



The Role of Artificial Intelligence in Mitigating Cognitive Biases in Managerial Decision-Making: A Qualitative Analysis

Johannes Stephan Lamprecht

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Abstract

Title: The Role of Artificial Intelligence in Mitigating Cognitive Biases in Managerial Decision-Making: A Qualitative Analysis

Author: Johannes Stephan Lamprecht

The rapid development in integrating artificial intelligence (AI) into decision-making processes within organizations generated a wider interest in its potential to improve managerial decision quality by minimizing the effect of cognitive biases on the outcome. This thesis explores how AI tools can reduce the impact of two biases that are present in this context: confirmation bias and availability bias. Through the insights of 12 interviews with professionals working across different industries, the study provides a deep analysis of the effectiveness and limitations of AI in debiasing organizational decisions. The findings show that AI shows high potential in challenging availability bias through its ability to make data-driven decisions, its potential to minimize the effect of confirmation bias is still highly dependent on an effective human-AI collaboration. Furthermore, the study reveals several challenges connected to the process, such as over-reliance on AI advice, data quality concerns, and the impact of AI being not sufficiently aligned with organizational objectives. This research provides recommendations for managers who utilize AI to leverage its capabilities while maintaining a balance between AI-driven insights and human judgment.

Keywords: Artificial Intelligence (AI), cognitive biases, decision-making, confirmation bias, availability bias, AI adoption, bias mitigation, Human-AI interaction, strategic decision-making, qualitative analysis

Sumário

Título: O Papel da Inteligência Artificial na Mitigação de Viés Cognitivo na Tomada de Decisão Gerencial: Uma Análise Qualitativa

Autor: Johannes Stephan Lamprecht

O rápido desenvolvimento da integração da inteligência artificial (IA) nos processos de tomada de decisão nas organizações gerou um maior interesse em seu potencial para melhorar a qualidade das decisões gerenciais, minimizando o efeito dos vieses cognitivos nos resultados. Esta tese explora como as ferramentas de IA podem reduzir o impacto de dois vieses presentes neste contexto: o viés de confirmação e o viés de disponibilidade. Através de insights obtidos em 12 entrevistas com profissionais de diferentes indústrias, o estudo fornece uma análise profunda da eficácia e das limitações da IA na mitigação dos vieses nas decisões organizacionais. Os resultados mostram que a IA demonstra um grande potencial para desafiar o viés de disponibilidade através de sua capacidade de tomar decisões baseadas em dados, mas seu potencial para minimizar o efeito do viés de confirmação ainda depende fortemente de uma colaboração eficaz entre humanos e IA. Além disso, o estudo revela uma série de desafios associados ao processo, como a dependência excessiva dos conselhos da IA, preocupações com a qualidade dos dados e o impacto de a IA não estar suficientemente alinhada com os objetivos organizacionais. Esta pesquisa fornece recomendações para gestores que utilizam IA para aproveitar suas capacidades enquanto mantêm um equilíbrio entre os insights fornecidos pela IA e o julgamento humano.

Palavras-chave: Inteligência Artificial (IA), vieses cognitivos, tomada de decisão, viés de confirmação, viés de disponibilidade, adoção de IA, mitigação de vieses, interação humano-IA, tomada de decisão estratégica, análise qualitativa.

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List of Abbreviations

AI – Artificial Intelligence

ROA – Reliance on Advice

TAM – Technology Acceptance Model

VUCA – Volatile, Uncertain, Complex and Ambiguous

XAI – Explainable Artificial Intelligence

1. Introduction

In recent years, the integration of artificial intelligence (AI) technologies into various aspects of society has increased significantly, revolutionizing industries, increasing productivity, and reshaping human interactions. One area where AI shows promise is in decision-making processes within organizations. The ability of AI systems to process large amounts of data, identify patterns, and generate insights has positioned them as valuable tools for supporting and augmenting human decision-making. However, despite their potential benefits, concerns persist regarding the impact of AI on decision outcomes, particularly in mitigating cognitive biases that may influence the quality of decisions.

This thesis seeks to explore the nuanced relationship between AI and decision-making within organizations, focusing on how AI tools can potentially reduce cognitive biases. By conducting in-depth interviews with professionals across various industries, this study aims to capture their experiences and perspectives on the effectiveness of AI as a debiasing tool. The research findings will contribute to a deeper understanding of AI's role in decision-making and its potential to improve decision quality within organizations.

