, I also wonder what happens if people are motivated to stick with their (biased) pre-advice answers. Thus, the next chapter will focus on the role of social influence and peer pressure (on advice taking) in strategic decisions.

## 2.5. The role of peer pressure and social influence on advice taking

### 2.5.1. The role of social influence on advice taking in group decisions

As before stated, humans can have different motives to stick with their (biased) pre-advice answers. Since key strategic decisions are rather taken in groups or teams (Kameda et al., 1997) and not by a single person, it is important to consider factors that can affect human´s individual judgments as part of team or group decisions. Social influence (which can appear in case of social or peer pressure) is a key factor that influences judgments when taking decisions as part of a group. Thus, social influence is a common feature which tends to affect people judgments and decisions (Di Corrado et al., 2011; Goodmon et al., 2020; Smith et al., 2011), to the extent

that it “can sometimes incorrectly alter someone's independent judgment” (Goodmon et al., 2020, p. 442).

Research has shown that social influence tends to lead to group conformity or consensus. What started with the classic Asch conformity experiments (Asch, 1956), in which more than 70% of the participants decided to conform with the (clearly) wrong answers of an unanimous majority, rapidly evolved into a clear research area, with many different studies having later shown the robustness of the effect of social influence. For example, Goodmon et al. (2020) showed how people tend to conform to the majority´s answer in an assignment of selecting punishments for sexual harassment. Gardner and Steinberg (2005) showed the effect of social and peer influence on risk taking decisions. Levitan and Verhulst (2016) demonstrated the impact of social influence on conformity with political attitudes. Social influence can be so powerful that in some cases even though people know that their own independent decision is the obvious right choice and the judgment of the unanimous majority is incorrect, people still tend to fall prey to conformity and select the same (wrong) answer as the majority of the group (Cialdini & Goldstein, 2004; Goodmon et al., 2020; Wood, 2000).

There are two main types of social influence that can affect people judgments and lead to social conformity in team or group decisions (Goodmon et al., 2020; Smith et al., 2011). These two types of social influence are known as normative social influence and informational social influence (Cialdini & Goldstein, 2004; Deutsch & Gerard, 1955; Zarnoth & Sniezek, 1997). On one hand, informational social influence occurs “when one believes that others have authority, have more knowledge, and are correct in their judgments/actions” (Goodmon et al., 2020, p. 443), leading people to accept opinions of others as correct and evidence about reality (Deutsch & Gerard, 1955; Wood, 2000). On the other hand, normative social influence “arises when one conforms to the majority's answer/decision in order to be accepted by others” (Goodmon et al., 2020, p. 443), even if the majority´s answer is obviously wrong.

It is important to note that both of these types of social influence can have an important effect (together or independently) on groups and team decisions and can lead individual decision makers to change their own decisions in order to conform with the group or team (Cialdini & Goldstein, 2004; Di Corrado et al., 2011; Goodmon et al., 2020), thus, leading participants to deciding to ignore the advice. Based on these findings, the next hypothesis of this study reads as follows:

**H5**: *Social influence will lead to more conformity, meaning that participants will rely less on the advice and recommend prices similar to the values provided by the unanimous majority of the top managers*.

Considering the robustness of these two types of social influence and the fact that "individuals readily succumb to influence from others" (Rader et al., 2017, p. 2), it is important to study how social influence will affect advice taking from different types of advisors (AI advisor vs human advisor). As before mentioned, research has shown the impact of social influence and how it can lead to conformity (Brandstetter et al., 2014). This can happen because in situations of social influence, humans tend to give more importance to the group norm than to their own individual norm (Riva et al., 2022). Bogert et al. (2021) studied how people reacted to receiving advice from AI in comparison to receiving advice from a crowd (social advice). The results of their study show that people tend to rely more on AI advice than on social advice, thus leading to a higher WOA (from AI advice). Moreover, the findings show that the more objective the task is perceived to be, the bigger is the difference between the reliance on advice from AI and reliance from social advice (Bogert et al., 2021). Since participants of this study were confronted with a scenario of unanimous majority, which is a type of social influence, to some extent similar to social advice in the sense that a group of peers shares a same answer, and considering that in such scenarios advice from AI tends to be more appealing than social advice, I would expect social influence to moderate the reliance on advice. Based on this, I hypothesized the following:

**H6:** *Social influence will moderate the relationship between the type of advisor and the WOA such that it will lead to lower reliance on advice, but this impact is lower for the AI group.*

As before stated, this thesis also investigates the presence of motivated reasoning under social influence. Thus, the next subchapter will examine if there is a motivated component in advice taking under the existence of social influence

### 2.5.2. Motivated reasoning under social influence

Motivated reasoning refers to the fact that humans tend to have certain motivation that affect their reasoning in order to reach preferred outcomes (Kunda, 1990). Epley and Gilovich (2016) mention that on one hand motivated reasoning shapes human´s reasoning in a way that leads them to focus on processing the information that supports and is consistent with their preferred

outcomes and on the other hand, motivated reasoning makes people disregard contradictory information. According to Kunda (1990) there are two different categories of motives or goals that need to be considered when discussing motivated reasoning. Humans tend to have either the motive or goal of being accurate, or motives and goals known as directional goals. Directional goals appear when humans have the motive to "arrive at a particular, directional conclusion" (Kunda, 1990, p. 480).

When individuals have the goal of being accurate, they tend to undergo a more objective information processing, which in turn allows them to be more resistant to cognitive biases. But when humans have a directional goal or motivation to arrive at a specific conclusion, their information processing will rather focus on the information that they consider goes hand in hand with their desired specific conclusion and disregard information that does not back it up (Epley & Gilovich, 2016; Kunda, 1990; Whitmarsh & Capstick, 2018). For example, if a person that is addicted to drinking soda and thinks that drinking soda is good, it is more likely that this person will rather focus on processing the information of an article that lists the benefits of drinking soda and disregard the information provided by an article listing the negative effects of drinking soda. Doing this will help these people arrive to the conclusion that drinking soda is "certainly good" for them.

Nevertheless, it is important to mention that motivated reasoning is constrained because people do not always arrive to their desired conclusion (Epley & Gilovich, 2016). Moreover, in order to arrive to their desired conclusion, people need to "muster up the evidence necessary to support it" (Kunda, 1990, p. 483). Thus, taking into consideration that in this study, some participants underwent a manipulation condition in which all the other team members (unanimous majority) provided the same answer as the participant´s first recommendation, I expect participants of the manipulation condition to have access to more "supporting" information of their (biased) first recommendation. Consequently, I expect the participants of the manipulation condition to be more motivated to stick with their first recommendation, disregard the expert or AI advice, and thus provide the same answer as all the other group members.

Another important aspect to consider is the preference for consistency. Cialdini et al (1999) and Guadagno and Cialdini (2010) investigated the effect of preference for consistency on social influence processes. Preference of consistency refers to the fact that people "value personal consistency and strive to respond to most situations in a manner consistent with prior

attitudes, behaviors, and commitments, particularly when the concept of consistency is salient to them" (Guadagno & Cialdini, 2010, p. 153). Another definition of preference for consistency is that humans tend to prefer receiving new information that is compatible, congruent, and in harmony with their previous choices, beliefs, information, and attitudes (Brown et al., 2005; Petrova et al., 2007). People tend to prefer consistency for two reasons: on one hand receiving new information that is consistent with previous choices, beliefs, information, and/or attitudes gives them a sense of equilibrium, whereas inconsistent information can provoke feelings of discomfort (Brown et al., 2005). On the other hand, people also like to be seen as consistent, because of the commitment they have towards previous personal choices (Cialdini et al., 1999; Petrova et al., 2007). This is particularly the case when the commitment is "active, public, and freely chosen" (Cialdini et al., 1999, p. 1244).

Considering that preference for consistency can tremendously impact the way people behave, in addition to the fact that humans tend to aim at being consistent with their previous choices and beliefs, research has investigated its robustness (Cialdini et al., 1999; Petrova et al., 2007). One clear example of the impact of preference for consistency on human´s behavior is the widely known foot-in-the-door-technique. The foot-in-the-door technique is commonly used to exploit people´s commitment to their previous choices (Guadagno & Cialdini, 2010). For instance, when people first get asked to do a small favor, people tend to agree to it. Consequently, when later people get asked for a bigger favor, some people feel committed to their previous behavior (accepting to do the favor) and thus decide to also agree to the bigger favor. In this sense, people are motivated to a certain answer or behavior due to the commitment they have with their previous answers or behaviors, as they are striving for consistency (Cialdini et al., 1999; Guadagno & Cialdini, 2010; Petrova et al., 2007).

Considering that the participants underwent a scenario in which they were given the chance to provide a first recommendation in an active, public, and freely manner and then were given the chance to revise it, I expect the participants to be motivated to stick to their initial answer and ignore the advice received. Based on this information, I derived the next three hypotheses:

> **H7**: U*nder social influence participants will be more motivated to (mantain their initial recommendation, meaning that they will) provide the group's answer.*
>
> **H8**: *Motivated reasoning to maintain one´s own first recommendation will reduce the participants´ reliance on advice.*

**H9:** *Motivated reasoning to maintain one´s own first recommendation will mediate the effect of social influence on reliance on advice, such that the presence of motivated reasoning will further diminish the participants´ reliance on advice*.

# 3. Methodology

## 3.1. Research design

Building on the study by Fortuin (2022), the aim of this dissertation was to test the effect of advice received from two different types of advisors (human advice and AI advice from a machine learning algorithm) on final judgments and decisions in a scenario of social influence. The advice from a human expert and from a state-of-the-art machine learning algorithm was used as a debiasing technique to mitigate the possible effects of anchoring and improve decision making. Moreover, I also intended to study the effect of social influence (e.g., social or peer pressure) on reliance of advice (from AI tools and human advisors) in group decisions. Thus, I decided to conduct an experimental online study following a quantitative approach. In order to determine causal relationships (Charness et al., 2012), the study consisted of a 2 (AI advice vs human advice) x 2 (social influence/social pressure vs control) between-subjects design. This resulted in the four different conditions shown in Table 2.

| Condition number | Condition |
|---|---|
| 1 | AI advice x control |
| 2 | Human advice x control |
| 3 | AI advice x social influence |
| 4 | Human advice x social influence |

*Table 2: Conditions of the study*

The study was conducted via an online questionnaire created with Qualtrics. The participants of the questionnaire were randomly assigned to only one of the four conditions to prevent any type of knowledge transportation between conditions.