1.1 Research Context

Decision-making is a fundamental aspect of organizational strategy and performance. However, cognitive biases, systematic patterns of deviation from norm or rationality in judgment, can have a negative influence on decision quality. Cognitive biases such as confirmation bias, where individuals favor information that aligns with their existing beliefs, and availability bias, where decisions are overly influenced by readily retrievable information, are particularly present in organizational settings. Research suggests that approximately 70% of business decisions are influenced by such biases, underscoring the critical need to address their impact (Yeung, 2023).

Artificial intelligence offers promising possibilities to counteract these biases by providing data-driven, objective insights. AI systems can process large datasets and identify patterns that may not be immediately present to human decision-makers, potentially leading to more rational and unbiased decision outcomes (Acciarini et al., 2020). However, the effectiveness of AI in mitigating cognitive biases has not been thoroughly explored in real-world organizational contexts. This research aims to fill this gap by gathering qualitative insights from industry professionals who interact daily with AI in their decision-making processes.

1.2 Purpose of the Thesis

The primary goal of this thesis is to examine the extent to which artificial intelligence can be leveraged to debias decision-making processes within organizations. The focus will be on two cognitive biases: confirmation bias, which drives individuals to favor information that aligns with their existing beliefs, and availability bias, where decisions are influenced by information that is most readily available from memory. Through qualitative interviews with professionals who have first-hand experience with AI in decision-making, this research explores three key areas:

1. **Understanding Cognitive Biases:** How do professionals perceive the impact of biases like confirmation and availability on their decision-making? How does the organizational context influence the presence or mitigation of these biases?

2. **Evaluating AI's role in debiasing:** What are the experiences and perspectives of professionals regarding AI's effectiveness in reducing cognitive biases? Which AI tools or methodologies are considered most effective?
3. **Assessing AI's Strengths and Limitations:** How do human judgment and AI tools interact in practice? What are the perceived limitations of AI, especially in fully addressing the complexities of human cognition?

This research contributes to the ongoing discourse on AI as a supporting tool for human cognition, proposing that thoughtful integration of AI can improve decision-making by mitigating cognitive biases. By employing a qualitative approach, this study aims to capture the experiences of professionals, offering insights that might be overlooked in quantitative analyses.

1.3 Structure of the Thesis

This thesis is systematically organized into several chapters, each dedicated to exploring different aspects of the research:

The first chapter introduces the research context, explains the rationale behind the study, and outlines the primary purpose, aims, and objectives. It establishes the significance of the research within the broader field of organizational decision-making and AI, setting the stage for the investigation.

The second chapter provides a review of existing literature, constructing the theoretical framework for the study. This chapter identifies key cognitive biases, evaluates the current state of AI's role in mitigating these biases, and justifies the relevance of this research.

The third chapter details the research design, with a focus on the qualitative interview method used in this study. It describes participant selection, data collection, and the analytical techniques used, along with the measures taken to ensure reliability and validity.

The fourth chapter presents the findings from the qualitative interviews, categorizing and analyzing responses to uncover patterns related to AI's role in mitigating cognitive biases. It offers insights into the practical application of AI in decision-making.

The fifth chapter interprets the findings in the context of existing literature, discussing implications for organizational decision-making, and evaluating AI's potential as a debiasing tool. This chapter also examines the limitations of the study and suggests directions for future research.

The last chapter summarizes the key findings and reflects on the broader implications of the study. It provides a final assessment of AI's potential as a debiasing tool and offers recommendations for practice and future research.

2. Literature Review

In an era where data-driven decision-making is omnipresent, the emergence of artificial intelligence (AI) has transformed organizational processes, promising improved accuracy and efficiency. This literature review examines the intersection of AI and decision-making within organizations, focusing on the potential of AI to mitigate cognitive biases that might hinder optimal decision outcomes. The review begins with a theoretical framework that positions AI within the context of decision sciences, exploring a selection of the various biases that influence human judgment. The following sections consist of empirical studies and conceptual analyses that assess the effectiveness of AI in reducing these biases.

By the end of this chapter, the reader will gain an understanding of the current research context on AI's capacity to enhance decision-making within organizations, setting the foundation for the empirical investigation that follows.

2.1 Theoretical Framework

2.1.1 Strategic Decision-Making

Strategic decision-making is a critical component of organizational management, involving choices that determine an organization's long-term direction and resource allocation. These decisions are often made under uncertainty and complexity, where outcomes are unpredictable and stakes are high (Mintzberg, Raisinghani, & Theoret, 1976). Understanding the processes involved in strategic decision-making is essential for improving decision quality.

Herbert Simon's (1957) theory of bounded rationality provides significant insights into these processes. Simon posits that decision-makers operate under constraints of limited information, cognitive capacity, and time, leading them to "satisfice", which means selecting a solution that meets minimum criteria rather than the optimal one (Gigerenzer & Selten, 2001). This concept highlights the practical limitations of human cognition in complex environments.

Decision-makers frequently rely on heuristics, which are mental shortcuts that expedite decision-making but introduce systematic biases (Tversky & Kahneman, 1974). Key biases include anchoring, availability, and confirmation biases. For instance, anchoring bias may cause undue reliance on initial information, while availability bias can lead to overestimating the importance of recent or easily recalled information. Confirmation bias further skews decisions by leading individuals to favor information that aligns with their pre-existing beliefs (Nickerson, 1998).

AI offers a potential counterbalance to these biases by providing data-driven insights less prone to cognitive bias (Brynjolfsson & McAfee, 2017). This underscores the need for a deeper exploration of AI's role in enhancing strategic decision-making quality.

2.1.2 System 1 and System 2

Daniel Kahneman's dual-process theory, presented in "Thinking, Fast and Slow" (2011), is essential for understanding the cognitive processes underlying decision-making. Kahneman differentiates between two systems of thought:

System 1 operates intuitively and automatically, relying on heuristics for quick decision-making. While it is efficient, it is also vulnerable to cognitive biases, which can lead to systematic judgment errors (Kahneman, 2011). This system excels in situations requiring fast responses but is less effective in complex or unfamiliar contexts (Tversky & Kahneman, 1974).

System 2 is characterized by slow, deliberate, and effortful information processing, making it crucial for solving intricate problems that require careful analysis. Unlike System 1, System 2 can overcome intuitive responses, enabling more rational and controlled decision-making (Kahneman, 2011).

In strategic decision-making, both systems come into play. System 1's speed is crucial in high-pressure environments, but its heuristic nature often introduces biases. Conversely, System 2's analytical approach is essential for addressing complex, high-stakes decisions that require thorough consideration of data. Effective decision-making within organizations demands a balance between these two systems. Understanding when and how to engage System 2 is key to mitigating biases and improving decision quality (Kahneman, 2011).

The interplay between these systems underscores AI's importance in decision-making. By offering data-driven insights, AI can support or challenge the intuitive judgments of System 1, thereby improving decision accuracy and reducing bias impacts (Brynjolfsson & McAfee, 2017).

2.2 Relevant Biases in this Context

Cognitive biases significantly influence decision-making, especially in strategic contexts characterized by uncertainty and complexity. Understanding these biases is crucial for assessing AI's potential to mitigate their effects and improve decision quality. This section examines two critical biases, availability bias, and confirmation bias, due to their substantial impact on strategic decision-making.

2.2.1 Availability Bias

Availability bias is a cognitive shortcut that influences decision-making by causing individuals to rely on information that is most readily available or easily recalled, rather than assessing all relevant data. This bias occurs because people estimate event likelihood based on how easy examples come to mind, rather than through objective analysis (Tversky & Kahneman, 1973). For example, a manager might overestimate a marketing strategy's success based on recent exposure to a highly visible campaign, neglecting broader data that suggests a different outcome.

The reason behind availability bias is rooted in human memory and limited capabilities of processing information. When making decisions, individuals tend to focus on information that is most recent or emotionally striking, leading to skewed judgments (Schwarz et al., 1991). This bias can result in overestimating the frequency or probability of memorable events, such as dramatic occurrences while underestimating less present data.

In strategic decision-making, availability bias can lead to significant consequences. Organizations may emphasize recent market trends or highly publicized events, allocating resources based on skewed perceptions rather than on long-term data that may indicate more sustainable strategies (Bazerman & Moore, 2013). Such biases can lead to suboptimal decisions, including overinvestment in temporarily growing sectors or neglecting emerging risks that are less visible but potentially more impactful.

Empirical studies highlight the large influence of availability bias across various domains. For instance, Folkes (1988) found that consumers' perceptions of product reliability were heavily influenced by how easy it was to recall product failures, leading to distorted judgments. Similarly, Combs and Slovic (1979) demonstrated that media coverage of certain causes of death significantly influenced public risk perception, causing people to overestimate the likelihood of highly publicized

dangers (e.g. the likelihood of a plane crash). These examples illustrate how availability bias can distort decision-making in individual and organizational contexts.