Building on the study by Fortuin (2022), I also included trust in the advisor as a mediator of reliance on the advice and confidence in own (pre-advice) judgment as a moderator. As part of my study, a two-step decision making process was employed. In a first step, the participants were presented with an (high or low) anchor and were asked to make a decision (recommend

a share price). Between the first and second step, participants received advice from a human expert or a machine learning algorithm (recommended price = 50 Euros). In order to measure for the effect of social influence on reliance of advice, in the between-steps stage, just after receiving the advice (recommended price), participants of the manipulation conditions were presented with a scenario to induce social influence. The participants of the other two conditions were assigned to control groups, and thus were presented with a rather shorter scenario in which no social influence was induced. Then, in the second step, participants were asked if they wanted to revise their answer based on the advice they were provided.

## 3.2. Participants

The study was distributed via different channels, including social media (e.g., LinkedIn), two online research platforms (SurveySwap and SurveyCircle), and my personal network. All of the participants of the study were volunteers. A total of 251 questionnaires were fully completed between May 7$^{th}$ and May 15$^{th}$, 2023. Out of the 251 questionnaires, the total valid sample was composed by 211 questionnaires. The other 40 questionnaires were excluded of the sample because the participants did not pass the attention check or were outliers. Out of the 211 participants of the sample 59.7% were males, 39.8% were females, and 0.05% did not want to specify their gender. The age of the sample participants ranged from 17 to 62 and the average age was 27.26 years ($SD$ = 6.66).

Out of the 211 participants of the final sample 44.1% were working full-time and 41.2% were students. Around 52.1% of the participants had at least a bachelor´s degree. Since the questionnaire was distributed through different online channels, the sample was made of participants from 42 different nationalities, with Salvadoran people accounting for 22.7% of the total sample, followed by Austrian people accounting for 18.0% of the total sample. Moreover, on average, the participants considered that they have a slightly good understanding of artificial intelligence, algorithms, and machine learning, $M$ = 4.40, $SD$ = 1.32. See Appendix 2 for an overlook of the participants´ demographics.

## 3.3. Procedure

This study followed a similar procedure to the one of Fortuin (2022) and it included some adaptation to also test the effects of social influence on advice taking. The participants were first presented with a welcome text and an informed consent form. After agreeing with continuing the study and giving their informed consent, participants were asked basic

demographic questions. As part of the first block, participants were also asked to specify their level of understanding of artificial intelligence / algorithms / machine learning. For the next block, participants were randomly assigned to a high or a low anchor condition. As part of the anchoring condition participants were presented with a decision scenario about recommending a price of a share during an IPO. Immediately after giving their recommended price, participants were asked three questions to estimate how confident they were with their pre-advice recommendation.

Then, participants undergone an attention check. After the attention check, participants were given advice by either a human expert or a state-of-the-art machine learning algorithm. In case that the provided advice was from the machine learning algorithm, the participants received a short explanation about machine learning algorithms (Abraham et al., 2020; Palanichamy, 2019). The advice provided by the human expert and the machine learning algorithm was exactly the same. Immediately after receiving the advice, participants were asked three questions to assess how trustworthy they perceived the advisor to be.

In a next step, participants were randomized to either the manipulation condition (social influence) or the control condition. Participants of the manipulation condition first were presented with a scenario that aimed at inducing social influence and then were given the chance to revise their pre-advice recommendations based on the received advice. Participants of the control condition were immediately presented with the chance to revise their pre-advice condition based on the advice and did not undergo any other type of manipulation. Immediately after having the chance of revising their answers, participants from both the manipulation and control condition were presented with a question about the level of social pressure they felt to provide their (revised) answer. This question served as a manipulation check to control for the effect of the manipulation scenario.

In the last set of questions participants were presented with four different questions to test motivated reasoning and two questions regarding the perceived difficulty of completing this study. The participants were also offered the possibility of providing comments and feedback. The survey ended with a thank you text and the debriefing of the study. For a more detailed view of the study, please see Appendix 1.

## 3.4. Variable measurement

This subchapter will focus on describing the concrete variables of the study and how each of them was measured. Please refer to Appendix 3 to have a clearer view of the variables and their concrete measurements.

### 3.4.1. Independent variable

*Type of advisor (human advisor vs AI advisor)*: In this study type of advisor was a categorical independent variable. This independent variable was used to differentiate between the two different types of advisor (human advisor vs AI advisor). As mentioned previously, participants were randomly assigned to receive advice either from a human expert or advice from a state-of-the-art machine learning algorithm (AI advisor). The advice provided by the human advisor and the AI advisor was exactly the same. By doing this, differences within the different conditions can be attributed to the presence of different types of advisors.

*Social influence manipulation*: The second independent variable of this study was also a categorical variable. This independent variable was used to differentiate between participants that were presented with a scenario that aimed at inducing social influence and participants that were assigned to a control condition and thus were not presented with a social influence scenario. I relied on previous research for the formulation of the scenario to induce social influence. Based on studies by Asch (1956), and later adaptations by Bond and Smith (1996) and Goodmon et al. (2020), I presented a scenario in which all team members had to provide loud and clear their answers in front of everyone else. The participants were assigned the role of the last member to provide its answer. As part of the manipulation, every other team member provided (one by one) an unanimously (incorrect) answer. This allowed me to present the participants a scenario of unanimous majority before allowing them to provide an answer. Thus, in the manipulation condition, the participant, who was always the last to provide an answer, had to make a decision to conform with the team´s unanimous (incorrect) answer or to provide a different answer based on the advice received. In the control condition, participants did not undergo the social influence scenario. Thus, after receiving advice, participants were simply asked if they wanted to revise their answers.

### 3.4.2. Dependent variable

*Reliance on advice*: In order to measure how much the participants decided to rely on advice from both types of advisors (human advisor and AI advisor), the JAS paradigm was used. Building on the study by Fortuin (2022), I decided to use the JAS paradigm because it is a common measure used to determine the extent to which the participants incorporate external advice in their decisions (Bailey et al., 2022; Önkal et al., 2009). As part of the JAS paradigm in my study, participants were first asked to make a recommendation, then participants were given advice (by either a human advisor or an AI advisor) and were asked if they wanted to revise their pre-advice recommendation. Following different studies (Gino & Moore, 2007; You et al., 2022), I decided to use the weight of advice (WOA) to measure the participant´s reliance on advice. The WOA is measured as the difference between participants´ first recommendation and final recommendation divided by the difference between the participants´ first recommendation and the advice. The formula for the WOA reads as follows:

*WOA = (final recommendation – initial recommendation) / (advice - initial recommendation).*

If the participant decides to completely discount the advice and the final recommendation is equal to the initial recommendation, then this participant has a WOA of 0% but if the participant decides to fully rely on the advice and gives a final recommendation equal to the advice, then the participant has a WOA of 100%. Every value in between suggests partial discounting of the advice, meaning that participants weight their initial recommendation and the advice (Gino & Moore, 2007; Yaniv, 2004b).

### 3.4.3. Mediator, moderator, and control variables

*Confidence in own judgments and decisions*: As part of my study, I decided to measure participants´ confidence in their own judgments and decisions (initial recommendation) before receiving advice. This variable acted as a moderator and thus it was measured before the advice-giving stage and the manipulation condition. Following the study by Fortuin (2022) I measured this moderator with three items adapted from Dzindolet et al. (2003). For example, one item reads as follows "*I believe I performed well in this task*". Every item was measured with a seven-point Likert scale (1= Strongly disagree; 7 = Strongly agree). For an overview of the three items used, see Appendix 1.

*Trust in the advisor*: Based on the study by Fortuin (2022), I used three different items from Jamaludin and Ahmad (2013) and Gold et al. (2015) to measure participants´ trust in the advisor (human advisor and AI advisor). For example, one item used in the AI condition reads as follows "*I consider the machine learning algorithm to be reliable*". The three different items were measured with a seven-point Likert scale (1= Strongly disagree; 7 = Strongly agree). For an overview of the three items used, see Appendix 1. As part of the study trust in the advisor was used as a mediator. Thus, it was measured exactly after either the human advisor or the AI advisor provided advice to the participants.

*Motivated reasoning*: Testing for motivated reasoning was included in the questionnaire to study the participants´ motivation towards sticking to a certain response (the first recommendation that they provided). To measure the presence of motivated reasoning I used three different items. For example, one item reads as follows "*I felt motivated to stick to my initial estimate*". The three different items were measured with a seven-point Likert scale (1= Strongly disagree; 7 = Strongly agree). For an overview of the three items used, see Appendix 1.

*Understanding of AI, algorithms, and machine learning*: To measure the familiarity that each participant had about AI, algorithms, and machine learning I asked them to specify their level of understanding on these three terms. Following the study by Fortuin (2022) I adapted an scale from De Vries et al. (2021) to a seven-point Likert scale (1 = Extremely bad; 7 = Extremely good).

*Covariates:* Based on previous literature (Chua et al., 2023; Fortuin, 2022; Hou & Jung, 2021), I added demographics as covariate variables. I considered the following demographics: gender, age, nationality, employment status, and educational background. Participants were asked to provide their age (in years) and their nationality (country). Gender, employment status, and educational background were captured via a single choice format recommended by Qualtrics. See Appendix 1 for detailed information on the different that were used for measuring the different variables.

# 4. Results

## 4.1. Data preparation and final sample size

In order to assure the quality of the data and the survey, I conducted all necessary analyses with the statistics software IBM SPSS. After removing the participants that did not pass the attention check, I initiated the outliers detection process. I ran a test to check for univariate outliers. By using the z-scores method, I was able to find five different outliers. These five outliers had either a z-score smaller than -3 or bigger than +3, thus they removed from the final sample.

Variables such as the type of advisor (AI vs human), the anchor (low vs high anchor), the manipulation condition (control group vs social influence/social pressure manipulation) were transformed into dummy variables. The items of scale for measuring confidence in own (pre-advice) judgment and decisions, the items of the scale for measuring trust in the recommendation of the advisor, and the items of the scale for motivated reasoning were all recorded in the same direction respectively. Thus, no reverse coding was needed.

I also tested whether the different anchors (high vs low) had an impact on the dependent variable (WOA). I ran a one-way ANOVA with WOA as dependent variable and anchor type (low vs high) as factor or independent variable. The analyses showed that there was no significant difference between both the low and the high anchor, $p = .45$ (see Appendix 4 for more information on this analysis). Therefore, I decided to aggregate across them. Moreover, I also assessed the effectiveness of the social influence manipulation to see if the participants of the two manipulation groups were aware of the manipulation (Hoewe, 2017). Thus, an independent samples t-test was conducted. The results showed that the null hypothesis of independence can be rejected because there was a significant difference on the answers to the manipulation check (feeling social influence) between both (control vs manipulation) groups, $t(209) = -1.962$, $p = .026$. This means that the manipulation was successful because participants in the manipulation condition, $M = 3.98$, $SD = 1.78$, significantly felt more social influence than the participants in the control condition, $M = 3.51$, $SD = 1.68$ (see Appendix 5 for more information on this analysis).

As previously mentioned, after removing outliers and participants that did not pass the attention check, the final sample size includes a total of 211 participants. These participants were

randomly distributed along the four different conditions of the study as shown in the following table. For exact information about the distribution of the participants, see Appendix 6.

| | Control condition | Manipulation condition |
|---|---|---|
| AI advice | AI advice x control | AI advice x manipulation |
| Human advice | Human advice x control | Human advice x manipulation |

*Table 3: 2 x 2 matrix of the four different conditions of the study*

## 4.2. Scale reliability

The variable for confidence in own (pre-advice) judgment and decisions, the variable for motivated reasoning, and the variable for trust in the recommendation of the advisor were measured on a multi-item scale. Even though two of these scales have proven to be reliable in recent research (Fortuin, 2022), I tested the reliability of each of them with the present data. Thus, I conducted an analysis to determine the Cronbach´s Alpha (from now on also referred to as CA) of each scale. All scales proved to be reliable. The tests for the scale for confidence in own (pre-advice) judgment and decisions revealed a CA coefficient of .89. The CA coefficient for the scale for trust in the recommendation of the advisor was .90 (see Appendix 7). Considering that the conducted tests revealed that these two scales had a CA between 0.84 and 0.90, both scales can be considered extremely reliable (Taber, 2018). Initially, I used four different items for the scale of motivated reasoning. When using the four different items the scale only had a CA coefficient of .58, which is considered a low reliability. Since the scale with the four items proved not to be reliable, I looked at the inter-item correlation matrix. The inter-item correlation matrix shows that item 3 (motrea3) had a low correlation with the other three items, thus, it was discarded (see Appendix 7 for more information on this analysis). After discarding item 3, the scale, composed of item 1 (motrea1), item 2 (motrea2), and item 4 (motrea4) had a CA coefficient of .60. Thus, the scale can be considered reliable (Raharjanti et al., 2022). Since the three scales are considered reliable, I aggregated the three items of the confidence scale by their mean, the three items of the trust scale by their mean, and the three items of the motivated reasoning scale by their mean. Consequently, I created a variable for confidence in own judgments and decisions, a variable for motivated reasoning, and a variable for trust in the advisor.

## 4.3. Measuring the anchoring bias

To test the effect of the anchoring bias on the first (pre-advice) responses of the participants, following other studies (Bahník et al., 2019; Lalot et al., 2019), I decided to present different anchors to the participants. A total of 107 participants was presented with a low anchor (20 Euros) and 104 of them were presented with a high anchor (80 Euros). These values for the low and high anchor were chosen after presenting them with either the low or the high anchor, I asked them to give a first recommendation about the price of the share of a company. In order to prove the anchoring bias on the first recommendation of participants, I conducted an independent samples t-test comparing the first recommendations provided by participants presented with the low anchor with the first recommendations of participants presented with the high anchor. The results of the independent samples t-test display that the participants were significantly biased by the anchor (high vs low) they were exposed to. The results showed significant differences, $t$ (209) = -46.733, $p < .001$. The recommended share price from participants exposed to a low anchor, $M = 20.738$, $SD = 4.923$ was significantly lower than the recommended share price from participants exposed to a high anchor, $M = 78.163$, $SD = 11.689$ (see Appendix 8 for more information on this analysis to measure the effect of the different anchors).

## 4.4. Testing hypotheses

### 4.4.1. Testing H1-H4

In order to test hypotheses **H1-H4** I conducted an analysis on SPSS. These four hypotheses were tested with help of the Hayes PROCESS macro for SPSS. The Hayes PROCESS macro for SPSS, based on regression path analyses, is a suitable tool that uses a bootstrapping approach to expose moderated mediation effects (Hayes, 2018). In order to perform an analysis to test a moderated mediation effect that suits this study´s design, the model 14 of the macro was chosen (see figure 3). Model 14 is a mediation model that also analyzes the effect of a moderator variable (W) in the path between M and Y.

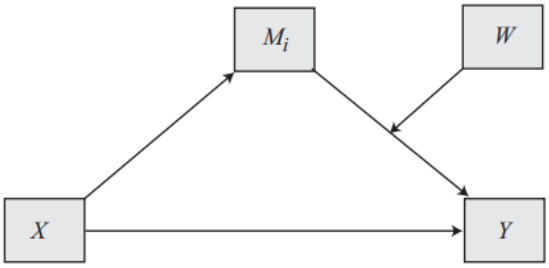


*Figure 3: Model 14 of Hayes PROCESS macro (Hayes, 2018)*

Model 14 of the Hayes PROCESS macro tests the indirect effect of X on Y. This effect is mediated by M. Moreover, this effect is also moderated by W. As shown in figure 3 and figure 4, the moderation is on the path b, which is the path between the mediator M and the dependent variable Y. In this study, the independent variable X represents the type of advisor dummy variable (0 = AI advisor; 1 = human advisor) and the dependent variable Y represents the reliance on advice variable, which is measured via the WOA. Moreover, the mediator M represents the trust in the advisor variable and the moderator W stands for the confidence in own judgments and decisions variable. Figure 4 portrays an adaptation of model 14 including the different variables used in this study.

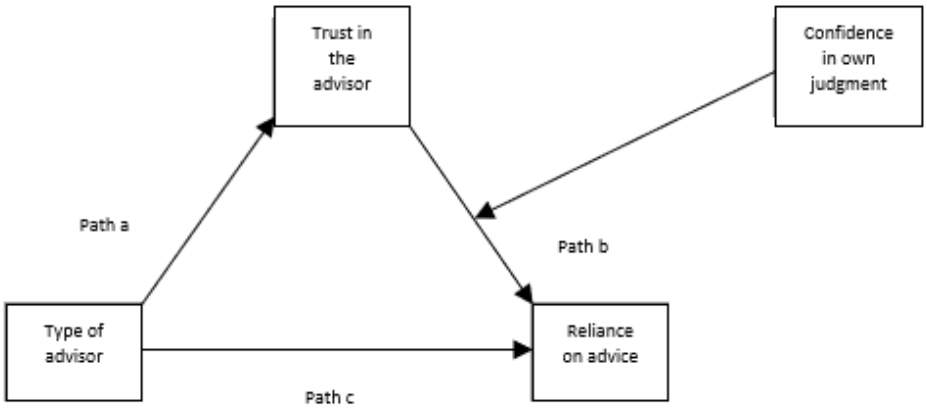


*Figure 4: Adapted model 14 including the variables of this study*

Model 14 is made of two different sub models. The first sub model estimates the path a between the IV and the mediator. The second sub model estimates path b and path c. The direct path b between the mediator and the DV is moderated by the moderator variable M. Path c represents the direct effect of the IV on the DV.

In the first sub model, model 14 regresses the M onto the X to reveal the effect of X on M (path a). The results showed that the type of advisor (AI advisor vs human advisor) has no significant effect on trust in the advisor, *t (8, 197)* = 1.86*, b* = .33*, p* = .06. Thus, H4 is not supported. These results revealed that the relationship between the type of advisor and the mediator variable trust in the advisor is positive, such that participants on average trusted more the human advisor than the AI advisor. Nevertheless, as the results are not significant, no conclusion can be drawn from them. This sub model explains 4% of the variance on trust in the advisor but it is not significant, $R^2$ = .04, *F* (8, 197) = 1.03*, p* = .41. Moreover, the covariates did not show any significant effect. See Appendix 9 for the full results of the first sub model of model 14.

In the second sub model, model 14 explains the relation between X and Y (path c), the relation between M and Y (path b) and the moderating effect of W on the relation between M and Y. The results of the second sub model reveal that trust in the advisor had a positive and significant effect on the DV. On average trust in the advisor increased the WOA of participants, *t*(11, 194) = 6.50*, b* = .16*, p* < .001. This means that higher trust in the advisor led to participants relying more on advice and adjusting more from their pre advice decision towards the advice, thus to a higher WOA, thereby supporting H1. The second sub model shows that confidence in own judgments and decisions, opposed to what was hypothesized on H2, had no significant effect on reliance on the advice (WOA), *t* (11, 194) = .16*, b* = .00*, p* = .87. Thus, H2 is not supported. The results also show that there is no significant direct effect of the type of advisor on the WOA of participants, *t* (11, 194) = -.97*, b* = -.06*, p* = .33. Thus, the type of advisor does not significantly influence whether participants decided to rely more on advice or not. Consequently, H3 is not supported. Looking at the confidence intervals of the Index of Moderated Mediation, the results show that there is no significant moderated mediation effect as 0 is included in the confidence interval, 95% CI [-.03, .002].