2.2.2 Confirmation Bias

Confirmation bias, first identified by psychologist Peter Wason in the 1960s, is a cognitive phenomenon where individuals tend to favor, seek out, and recall information that confirms their pre-existing beliefs or hypotheses while giving less consideration to alternative viewpoints. This bias operates not only on a cognitive level but is also motivated by a psychological need to affirm one's own beliefs and thereby minimizing cognitive dissonance (Nickerson, 1998).

The motivational aspect of confirmation bias is particularly significant. It arises from an individual's desire to maintain a consistent worldview and avoid the discomfort associated with conflicting information. This leads to selective information processing, where evidence supporting pre-existing beliefs is widely accepted, while contradictory evidence is either seen more critically or just ignored (Kunda, 1990). This selective validation of information can perpetuate this way of thinking, as it reinforces established beliefs even in the face of new and controversial data.

In strategic decision-making, confirmation bias can be especially unfavorable. Managers, for example, may become overly committed to a particular strategy, focusing on data that supports its success while downplaying evidence that highlights its potential disadvantages. This bias can hinder an organization's ability to adapt to new information, make necessary strategic adjustments, and avoid making negatively influenced decisions (Lovallo & Sibony, 2010).

Extensive research highlights the influence of confirmation bias in various decision-making contexts. Lord, Ross, and Lepper (1979) demonstrated that when individuals are presented with mixed evidence on a controversial issue, they tend to interpret the evidence in a way that reinforces their initial views and deepens their pre-existing beliefs. Similarly, Jonas et al. (2001) found that individuals are more likely to seek out information that confirms their views and avoid information that contradicts them, further deepening their biases.

2.2.3 Justification of Bias Choice

The focus on availability and confirmation biases in this research is justified by their significant impact on strategic decision-making and the practical challenges they pose for organizations.

Availability bias is particularly relevant because it affects how decision-makers perceive and evaluate information based on presence and recency. In dynamic business environments, managers often rely on recent or easily retrievable information to make quick decisions, potentially skewing strategic choices. Given the increasing volume of information in the digital age, mitigating availability bias is crucial for making balanced and informed decisions (Schwarz et al., 1991).

Confirmation bias, on the other hand, reinforces existing beliefs and resists change, which can be unfavorable to strategic decision-making. Managers may cling to outdated strategies or ignore critical feedback due to the motivated component of this bias, and the simple desire to be right. This can lead to missed opportunities for innovation or adaptation. By addressing confirmation bias, organizations can support a more open and adaptive decision-making culture, enhancing their ability to respond to new information and changing circumstances (Nickerson, 1998; Kunda, 1990).

These biases are critical to understanding the cognitive limitations AI can address. AI's potential to enhance data processing and challenge existing thought patterns justifies the focus on these biases. Furthermore, the contrast between availability bias (cognitive) and confirmation bias (motivated)

allows a comprehensive exploration of how AI can address different dimensions of cognitive biases in decision-making.

2.3 AI in the Decision-Making Context

2.3.1 The Rise of AI

The evolution of AI from a theoretical concept to a transformative tool in various industries underscores its significant impact on decision-making. The roots of AI trace back to the mid-20th century, starting with Alan Turing's idea of machines capable of performing tasks automatically that typically require human intelligence (Turing, 1950). Since then, AI has evolved through different phases, from early rule-based systems to machine-learning algorithms that can process large datasets and learn from them (Russell & Norvig, 2016).

In today's business environment, AI accelerates processes across many sectors. The strategic importance of AI lies in its ability to enhance decision-making by processing large datasets at high speeds, identifying patterns, and making predictive insights. These capabilities are of high value in volatile, uncertain, complex, and ambiguous (VUCA) environments, where traditional decision-making processes often fall short (Bennett & Lemoine, 2014). For example, in finance, AI-driven algorithms can predict potential market trends, while in healthcare, AI can assist in diagnosing diseases by analyzing medical images with high precision (Chui, Manyika, & Miremadi, 2018).

2.3.2 Current Research Status

The integration of AI into decision-making processes has started extensive research focusing on its benefits and challenges. One key area of research is AI's role in supporting human decision-making. Many studies indicate that AI systems can significantly enhance decision-making by providing data-driven insights that humans might overlook. This support of AI is particularly beneficial in complex and data-intensive fields, where AI can analyze large datasets to uncover hidden trends and patterns (Jarrahi, 2018; Rai, 2020).