Similar as in the first sub model, the results of the second sub model show that none of the covariates had a significant effect on the DV. The second sub model is significant and explains 21% of the variance, $R^2$ = .21*, F* (11, 194) = 4.63*, p* < .001. See Appendix 9 for the full results of the second sub model of model 14.

### 4.4.2. Testing H5, H7–H9

In order to test hypotheses **H5** and **H7-H9** I also conducted an analysis on SPSS. These four hypotheses were tested with help of the Hayes PROCESS macro for SPSS. I chose the model 4 of the macro (figure 5). This model allowed me to perform a mediation analysis with a single mediator.

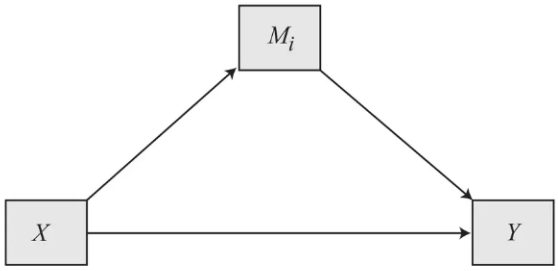


*Figure 5: Model 4 of Hayes PROCESS macro (Hayes, 2018)*

Model 4 of the Hayes PROCESS macro tests the indirect effect of X on Y. This effect is mediated by M. In this study, the independent variable X represents the social influence manipulation dummy variable (0 = control group; 1 = social influence manipulation) and the dependent variable Y represents the reliance on advice variable, which is measured via the WOA. Moreover, the mediator M represents the motivated reasoning variable. Figure 6 portrays an adaptation of model 4 including the different variables used in this study.

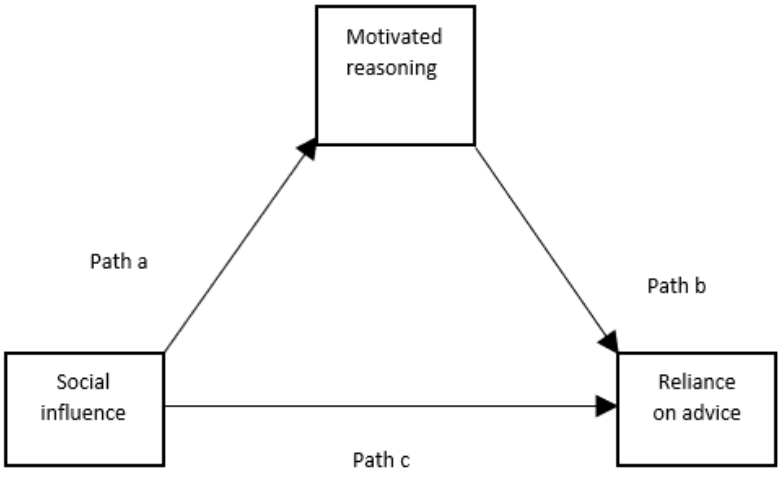


*Figure 6: Adapted model 4 including the variables of this study*

Similarly, as in model 14, model 4 is made of two different sub models. The first sub model estimates the path a between the IV and the mediator. The second sub model estimates path b and path c. Path c represents the direct effect of the IV on the DV. Path b represents the direct path between the mediator and the DV.

In the first sub model, model 4 regresses the M onto the X to reveal the effect of X on M (path a). The results showed that the social influence manipulation (control group = 0; social influence manipulation = 1) has no significant effect on motivated reasoning, $t$ (7, 200) = .65, $b$ = .11, p = .52. Thus, H7 is not supported. These results revealed that the relationship between the social influence manipulation and the mediator variable motivated reasoning is positive, such that on average participants of the manipulation condition were more motivated to stick to their initial answer and thus also to provide the same answer as the group than the participants in the control condition. Nevertheless, as the results are not significant, no conclusion can be drawn from them. This sub model explains 2% of the variance on motivated reasoning but it is not significant, $R^2$ = .02, $F$ (7, 200) = .46, $p$ = .86. Moreover, the covariates did not show any significant effect. See Appendix 10 for the full results of the first sub model of model 4.

In the second sub model, model 14 explains the relation between X and Y (path c) and the relation between M and Y (path b). The results of the second sub model reveal that motivated reasoning had a negative and significant effect on the DV reliance on advice. On average motivated reasoning decreased the WOA of participants, $t$ (8, 199) = -6.86, b = -.16, $p$ < .001. This means that higher levels of motivated reasoning led to participants relying less on advice and adjusting less from their pre advice decision towards the advice, thus to a smaller WOA, thereby supporting H8. The results also show that there is no significant direct effect of the social influence manipulation condition on the WOA of participants, $t$ (8, 199) = -.15, b = -.01, $p$ = .87. Thus, the social influence manipulation does not significantly influence whether participants relied more on advice or not. Consequently, H5 is not supported. Looking at the confidence intervals of the indirect effect of X (social influence manipulation) on Y (reliance on advice), the results show that there is no significant mediation effect as 0 is included in the confidence interval, 95% CI [-.08, .03]. Thus, H9 is not supported.

Similar as in the first sub model, the results of the second sub model show that none of the covariates had a significant effect on the DV. The second sub model is significant and explains

22% of the variance, $R^2 = .22$, $F(8, 199) = 6.95$, $p < .001$. See Appendix 10 for the full results of the second sub model of model 4.

### 4.4.3. Testing H6

H6 hypothesizes that social influence will moderate the relationship between the type of advisor and the WOA such that it will lead to lower reliance on advice, but this impact is lower for the AI group. To test this hypothesis, I ran a two-way ANOVA. For this analysis I used the reliance on advice (WOA) as DV and type of advisor and the social influence manipulation as the IVs. The analysis showed that there was no sufficient evidence to reject the interaction effect null hypothesis, $F(1, 198) = .036$, $p = .678$. Also, neither of the two IVs, type of advisor, $F(1,198) = .001$, $p = .954$, and social influence manipulation, $F(1,198) = .039$, $p = .666$, have a significant direct effect on reliance on advice. Thus, H6 is not supported. Moreover, the covariates did not show any significant effect. See Appendix 11 for the full results of this analysis.

# 5. Discussion

This chapter will focus on the main findings of this dissertation. Additionally, this chapter will also cover the relevance of this study, its contribution to the existing literature, its limitations, and its implications for future research. Moreover, this chapter will provide a section with the main conclusions of this study.

## 5.1. Summary of the results:

The use of AI is exponentially becoming more common across companies all over the world because it has proven to be a very practical tool that can help companies improve their operations (Chen et al., 2022; Tariq et al., 2021; Wamba-Taguimdje et al., 2020). In fact, AI has become so sophisticated and effective that it is able to outperform humans in many activities (Grace et al., 2018; Hashimoto et al., 2018; J. E. H. Korteling et al., 2021). Therefore, many organizations around the world rely on AI tools to assist and help its members during their decision-making processes. In this sense, AI tools can be used as debiasing methods to improve strategic decisions. Nevertheless, in many cases, humans, which are prone to cognitive biases (e.g., anchoring) are the ones responsible of taking the final choices, thus, they can decide if they want to rely on the advice and/or help provided by AI tools or if they want to stick with their (biased) reasoning. Thus, following the study of Fortuin (2022), I wanted to better understand how humans react to advice from AI tools and the extent to which they are willing to rely on it. As most strategic decisions in organizations are taken in teams, I looked to replicate Fortuin´s (2022) findings with an alternative paradigm, and to also analyzed the effect that social influence can have on human´s reliance on advice. To extend it further, I also investigated if in cases of social influence, a motivated component can arise and influence human´s advice taking.

H1 anticipated that trust in the advisor will increase the level of adjustment towards the advice, thus leading to a higher WOA. This hypothesis was supported by this study´s data. This result reinforces the existing research on the importance of trust in the advisor in advice taking. Research has shown that trust in the advisor is in fact one of the most important factors that affect advice taking (Bailey et al., 2022; Brooks et al., 2015). Accordingly, the more people trust an advisor (be it a machine learning algorithm or a human expert), the more people will be willing to rely on the advice and consider it in their decision making (Burton et al., 2019; Tauchert & Mesbah, 2019). Similar as H1, H2 dealt with another possible factor that could

influence human´s advice taking. Based on prior research (Bonaccio & Dalal, 2006; Chong et al., 2022) H2 proposed that the level of confidence in own (pre advice) decisions will influence the advice taking. H2 predicted that higher levels of confidence in own pre advice decisions (recommendations) will lead to a lower WOA, thus, to relying less on the received advice. Considering that the task at hand during the experiment of this study is an objective numerical task with a measurable answer, meaning that this task is rather an algorithmically appropriate task, H3 hypothesized that the AI advice will be a more suitable debiasing technique and have a higher positive effect on the reliance on advice than the human expert advice. Based on this same logic and the fact that people tend to rely more on human advice for rather subjective tasks and AI advice is preferred for objective tasks (Castelo et al., 2019; Yeomans et al., 2019), H4 hypothesized that an AI advisor will be consider more trustworthy than a human advisor. Nevertheless, none of these hypotheses (H2-H4) were supported by the present results.