Availability and confirmation bias can be counteracted by AI's objective data analysis. For example, AI algorithms can access diverse data sources and present balanced information, thereby helping decision-makers avoid over-reliance on recent and therefore more present events (Lai et al., 2021).

Despite these advantages, the deployment of AI in decision-making is not without challenges. Algorithmic bias, which can occur when AI systems perpetuate biases present in their training data, is a significant concern. This issue highlights the need for careful data management and algorithm design to make sure they are fair and reliable (O'Neil, 2016). Moreover, the lack of transparency of AI decision-making processes is very important for building trust in the systems. The nature of AI algorithms makes it difficult for users to understand how decisions are made, which is a challenge to its accountability (Doshi-Velez & Kim, 2017).

Human-AI interaction is another vital area of research. The effectiveness of AI in decision-making largely depends on human acceptance of AI systems. Studies by Logg, Minson, and Moore (2019) reveal that trust and perceived reliability are important factors influencing whether humans rely on AI-generated results. Clear and understandable AI recommendations can increase user trust and potentially increase better decision outcomes.

2.3.3 Potentials and Limitations

The integration of Artificial Intelligence (AI) into organizational decision-making processes holds large potential but also comes with its limitations. Understanding both the opportunities and the challenges is crucial for effectively leveraging AI in business practices.

One of the main potentials is AI's ability to process vast amounts of data and perform complex calculations far exceeds human capabilities, which can significantly reduce decision-making time and increase efficiency. For example, Chen et al. (2012) highlight the power of AI's predictive analytics, which can anticipate future trends and enable proactive decision-making. This capability is particularly valuable in dynamic organizational fields, where timely and accurate decisions are critical for the future success of the organization.

Moreover, the synergy between human judgment and AI's analytical power creates a complementary relationship that improves overall decision quality. Brynjolfsson and McAfee (2017) emphasize that AI does not replace human intuition and experience but rather supports it, enabling more detailed and informed decisions. This integration is especially important in complex decision-making scenarios where both analytical and human insight are required.

This fact can also be useful in identifying and mitigating potential risks. Research by Li et al. (2020) demonstrates AI's role in risk assessment and optimization, improving the ability to manage uncertainties in decision-making environments. Organizations in volatile markets facing complex operational challenges depend on substantial risk management, and AI tools can help support this task.

A part of this is analyzing key organizational metrics such as performance, productivity, and culture. Alasmri and Basahel (2022) note that the decision-support capabilities of AI within an organisation develop effective strategic planning and operational efficiencies, leading to improved outcomes and improved overall organizational performance.

Despite its potential, AI adoption is accompanied by several significant challenges. One of the principal issues is the "black box" nature of many AI systems, where the reasoning behind decisions is a lack of transparency. This can hinder trust and acceptance among users. Lipton (2016) and Vincent (2021) discuss the critical need for explainable AI (XAI) to enhance understanding and trust in AI-driven decisions.

Another challenge is the issue of replicability in AI decisions. Arora et al. (2023) highlight that AI processes may not consistently reproduce the same outcomes, leading to variability in decision-making. This unpredictability can undermine confidence in the results and can ultimately lead to frustration in certain use cases or even employees refraining from using AI tools for future decisions. Opposed to this, another limitation is the risk of over-reliance on AI. Bolander (2019) points out that an over-dependence on AI can lead to poorer decisions if AI recommendations are misunderstood or misapplied. Cao et al. (2021) stress the importance of managerial support and appropriate training to maximize the benefits of AI while minimizing its risks.

In the following chapter, we will further focus on certain aspects of human-AI interaction that have been mentioned in the previous chapters to support a deeper understanding of the interplay between human judgment supported by AI tools.

2.4 Human-AI Interaction

As AI continues to be integrated into various organizational processes, the dynamics of human-AI interaction are a critical factor in determining the success of these technologies. This section explores how some of the mentioned human factors such as trust, algorithm aversion, and reliance on AI-generated advice influence the effectiveness of AI in mitigating cognitive biases and improving decision-making outcomes.

2.4.1 Trust in AI

Trust is a fundamental component in the effective adoption and utilization of AI systems within organizations. Similar to a lack of trust between co-workers, even the most advanced AI technologies may face resistance from users, limiting their potential. Trust in AI involves the belief that AI systems are reliable, transparent, and capable of delivering accurate and beneficial outcomes (Gefen et al., 2003). This trust is built not only on the technical performance of AI systems but also on how users perceive the AI's ability to align with their own goals and values (Madhavan & Wiegmann, 2007).

The Technology Acceptance Model (TAM) provides a useful framework for understanding how trust in AI develops, with more recent research highlighting additional factors specific to AI. While TAM traditionally emphasizes the perceived usefulness of use as a critical driver of technology acceptance (Davis, 1989), AI presents unique challenges where transparency and ethical concerns play an elevated role. For AI systems, trust is not only influenced by technical accuracy but also by how transparent and interpretable the AI's decision-making processes are perceived to be (Miller, 2019). Studies have shown that when users understand how AI systems work, they are more likely to trust and adopt these systems (Binns et al., 2018). Moreover, perceived control and the ability to influence or oversee AI systems further contribute to trust in AI (Shin, 2020).

In the context of organizational decision-making, trust in AI is particularly important because it affects how much weight decision-makers give to AI-generated advice. Research suggests that when users trust AI, they are more likely to see it as reliable and use its recommendations in their decisions, thereby improving the overall quality of those decisions (Logg, Minson, & Moore, 2019). This aspect of trust will be explored in the interviews, where industry professionals will share their experiences and perspectives on the role of trust in AI within their organizations.

2.4.2 Overcoming Algorithm Aversion - Transparency

Despite the potential benefits of AI, many users remain hesitant to fully accept these technologies due to concerns about reliability, transparency, and the potential for error. This phenomenon is called algorithm aversion (Dietvorst, Simmons, & Massey, 2015). It can significantly undermine the effectiveness of AI systems, particularly when users go back to only human judgment following perceived AI errors, even when such errors are small.

Enhancing the transparency and explainability of AI systems is key to overcoming this aversion. When users understand how AI makes decisions, their trust in these systems increases, making them more likely to rely on AI recommendations (Lipton, 2016). The concept of XAI has emerged as a response to this need, aiming to make AI decision-making processes more transparent and understandable to users (Ribeiro et al., 2016). Organizations can reduce the psychological distance between humans and machines, thereby increasing user confidence in AI-generated insights.

The interviews will also try to address algorithm aversion in organizations, exploring the strategies used to build trust among users. Insights from these interviews will uncover effective integration into decision-making processes.

2.4.3 Reliance on Advice

Reliance on advice (ROA) is a critical aspect of decision-making, especially in the context of integrating AI into organizational processes. The extent to which individuals rely on external advice, including AI-generated recommendations, depends on several factors, such as the perceived reliability and accuracy of the AI system, as well as the decision-maker's confidence in their own judgment.

Research suggests that individuals are more likely to rely on AI advice when it is perceived as more reliable or accurate than their own knowledge or expertise, particularly in complex, high-stakes, or data-intensive situations (Ghasemaghaei, 2020; Longoni, Bonezzi, & Morewedge, 2019).

Furthermore, the nature of the task can significantly affect the level of reliance. In routine or structured tasks, where AI's pattern recognition and predictive capabilities excel, decision-makers are more likely to rely on AI-generated advice. In contrast, for more subjective or ambiguous tasks requiring human intuition or judgment, reliance on AI may be reduced as decision-makers seek to retain control over complex evaluations (Ghasemaghaei, 2020).

2.4.4 Motivation

Motivated reasoning, especially important in the context of confirmation bias, was first defined by Kunda (1990), and is a cognitive process where individuals favor information that aligns with their desires and pre-existing beliefs (Nickerson, 1998).

AI can hereby offer potential solutions through its ability to analyse large datasets and provide more objective insights (Hilbert, 2012). Research by Dasgupta et al. (2021) shows that AI can counteract motivated reasoning by presenting data that individuals might otherwise overlook, thereby promoting more balanced decision-making. By structuring information to reduce bias, AI can help decision-makers overcome their intuitive judgments, which are often influenced by recent or emotionally charged events (Tversky & Kahneman, 1974).

However, the success of AI in debiasing depends on the interplay between acceptance, trust, and motivation. Jussupow et al. (2020) highlight that if AI-generated insights are perceived as too complex or misaligned with human intuition, users may resist integrating them into their decisions overall.