Based on the robustness of social influence and its effect on group and/or teams, be it by normative social influence or by informational social influence, social influence (e.g., presented by unanimous majority in a team) can provoke that individual decision makers change their opinion and decide to ignore advice because they prefer to conform to their team´s unanimous choice (Di Corrado et al., 2011; Goodmon et al., 2020; Smith et al., 2011). Thus, H5 predicted that social influence will lead to people leaning towards social proof, meaning that they will rely less on advice, and H6 predicted that social influence will moderate the relationship between reliance on advice and the type of advisor, such that under social influence the participants will have a lower reliance on advice, but this impact is lower for the participants that receive AI advice. Both, H5 and H6 were not supported. In addition to studying the effects of a cognitive bias such as anchoring, I additionally tested for the existence and effects of a motivated component in advice taking. In H7 I hypothesized that under social influence (presented by a unanimous majority) individuals will be more motivated to stick to their initial (pre advice) recommendation and provide the same answer as every other team member. H7 was based on the premise that people wanting to stick to their initial answer will rather reject the advice received because they find and focus on the supporting evidence that their recommendation is correct because every other team member will also provide the same recommendation. Nonetheless, H7 was not supported. Furthermore, as I wished to look into what might mediate a potential effect from source of advice on advice taking in situations of social influence, H9 predicted that motivated reasoning will mediate the effect of social influence on reliance on advice, meaning that higher levels of motivated reasoning will further

diminish the WOA. The results do not support H9. Similar to H9, Based on the premise that people tend to aim for consistency with their previous decisions and behaviors (Cialdini et al., 1999; Guadagno & Cialdini, 2010; Petrova et al., 2007) and the fact that participants were asked to give a first recommendation, in H8 I hypothesized that participants will be motivated (e.g., motivated reasoning) to mantain their own´s first recommendation, which in turn will negatively affect the reliance on advice of all participants. The present results support H8, showing that there is in fact a motivated component that affects advice taking. These results show that besides the robustness of the anchoring effect, motivated reasoning towards a specific desired conclusion and/or outcome and the motivation to be consistent is an aspect that needs to be carefully dealt with when dealing with strategic decisions.

## 5.2. Academic and managerial implications

Even though the results of this thesis are limited, they provide some important findings. For instance, these findings highlight the robustness of the anchoring paradigm and its possible effects on strategic decisions. Thus, this study reinforces the findings of recent research, which show the presence and effect of anchoring on strategic decisions across different business domains (Alevy et al., 2015; Elaad et al., 2010; Zeckhauser et al., 2020; Zong & Guo, 2022).

Moreover, I intended to study the effectiveness of advice as a form of debiasing and its effects in group contexts in order to analyze the impact of social influence on the decision makers´ reliance on advice. Recent studies have shown the increasing importance of the use of AI-assisted decision making in work settings. Thus, building on the study by Fortuin (2022), I investigated human´s acceptance of AI advice in comparison to human experts´ advice. The results show that there is no significant difference in advice taking between receiving advice from a state-of-the-art machine learning algorithm or receiving advice from a human expert. More importantly, the results show that trust on the advisor has a significant effect on advice taking. Indeed, the more people trust the advisor (be it either a state-of-the-art machine learning algorithm or a human expert), the more people are willing to rely on the advice and incorporate it into their decision-making process. This aspect should be carefully considered by companies introducing external sources of advice to their decision making. In order to have an effective use of external advice, companies should spend effort on increasing the perceived trustworthiness of the source of advice. To do so, companies must emphasize the accuracy of the advisor (Chong et al., 2022; Enholm et al., 2021). Furthermore, companies should carefully consider that this perceived trustworthiness can be difficult to achieve and certainly is

extremely difficult to maintain. For instance, if an advisor (AI or human) makes a mistake, the negative effect that mistake can have on the advisor´s perceived trustworthiness can be substantial, especially in the case of AI (Chong et al., 2022; Dietvorst et al., 2015).

Additionally, the results of this dissertation suggest that, besides the existence of a cognitive component such as the anchoring bias, there is also a motivated component that affects advice taking in strategic decision making. These findings deserve much consideration as humans are quite prone to fell prey to motivated reasoning (Epley & Gilovich, 2016). Companies need to highlight the importance of the task at hand and demonstrate employees the need of arriving to an accurate answer. By doing this, even if there is supporting evidence towards a desired (biased) outcome, people will not directly dismiss other opposing evidence (e.g., AI or human advice), but will rather consider all the available information in an objective manner in order to arrive to an objectively accurate decision. In this sense, on one hand companies should focus on providing their employees with the right incentives so that they are driven rather by accuracy goals instead of by directional goals (Kunda, 1990). Thus, companies should focus on offering their employees the right instruments, such as trustworthy AI tools and advice from human experts, that will support them in their efforts to arrive to an accurate answer (Kunda, 1990). On the other hand, companies must focus on the importance of building the right team. Teams should be composed of a set of people that prioritize accuracy over directional goals.

## 5.3. Limitations and future studies

As before stated, this thesis provides insights on the decision-making literature, nevertheless it also has some limitations. This section focuses on these limitations an on providing a guide on the important aspects that future studies need to consider addressing these limitations.

First, it is important to mention that there were crucial time and resources constraints that limited this study, especially the experimental part of it. For instance, one of the main limitations of this dissertation is that the whole experiment setting was presented via an online questionnaire. Even though, based on past research, I tried to replicate a scenario to manipulate social influence and indeed the participants of the social influence manipulation significantly felt more social pressure than the participants of the control condition, these differences in feeling social pressure were not as high as expected. Thus, future research should focus on reproducing the whole study in a presential setting. It can be assumed that replicating the whole experiment in a presential setting and adding important features (such as a group of confederates, presenting the whole scenario on a face to face setting, etc.) could lead to a better

evaluation of the study and to finding more significant results (Bond & Smith, 1996; Goodmon et al., 2020).

Moreover, the length of this online questionnaire limited the scope of the study. Since the data collection process was through an online questionnaire filled by voluntary participants, I aimed at building a questionnaire which would take maximal 10 minutes to fill in order to get as many participants as possible. Thus, I did not have the chance to measure some relevant variables. For instance, I was not able to measure the susceptibility to social influence of the participants. Future research could approach this topic by conducting two different experiments on the same participants. In a first experiment, participants should be asked to fill out many different scales including a scale for measuring susceptibility to social influence (e.g., the SSI scales mentioned (Stöckli & Hofer, 2020)). In a second experiment, participants would undergo a similar experiment to the one I did. By doing this, the participant´s susceptibility to social influence could be assessed with the first experiment. The second experiment will serve as the main experiment in which the social influence manipulation condition will be introduced. Introducing the variable for susceptibility to social influence could help distinguish between participants that are highly susceptible to social influence and participants that are not. Thus, it could help assess the robustness of the effect of social influence on advice taking.

Furthermore, I aimed at presenting the participants with a scenario in which they were confronted with strategic decisions. Thus, I presented them with scenario in which they had to make a strategic decision regarding an IPO valuation. Since I only presented them with a strategic decision in one domain of business, future studies should focus on presenting the participants with strategic decisions across different business domains to increase its generalizability of the study. The same applies for the way in which I presented social influence (unanimous majority) and biases (cognitive bias). Thus, in order to increase its generalizability, future studies should introduce social influence via different forms such as persuasion or leadership (Smith et al., 2011) and research AI effectiveness as a debiasing technique among different biases.

## 6. Conclusion

The use and importance of artificial intelligence in the business domains is exponentially increasing. Not too long ago, companies used to only ask for advice of human experts, but nowadays AI, due to its effectiveness, efficiency, and (many times) capacity to outperform

humans is being also used by companies to improve its decision making. Nevertheless, humans still have the final say in most strategic decisions. Therefore, the results of this study show the importance of building trustworthy AI tools because otherwise humans will not necessarily rely on AI advice and will still be prone to cognitive biases. Additionally, beside the cognitive component, there is also presence of a motivated component that affects advice taking in strategic decisions. Due to limitations and constraints in this study, future research should further analyze the extent to which different forms of social influence can affect this motivated component that can alter advice taking.

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# Appendix

## Appendix 1: Questionnaire

**Q1 – Informed consent:** Welcome! Thank you for taking part in this short survey. In this survey we will ask you questions about how you perceive yourself in daily situations. This survey is expected to take no longer than 5 minutes. Your responses will be anonymous and confidential and will only be used for research purposes. Your participation is voluntary. You have the right to decline to participate and to withdraw once participation has begun. To do so, simply close this web page. There are no foreseeable consequences of participating, declining, or withdrawing from this study. If you have any questions regarding this study, please contact me, Douglas Escobar, at s-dmagana@ucp.pt. Do you consent to participate in this study?

- ○ I consent
- ○ I do not consent

### Q2-Q6 – demographics:

### Q2 – Gender

How do you describe yourself?

| Male | Female | Non-binary / third gender | Prefer to self-describe | Prefer not to say |
|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ |

### Q3 – Age

How old are you?

### Q4 – Nationality

What is your nationality?

### Q5 – Employment status

What best describes your employment status over the last three months?

| Working full-time | Working part-time | Unemployed and looking for work | A homemaker or stay-at-home parent | Student | Retired | Other |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

### Q6 – Education

What is the highest level of education you have completed or the highest degree you have received?

| Less than High School degree | High School degree | Associate degree | Professional degree | Bachelor´s degree | Master´s degree | Doctoral degree | other |
|---|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

### Q7 – Understanding of AI, algorithms, machine learning

Please specify your level of understanding of Artificial intelligence / Algorithms / Machine Learning

| Extremely bad | Moderately bad | Slightly bad | Neither good nor bad | Slightly good | Moderately good | Extremely good |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

You will now be presented with a scenario. Please imagine yourself in the described situations and answer as realistically as possible. In this scenario there will be two key moments: an "Informal Meeting" and a "Board Meeting with the CEO".
Please Imagine that you are a top manager at the company “INNOVATESMART”. This year, the company is going public (INNOVATESMART will be offering its shares to the public in a new stock issuance for the first time). Before going public, the top managers (you and 4 more) of the company have to determine the initial price that the shares of INNOVATESMART are going to have during this IPO.

**If high anchor** - Similar companies to INNOVATESMART (operating in the same industry with similar products, similar track records, similar quality of management, and similar growth prospect) have a share price of 80 Euros per share (on average).
**If low anchor** - Similar companies to INNOVATESMART (operating in the same industry with similar products, similar track records, similar quality of management, and similar growth prospect) have a share price of 20 Euros per share (on average).

Let´s assume...
There is an "informal meeting" between all top managers (you and the other 4 top managers).
During this informal meeting there is a casual conversation about what should be the share price of INNOVATESMART during the IPO. During this meeting you are asked the following question: How much do you think the share price of INNOVATESAMRT should be during the IPO?

## Q8 – First recommendation

Based on the description above, how much do you think the share price of INNOVATESMART should be during the IPO? Please write your answer below. Please provide a only a recommended price in form of a numerical value.

## Q9 – Confidence in own judgments and decisions

Q9 Please state your agreement with the following three statements regarding the previous task:

| | Strongly disagree (1) | Disagree (2) | Somewhat disagree (3) | Neither agree nor disagree (4) | Somewhat agree (5) | Agree (6) | Strongly agree (7) |
|---|---|---|---|---|---|---|---|
| I believe I performed well in this task. (1) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I am confident in my answer. (2) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I believe my estimate is accurate. (3) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

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## Q10 – Attention check

Please select "somewhat agree" so we know you are paying attention.

| Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

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## If condition = human advice

Now consider the following:
After that "informal meeting", INNOVATESMART hired an external company to make an estimation of what should be the initial share price of INNOVATESMART during the IPO. An expert assessed INNOVATESMART, and the market based on various relevant data (including reports about team capabilities, estimated market growth, etc.). Please consider that this expert has an extremely high success rate.
The expert estimated that the optimal share price of INNOVATESMART during the IPO is 50 Euros per share.

## Q11 – Trust in the advisor

Please state your agreement with the following three statements regarding the expert recommendation:

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| I believe this recommendation is trustworthy | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I consider the Human expert to be reliable | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I trust the decision of the Human expert | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

## If condition = AI advice

Now consider the following:
After that "informal meeting", INNOVATESMART hired an external company to make an estimation of what should be the initial share price of INNOVATESMART during the IPO. A new state-of-the-art machine learning algorithm* assessed INNOVATESMART and the market based on various relevant data (including reports about team capabilities, estimated market growth, etc.). Please consider that this machine learning algorithm has an extremely high success rate.
The machine learning algorithm estimated that the optimal share price of INNOVATESMART during the IPO is 50 Euros per share.

* "*A Machine learning algorithm, which is a part of AI, uses an assortment of accurate, probabilistic, and upgraded techniques that empower computers to pick up from the past point of reference and perceive hard-to-perceive patterns from massive, noisy, or complex datasets*" (Abraham et al., 2020). In other words, "*machine learning algorithms are mathematical model mapping methods used to learn or uncover underlying patterns embedded in the data. Machine learning comprises a group of computational algorithms that can perform pattern recognition, classification, and prediction on data by learning from existing data (training set)"* (Palanichamy, 2019).

## Q11 – Trust in the advisor

Please state your agreement with the following three statements regarding the state-of-the-art machine learning algorithm recommendation:

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| I believe this recommendation is trustworthy | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I consider the machine learning algorithm to be reliable | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I trust the decision of the machine learning algorithm | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

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Now let´s assume that a "Board Meeting with the CEO" is taking place in the main meeting room of INNOVATESMART.

You, the other 4 top managers and the CEO are the only people participating at this meeting.

**If condition = control**

During the "Board Meeting with the CEO", every top manager of the company is being asked to give a specific recommendation about what the share price of INNOVATESMART should be during the IPO. As part of this process, the CEO of INNOVATESMART will openly ask every top manager (one by one) to give its recommendation about the share price of INNOVATESMART during the IPO.

Consider you are the first top manager to be asked by the CEO.
The CEO of the company asks you the following question: *How much do you think the share price of INNOVATESMART should be during the IPO?*

**Q12 – Revision of the recommendation**

Please provide your answer below. Please provide only a recommended price in form of a numerical value.

**If condition = manipulation**

During the "Board Meeting with the CEO", every top manager of the company is being asked to give a recommendation about what the share price of INNOVATESMART should be during the IPO. As part of this process, the CEO of INNOVATESMART will openly ask every top manager (one by one) to give its recommendation about the share price of INNOVATESMART during the IPO. Every top manager (one by one) has given its answer in front of everybody else.

Consider that the top managers have provided their answers LOUD and CLEAR in front of everybody at the meeting.
The first top manager who was asked, recommended the same share price as the one you mentioned during the informal meeting, that is, the same price you recommended at the beginning of the survey.
The second top manager who was asked, recommended the same share price as the one you mentioned during the informal meeting, that is, the same price you recommended at the beginning of the survey.
The third top manager who was asked, recommended the same share price as the one you mentioned during the informal meeting, that is, the same price you recommended at the beginning of the survey.
The fourth top manager who was asked, recommended the same share price as the one you mentioned during the informal meeting, that is, the same price you recommended at the beginning of the survey.
Summary of the answers: Every top manager recommended the same share price as the one you mentioned during the informal meeting, just before they heard the recommendation from the expert.

Consider you are the last top manager to be asked by the CEO. Every other top manager has already given their recommendation, as described above (e.g., if during the informal meeting you said that the price should be "X" Euros, every other top manager said the price should be "X" Euros, if during the informal meeting you said the price should be "Y" Euros, every other top manager said the price should be "Y" Euros).

Remember also that the external expert recommendation was a price of 50 Euros per share.

Now that your turn has come, the CEO of the company asks you the following question in front of the other 4 top managers, which have all given the same answer as you in the "informal meeting":
How much do you think the share price of INNOVATESMART should be during the IPO?

**Q12 – Revision of the recommendation**

Please provide your answer below. Please provide only a recommended price in form of a numerical value.

## Q13 – Manipulation check

I felt social/peer pressure to provide the specific final answer I provided.

| Strongly disagree | Disagree | Somewhat disagree | Neither disagree nor agree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

## Q14-Q17 – Motivated reasoning

### Q14

I felt motivated to stick to my initial estimate.

| Strongly Disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

### Q15

I felt attached to the value I provided.

| Strongly Disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

### Q16

I want the value I provided to be the correct one.

| Strongly Disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

### Q17

I felt impelled to provide the value I provided.

| Strongly Disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

---

## Q18-Q19 – Difficulty questions

### Q18

Imagining the previously described scenario was …

| Extremely difficult | Moderately difficult | Slightly difficult | Neither easy nor difficult | Slightly easy | Moderately easy | Extremely easy |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

### Q19

Answering the questions of this study was …

| Extremely difficult | Moderately difficult | Slightly difficult | Neither easy nor difficult | Slightly easy | Moderately easy | Extremely easy |
|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ |

---

## Q20 – Comments

Do you have any comments you would like to share with the researcher? If so, please write them in the box below. Otherwise, just leave it blank.

## End of survey

Thank you for participating in this study. Your responses have been transmitted. The goal of this study was to measure the effect of advice from different sources (AI advice vs Human advice) on decision making, as well as the role of peer pressure, so half the participants were exposed to peer pressure. If you have any questions or comments, do not hesitate to send me an email via s-dmagana@ucp.pt.

Have a nice day!

## Appendix 2: Demographics and statistics

### Demographic characteristics

| | | N | % |
|---|---|---|---|
| Gender | Male | 126 | 59.7 |
| | Female | 84 | 39.8 |
| | Non-binary | 0 | 0 |
| | Prefer not to say | 1 | 00.5 |
| | Total | 211 | 100 |
| Education level | Less than HS degree | 0 | 0 |
| | HS degree | 33 | 15.3 |
| | Associate degree | 3 | 1.4 |
| | Professional degree | 12 | 5.6 |
| | Bachelor´s degree | 110 | 52.3 |
| | Master´s degree | 44 | 20.8 |
| | Doctoral degree | 4 | 1.9 |
| | Other | 5 | 2.8 |
| | Total | 211 | 100 |
| Age | 17 | 1 | 0.5 |
| | 18 | 1 | 0.5 |
| | 19 | 1 | 0.5 |
| | 20 | 3 | 1.4 |
| | 21 | 7 | 3.3 |
| | 22 | 14 | 6.6 |
| | 23 | 28 | 13.3 |
| | 24 | 24 | 11.4 |
| | 25 | 24 | 11.4 |
| | 26 | 22 | 10.4 |
| | 27 | 21 | 10.0 |
| | 28 | 12 | 5.7 |
| | 29 | 13 | 6.2 |
| | 30 | 6 | 2.8 |
| | 31 | 5 | 2.4 |
| | 32 | 4 | 1.9 |
| | 33 | 2 | 0.9 |
| | 34 | 2 | 0.9 |
| | 35 | 4 | 1.9 |
| | 36 | 1 | 0.5 |
| | 37 | 1 | 0.5 |
| | 39 | 1 | 0.5 |
| | 40 | 1 | 0.5 |
| | 41 | 3 | 1.4 |
| | 42 | 1 | 0.5 |
| | 43 | 2 | 0.9 |
| | 45 | 1 | 0.5 |
| | 46 | 1 | 0.5 |
| | 47 | 1 | 0.5 |
| | 54 | 1 | 0.5 |
| | 58 | 1 | 0.5 |
| | 59 | 1 | 0.5 |
| | 62 | 1 | 0.5 |
| | Total | 211 | 100 |