3. Methodology

This chapter outlines the research design and methods used to explore the role of AI in mitigating cognitive biases within managerial decision-making. The study employs a qualitative approach, to capture the complexities and many details of how AI influences decision-making outcomes, particularly in reducing biases like confirmation and availability bias.

The methodology includes data collection, sample selection, and data analysis, ensuring a broad understanding of the research problem.

3.1 Research Design

The research design for this study is rooted in a qualitative framework, which is well-suited to exploring the detailed and context-dependent nature of cognitive biases. Qualitative research, as defined by Kromrey (2002), aims to gain deep insights into complex situations by exploring and interpreting the meanings that individuals or groups assign to them.

Given the exploratory nature of the research questions, semi-structured interviews were chosen as the primary data collection method. This approach allows flexibility in exploring predefined topics while addressing new insights introduced by participants (Misoch, 2019).

The research design is further informed by the work of Taherdoost (2022), who emphasizes the advantages of a structured yet adaptable interview framework. The flexibility inherent is beneficial in the context of this study, where the ability to respond to emerging themes during interviews can provide more detailed data.

3.2 Data Collection Procedure

The data for this study were gathered through a series of semi-structured interviews conducted with 12 employees from various companies. While participants were selected from different industry sectors to ensure a broad understanding of industry dynamics, a particular emphasis was placed on the consulting sector. This focus was chosen due to the assumption that management consultants possess a broad knowledge of general industry dynamics, given the nature of their work across multiple sectors.

The selection of interview participants was carried out through personal networks and LinkedIn, ensuring a diverse and representative group of participants. To qualify, they were required to have been with their respective companies for more than one year to ensure they had a deep understanding of their corporate culture and could provide informed insights. Employees who had been with their companies for less than a year were excluded for the same reason.

Potential interviewees were approached in several stages. After the first contact, where the research background was shared, it was followed by the distribution of a consent form (see Appendix C), which included a detailed explanation of the study's purpose, as well as the measures taken to ensure confidentiality and anonymity. Before the interview, demographic data was collected.

The interviews themselves were conducted remotely via Microsoft Teams or Zoom, with audio recordings made using the internal recording tool. The estimated duration of each interview was between 30 to 60 minutes.

The interviews were later transcribed using the tool Transkriptor. The text files retrieved from the tool were then written in a standardized format. To ensure a detailed and nuanced response, all participants were interviewed in their native language, German, and the answers were then translated to the best of our ability. In particular, the paid version of the translation tool DeepL was used for this purpose. To maintain anonymity, company names are not disclosed. All participants had an educational background in economics and business administration, which ensured that they had exposure to the topics related.

3.3 Sample & Procedure

The interview questions were carefully designed to align with the research questions and to ensure that the data collected would be both relevant and insightful.

The interview script was conceptualized to explore three main areas:

1. The impact of AI tools on reducing cognitive biases in decision-making,
2. The benefits and challenges associated with AI implementation in managerial contexts, and
3. The strategies necessary for successful AI integration within organizations.

By structuring the interview around these themes, the study aimed to capture a comprehensive view of how AI is perceived and utilized within various corporate environments (Leedy & Ormrod, 2001; Kuckartz, 2019).

Following the guidelines proposed by Taherdoost (2022), the questions were designed to ensure both consistency and adaptability. The script was organized to address each of the research questions methodically, starting with broad inquiries to establish context and gradually narrowing down to more specific aspects of AI's role in mitigating cognitive biases.

The introductory question was designed to introduce the participant and to put their responses into context with their professional experience. By understanding the participants' backgrounds and their familiarity with AI tools, follow-up questions can be tailored more effectively and interpret responses with a better understanding of each participant's perspective (Misoch, 2019). It also provides insight into the extent of their exposure to AI, which is important for evaluating the depth and relevance of their subsequent responses.

The second question directly addresses the first research question. It was asked broadly enough to allow participants to discuss various aspects of AI's influence, from operational decisions to strategic initiatives. By allowing participants to reflect on specific instances where AI affected decision-making, the study could gather detailed examples that illustrate the role of AI in reducing biases (Nickerson, 1998).

The third question is aimed at uncovering the positive outcomes associated with AI implementation in decision-making. By focusing on both benefits and opportunities, this question encourages participants to reflect on the potential advantages of AI. The examples provided by participants would serve to highlight the practical applications and effectiveness of AI tools in real-world scenarios (Grbich, 2013).

The fourth question seeks to identify the challenges and limitations that participants have faced when integrating AI tools. This question is designed to get responses that could reveal resistance to AI adoption and any unintended consequences of AI use (Corbin & Morse, 2003).