**Sample nationalities**

| | | N | % |
|---|---|---|---|
| Nationality | Afghan | 1 | 0.5 |
| | Argentinian | 3 | 1.4 |
| | Asian | 1 | 0.5 |
| | Australian | 14 | 6.6 |
| | Austrian | 38 | 18.0 |
| | Belgian | 2 | 0.9 |
| | Brazilian | 1 | 0.5 |
| | British | 3 | 1.4 |
| | Bulgarian | 1 | 0.5 |
| | Canadian | 1 | 0.5 |
| | Chinese | 2 | 0.9 |
| | Colombian | 4 | 1.9 |
| | Croatian | 1 | 0.5 |
| | Cypriot | 1 | 0.5 |
| | Dutch | 2 | 0.9 |
| | Ecuadorean | 1 | 0.5 |
| | German | 28 | 13.3 |
| | Ghanaian | 1 | 0.5 |
| | Guatemalan | 10 | 4.7 |
| | Hispanic | 1 | 0.5 |
| | Hungarian | 3 | 1.4 |
| | Indian | 1 | 0.5 |
| | Italian | 4 | 1.9 |
| | Latvian | 1 | 0.5 |
| | Lebanese | 2 | 0.9 |
| | Malaysian | 1 | 0.5 |
| | Mexican | 3 | 1.4 |
| | New Zealander | 1 | 0.5 |
| | Nicaraguan | 2 | 0.9 |
| | Panamanian | 1 | 0.5 |
| | Peruvian | 1 | 0.5 |
| | Polish | 2 | 0.9 |
| | Portuguese | 2 | 0.9 |
| | Romanian | 1 | 0.5 |
| | Salvadoran | 48 | 22.7 |
| | Serbian | 1 | 0.5 |
| | Singaporean | 1 | 0.5 |
| | Slovak | 1 | 0.5 |
| | Slovenian | 1 | 0.5 |
| | South African | 1 | 0.5 |
| | Spanish | 9 | 4.3 |
| | Turkish | 1 | 0.5 |
| | Uruguayan | 1 | 0.5 |
| | US American | 5 | 2.4 |
| | White | 1 | 0.5 |
| | Total | 211 | 100 |

Since the analysis was conducted on SPSS, I converted the nationality variable (string variable) into a numeric variable. I did this with the "transform, automatic recode" option available on SPSS. By doing this, I was able to run an analysis in which the nationality variable was used as a control variable. The new numeric nationality variable replaced each nation by a number, as follows:

| Code | Nation | Code | nation |
|---|---|---|---|
| 1 | Afghan | 24 | Latvian |
| 2 | Argentinian | 25 | Lebanese |
| 3 | Asian | 26 | Malaysian |
| 4 | Australian | 27 | Mexican |
| 5 | Austrian | 28 | New Zealander |
| 6 | Belgian | 29 | Nicaraguan |
| 7 | Brazilian | 30 | Panamanian |
| 8 | British | 31 | Peruvian |
| 9 | Bulgarian | 32 | Polish |
| 10 | Canadian | 33 | Portuguese |
| 11 | Chinese | 34 | Romanian |
| 12 | Colombian | 35 | Salvadoran |
| 13 | Croatian | 36 | Serbian |
| 14 | Cypriot | 37 | Singaporean |
| 15 | Dutch | 38 | Slovak |
| 16 | Ecuadorean | 39 | Slovenian |
| 17 | German | 40 | South African |
| 18 | Ghanaian | 41 | Spanish |
| 19 | Guatemalan | 42 | Turkish |
| 20 | Hispanic | 43 | Uruguayan |
| 21 | Hungarian | 44 | US American |
| 22 | Indian | 45 | White |
| 23 | Italian | | |

**Sample understanding of AI, algorithms, and machine learning**

In order to measure the participants´ understanding of AI, algorithms, and machine learning, participants were asked to assess their own understanding (from 1 = extremely bad to 7 = extremely good). On average, the participants of the sample had rather a slightly good understanding of AI, algorithms, and machine learning.

| | | N | Percent |
|---|---|---|---|
| AI understanding | Extremely bad | 8 | 3.8 |
| | Moderately bad | 14 | 6.6 |
| | Slightly bad | 18 | 8.5 |
| | Neither good nor bad | 63 | 29.9 |
| | Slightly good | 65 | 30.8 |
| | Moderately good | 40 | 19.0 |
| | Extremely good | 3 | 1.4 |
| | Total | 211 | 100 |

**Population statistics**

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Age | 211 | 17 | 62 | 27.26 | 6.66 |
| AI understanding | 211 | 1 | 7 | 4.40 | 1.32 |

## Appendix 3: Overview of the variables

| Variables | Description |
|---|---|
| **Dependent variable** | |
| Reliance on advice (WOA) | (final recommendation – initial recommendation)/(advice - initial recommendation) |
| **Independent variables** | |
| Type of advisor | Dummy variable (0 = AI advisor; 1 = human advisor) |
| Social influence/peer pressure | Dummy variable (0 = control condition; 1 = manipulation condition) |
| **Mediator, moderator, and control variables** | |
| Trust in the advisor | Measured with a Likert scale from 1 to 7 |
| Confidence in own judgments and decisions | Measured with a Likert scale from 1 to 7 |
| Motivated reasoning | Measured with a Likert scale from 1 to 7 |
| Understanding of AI, algorithms, and ML | Measured with a Likert scale from 1 to 7 |
| Demographics | Gender, age, nationality, employment, and educational background |

## Appendix 4: Testing the effect of anchors (low vs high) on reliance of advice (WOA)

I decided to test the effect of the two different anchors (low anchor vs high anchor) on reliance on advice (WOA), which is the dependent variable of the study. I ran a one-way ANOVA with reliance on advice (WOA) as DV and anchor type (low anchor vs high anchor) as IV. The results show that the differences between the reliance on advice (WOA) of participants presented with a low anchor and participants presented with a high anchor were not significant (*F(1, 206) = .56, p = .45*).

**Descriptives**

WOA

| | N | Mean | Std. Deviation | Std. Error | 95% Confidence Interval for Mean | | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound | | |
| low anchor | 107 | .395374682 | .353614166 | .034185172 | .327599254 | .463150110 | .000000000 | 1.17857143 |
| high anchor | 101 | .442585118 | .539231785 | .053655568 | .336133999 | .549036237 | -2.33333333 | 3.50000000 |
| Total | 208 | .418298980 | .452835671 | .031398504 | .356397131 | .480200830 | -2.33333333 | 3.50000000 |

**ANOVA**

WOA

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | .116 | 1 | .116 | .564 | .454 |
| Within Groups | 42.332 | 206 | .205 | | |
| Total | 42.447 | 207 | | | |

Considering that the differences of both anchors (low anchor vs high anchor) on the dependent variable reliance on advice (WOA) were not significant, I decided to aggregate across anchor types. This allows

me to reduce the number of groups from eight to four. The following tables show the number of participants on the eight different groups (before aggregating across anchor types). For more information about the distribution of the participants across the definite four groups, see Appendix 6.

## Appendix 5: Manipulation check

The participants of the study were randomly assigned to either the control condition or the manipulation condition. In the manipulation condition, participants were presented with a scenario of social proof, in which there was a unanimous majority in order to induce social influence. After being presented with this scenario, participants were asked if they wanted to revise their initial recommendation. Participants of the control condition were presented with a shorter scenario in which no social influence was induced. 106 participants were assigned to the manipulation condition and the rest 105 were assigned to the control condition.

To check if the manipulation served as intended and increased the social pressure that participants felt, I ran an independent samples t-test. The results show that there is significant difference between participants of the control condition and participants of the manipulation condition ($t(209) = -1.962$, $p = .026$). Participants of the manipulation condition significantly felt more social influence (peer pressure) (*M = 3.98, SD = 1.78*) than participants of the control condition (*M = 3.51, SD = 1.68*). Thus, participants of the manipulation condition were aware of the manipulation they had experienced.

**Group Statistics**

| | control | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| SPfeel | control | 105 | 3.51428571 | 1.676272684 | .163587463 |
| | manipulation | 106 | 3.98113208 | 1.778073500 | .172701765 |

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Significance | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | One-Sided p | Two-Sided p | Mean Difference | Std. Error Difference | Lower | Upper |
| SPfeel | Equal variances assumed | .079 | .779 | -1.962 | 209 | .026 | .051 | -.466846361 | .237946432 | -.935929070 | .002236347 |
| | Equal variances not assumed | | | -1.963 | 208.492 | .026 | .051 | -.466846361 | .237879713 | -.935804202 | .002111479 |

## Appendix 6: Distribution of the participants across the four different conditions

Preliminary distribution of the participants across eight different conditions

| Group number | Condition | % | N |
|---|---|---|---|
| 1 | Low anchor x AI advice x control | 11.4 | 24 |
| 2 | High anchor x AI advice x control | 15.6 | 33 |
| 3 | Low anchor x human advice x control | 10.4 | 22 |
| 4 | High anchor x human advice x control | 12.3 | 26 |
| 5 | Low anchor x AI advice x manipulation | 13.7 | 29 |
| 6 | High anchor x AI advice x manipulation | 10 | 21 |
| 7 | Low anchor x human advice x manipulation | 15.2 | 32 |
| 8 | High anchor x human advice x manipulation | 11.4 | 24 |
| | Total | 100 | 211 |

Distribution of the participants across the definitive four conditions of the study. The four definitive conditions of the study were defined after aggregating across the different anchor types (see Appendix 4).

| Group number | Condition | % | N |
|---|---|---|---|
| 1 | AI advice x control | 27.0 | 57 |
| 2 | Human advice x control | 22.8 | 48 |
| 3 | AI advice x social influence/peer pressure | 23.7 | 50 |
| 4 | Human advice x social influence/peer pressure | 26.5 | 56 |
| | Total | 100 | 211 |

## Appendix 7: Scale reliability

As before stated, I used three different scales to measure the trust in the advisor, the confidence in own judgments and decisions, and motivated reasoning. The scale for confidence in own judgments and decisions was composed of three different items. It yielded a Cronbach´s alpha of .89. Thus, it proved to be extremely reliable (Taber, 2018).

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| .894 | .895 | 3 |

**Item Statistics**

| | Mean | Std. Deviation | N |
|---|---|---|---|
| conf 1 | 4.74 | 1.237 | 209 |
| conf 2 | 4.79 | 1.452 | 209 |
| conf 3 | 4.69 | 1.435 | 209 |

The scale for trust in the advisor was also composed of three different items. These three items proved to have an extremely high internal consistency. The Cronbach´s Alpha of this scale was .90. Thus, this scale is also considered extremely reliable (Taber, 2018).

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| .895 | .896 | 3 |

**Item Statistics**

| | Mean | Std. Deviation | N |
|---|---|---|---|
| Trust 1 | 4.62 | 1.417 | 211 |
| Trust 2 | 4.82 | 1.281 | 211 |
| Trust 3 | 4.51 | 1.399 | 211 |

Motivated reasoning was initially tested with a scale composed of four different items. The Cronbach´s alpha of the scale with the four different items proved to be too low to be considered reliable.

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| .584 | .581 | 4 |

**Item Statistics**

| | Mean | Std. Deviation | N |
|---|---|---|---|
| motrea1 | 4.023697 | 1.7578145 | 211 |
| motrea2 | 4.028436 | 1.6844236 | 211 |
| motrea3 | 5.052133 | 1.5529182 | 211 |
| motrea4 | 4.303318 | 1.4550203 | 211 |

I ran the respective analyses to identify the inter-item correlation and relevant information about the four different items.

**Inter-Item Correlation Matrix**

| | motrea1 | motrea2 | motrea3 | motrea4 |
|---|---|---|---|---|
| motrea1 | 1.000 | .437 | .118 | .198 |
| motrea2 | .437 | 1.000 | .258 | .344 |
| motrea3 | .118 | .258 | 1.000 | .189 |
| motrea4 | .198 | .344 | .189 | 1.000 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Corrected Item-Total Correlation | Squared Multiple Correlation | Cronbach's Alpha if Item Deleted |
|---|---|---|---|---|---|
| motrea1 | 13.383886 | 11.257 | .360 | .194 | .518 |
| motrea2 | 13.379147 | 10.132 | .525 | .288 | .372 |
| motrea3 | 12.355450 | 13.335 | .251 | .078 | .595 |
| motrea4 | 13.104265 | 12.922 | .340 | .132 | .532 |

Based on this, I decided to remove item number 3, due to its low correlation with the other three items. After removing item number 3, the motivated reasoning scale achieved a Cronbach´s alpha of .60. Thus, this scale can be considered as reliable (Raharjanti et al., 2022).

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| .595 | .593 | 3 |

**Item Statistics**

| | Mean | Std. Deviation | N |
|---|---|---|---|
| motrea1 | 4.023697 | 1.7578145 | 211 |
| motrea2 | 4.028436 | 1.6844236 | 211 |
| motrea4 | 4.303318 | 1.4550203 | 211 |

## Appendix 8: Measuring the anchoring bias

I tested the effect of the different anchors (low anchor vs high anchor) on the first recommendation provided by the participants. The results of the independent samples t-test showed that there was a significant difference between the first recommendations provided by participants presented with a low anchor (*M = 20.738, SD = 4.923*) and the first recommendations provided by participants presented with a high anchor (M = 78.163, SD = 11.689).

**Group Statistics**

| | anchor | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| recom1 | low anchor | 107 | 20.73831776 | 4.922678456 | .475893289 |
| | high anchor | 104 | 78.16346154 | 11.6894364 | 1.146243546 |

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Significance | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | One-Sided p | Two-Sided p | Mean Difference | Std. Error Difference | Lower | Upper |
| recom1 | Equal variances assumed | 34.889 | <.001 | -46.733 | 209 | <.001 | <.001 | -57.4251438 | 1.228779480 | -59.8475344 | -55.0027532 |
| | Equal variances not assumed | | | -46.269 | 137.596 | <.001 | <.001 | -57.4251438 | 1.241107848 | -59.8792544 | -54.9710332 |

**Appendix 9: Testing hypotheses H1-H4 with Hayes PROCESS macro**

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model: 14
    Y: WOA
    X: advisor
    M: trust
    W: conf

Covariates:
 gender   age      emplo    edu      Aiunder  national control

Sample
Size:  206

**************************************************************************
OUTCOME VARIABLE:
 trust

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2007      .0403     1.5481     1.0333     8.0000   197.0000      .4123

Model
              coeff         se          t          p       LLCI       ULCI
constant     -.3232      .6945     -.4654      .6421    -1.6929     1.0464
```

```
advisor       .3279      .1759     1.8644      .0638     -.0189      .6747
gender        .1968      .1705     1.1542      .2498     -.1394      .5330
age           .0035      .0149      .2345      .8149     -.0260      .0330
emplo         .0045      .0488      .0918      .9269     -.0917      .1007
edu           .0047      .0643      .0728      .9420     -.1222      .1315
Aiunder      -.0568      .0669     -.8490      .3969     -.1889      .0752
national     -.0055      .0067     -.8142      .4165     -.0187      .0078
control       .2311      .1754     1.3173      .1893     -.1149      .5770

**************************************************************************
OUTCOME VARIABLE:
 WOA

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4561      .2081      .1732     4.6337    11.0000   194.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .7789      .2339     3.3295      .0010      .3175     1.2403
advisor      -.0582      .0599     -.9720      .3323     -.1764      .0599
trust         .1644      .0253     6.5031      .0000      .1146      .2143
conf          .0040      .0249      .1623      .8712     -.0450      .0531
Int_1        -.0309      .0202    -1.5341      .1266     -.0707      .0088
gender       -.0624      .0575    -1.0857      .2790     -.1758      .0510
age           .0000      .0051     -.0059      .9953     -.0100      .0099
emplo         .0119      .0164      .7252      .4692     -.0204      .0441
edu          -.0074      .0216     -.3439      .7313     -.0500      .0352
Aiunder      -.0312      .0227    -1.3775      .1700     -.0760      .0135
national     -.0037      .0023    -1.6096      .1091     -.0083      .0008
control      -.0617      .0589    -1.0468      .2965     -.1780      .0546

Product terms key:
```

```
 Int_1    :        trust    x        conf

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      .0096     2.3533     1.0000   194.0000      .1266
----------
    Focal predict: trust    (M)
          Mod var: conf     (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   trust      conf       WOA        .
BEGIN DATA.
    -1.2450    -1.2348      .1579
      .0000    -1.2348      .4102
     1.2450    -1.2348      .6625
    -1.2450      .0000      .2105
      .0000      .0000      .4152
     1.2450      .0000      .6199
    -1.2450     1.2348      .2630
      .0000     1.2348      .4202
     1.2450     1.2348      .5774
END DATA.
GRAPH/SCATTERPLOT=
 trust    WITH     WOA      BY       conf     .


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

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
```

```
     -.0582      .0599     -.9720      .3323     -.1764      .0599

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 advisor     ->    trust       ->    WOA

       conf     Effect     BootSE   BootLLCI   BootULCI
    -1.2348      .0664      .0394     -.0036      .1523
      .0000      .0539      .0306     -.0029      .1181
     1.2348      .0414      .0237     -.0022      .0918

      Index of moderated mediation:
          Index     BootSE   BootLLCI   BootULCI
conf     -.0101      .0090     -.0331      .0020

************************ ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: The following variables were mean centered prior to analysis:
          conf     trust

------ END MATRIX -----
```

**Appendix 10: Testing hypotheses H5, H7-H9 with Hayes PROCESS macro**

```
x = IV = Control (social influence condition)
Y = DV = WOA (weight of advice -> advice taking)
M = moderator = moreaso (motivated reasoning)


Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : WOA
    X  : control
    M  : moreaso

Covariates:
 gender   age      emplo    edu      Aiunder  national

Sample
Size:  208




**************************************************************************
OUTCOME VARIABLE:
 moreaso
```

```
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1258      .0158     1.5190      .4597     7.0000   200.0000      .8627

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.0185      .6805     5.9053      .0000     2.6767     5.3604
control       .1116      .1724      .6474      .5181     -.2284      .4516
gender        .1349      .1681      .8027      .4231     -.1965      .4663
age           .0013      .0147      .0897      .9286     -.0276      .0303
emplo         .0301      .0482      .6244      .5331     -.0649      .1250
edu          -.0490      .0635     -.7711      .4415     -.1741      .0762
Aiunder      -.0349      .0660     -.5285      .5977     -.1650      .0952
national      .0051      .0066      .7750      .4393     -.0079      .0181

**************************************************************************
OUTCOME VARIABLE:
 WOA

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4673      .2183      .1667     6.9480     8.0000   199.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.3688      .2443     5.6025      .0000      .8870     1.8506
control      -.0091      .0572     -.1586      .8742     -.1218      .1037
moreaso      -.1607      .0234    -6.8589      .0000     -.2069     -.1145
gender       -.0084      .0558     -.1512      .8800     -.1184      .1015
age          -.0002      .0049     -.0452      .9640     -.0098      .0094
emplo         .0159      .0160      .9984      .3193     -.0156      .0474
edu          -.0117      .0211     -.5571      .5781     -.0533      .0298
```

```
Aiunder      -.0429      .0219    -1.9627      .0511     -.0861      .0002
national     -.0034      .0022    -1.5329      .1269     -.0077      .0010


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

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.0091      .0572     -.1586      .8742     -.1218      .1037

Indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
moreaso     -.0179      .0294     -.0828      .0342

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

**Appendix 11: Testing H6**

**Between-Subjects Factors**

| | | Value Label | N |
|---|---|---|---|
| advisor | 0 | AI | 105 |
| | 1 | human | 103 |
| control | 0 | control | 104 |
| | 1 | manipulation | 104 |

**Tests of Between-Subjects Effects**

Dependent Variable: WOA

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 1.460[a] | 9 | .162 | .784 | .632 |
| Intercept | 1.689 | 1 | 1.689 | 8.162 | .005 |
| gender | .044 | 1 | .044 | .214 | .644 |
| age | .003 | 1 | .003 | .016 | .899 |
| emplo | .085 | 1 | .085 | .411 | .522 |
| edu | .005 | 1 | .005 | .025 | .876 |
| Aiunder | .476 | 1 | .476 | 2.300 | .131 |
| national | .591 | 1 | .591 | 2.855 | .093 |
| advisor | .001 | 1 | .001 | .003 | .954 |
| control | .039 | 1 | .039 | .187 | .666 |
| advisor * control | .036 | 1 | .036 | .173 | .678 |
| Error | 40.987 | 198 | .207 | | |
| Total | 78.842 | 208 | | | |
| Corrected Total | 42.447 | 207 | | | |

a. R Squared = .034 (Adjusted R Squared = -.009)