The fifth question aims to generate practical recommendations for organizations looking to implement AI tools effectively. By asking participants to reflect on their own experiences and to suggest strategies for successful AI integration, the study aims to compile a set of best practices that are grounded in real-world applications. This question also serves to answer the third research question by identifying actionable steps that can enhance the effectiveness of AI in reducing cognitive biases (Rowley, 2012).

The sixth and last question was designed to allow the participants to mention any aspects that have not been shared in the previous questions.

3.4 Participants

Participants were selected for their diverse perspectives on AI in decision-making, with all having over a year of experience and backgrounds in economics or business administration. This ensured a broad understanding of industry dynamics, particularly in consulting. In the following table, more information about their position, company, gender, age, their potential management responsibility, the time they spent in their current company, and the number of employees working in their company is shown below.

Code	Position	Company	Gender	Age	Management Responsibility	Time in Position at Company (Years)	Number of employees in organisation
Participant 1	Junior Consultant	2	Female	26	No	2	50-250
Participant 2	Consultant	7	Female	28	No	2	More than 250
Participant 3	Senior Manager	3	Male	48	Yes	13	50-250
Participant 4	Manager	3	Male	61	Yes	14	50-250
Participant 5	Senior Associate	5	Male	29	No	4,2	More than 250
Participant 6	Senior Manager	3	Female	47	Yes	3,6	50-250
Participant 7	Associate	4	Female	26	No	2	More than 250
Participant 8	Junior Manager	1	Male	28	No	2,5	More than 250
Participant 9	Senior Manager	3	Male	43	Yes	11	50-250
Participant 10	Manager	3	Male	42	Yes	14	50-250
Participant 11	Consultant	3	Male	29	No	2,5	50-250
Participant 12	Associate	6	Female	26	No	1,6	More than 250

3.5 Method of Analysis

The analysis of the interview data is grounded in qualitative research methods, particularly content analysis and thematic analysis, as introduced by Leedy and Ormrod (2001). The goal of this analysis is to identify patterns, themes, and categories within the data that can show how AI tools are influencing decision-making processes and reducing cognitive biases.

The analysis process began with an examination of the interview transcripts, during which the text was scanned multiple times to identify key themes, categories, and patterns. This phase was important to establish a deep understanding of the data, enabling the following steps of the analysis in a broader view of the content (Elo & Kyngäs, 2008; Hsieh & Shannon, 2005; Zhang & Wildemuth, 2009).

Following the initial categorization, a coding framework was developed to systematically organize the data. The coding process was conducted using an inductive approach, where codes were derived directly from the interview content (Adeoye-Olatunde & Olenik, 2021). This method ensured that the analysis remained data-driven, allowing themes and patterns to emerge in responses. As the coding progressed, the framework was refined to capture all details of the data, ensuring that all relevant information was systematically categorized.

The next step involved converting the qualitative findings into a quantitative format. This was achieved by recording the frequency of each identified theme across the interviews. providing a structured overview of the data by combining qualitative and quantitative.

To enhance the clarity, graphs and charts are used to present the results of the analysis. These visualizations will help illustrate the relationships between different themes and categories, making it easier to identify the most present trends in the data. However, it is important to note that a reliability test could not be carried out in this case, as this work is an individual thesis. The absence of a reliability test means that the findings should be interpreted with caution, as the potential for subjective bias in the coding process cannot be entirely ruled out. Nevertheless, the systematic and transparent approach adopted in this analysis is intended to minimize such biases and ensure the credibility of the findings.

4. Results

This chapter presents the findings from the qualitative interviews conducted with twelve participants across various managerial levels and organizations. The results are structured according to the research questions, providing insights into the perceived effectiveness of AI as a debiasing tool, the benefits and challenges of AI implementation, and the strategies necessary for the successful integration of AI into decision-making.

The analysis is organized into different sections, each addressing one of the key research questions. The first section shows participants' perceptions of how AI tools influence decision-making and their potential to reduce cognitive biases. The following sections explore both the positive and negative impacts observed from AI implementation. The final chapter concludes by identifying the actions and strategies seen as essential by participants for the successful implementation of AI tools in managerial decision-making. The figures displaying the frequency of the statements (see Figure 1-4) help to identify the most important patterns within the data that answer the research questions.

4.1 Perception of AI Tools in Decision-Making

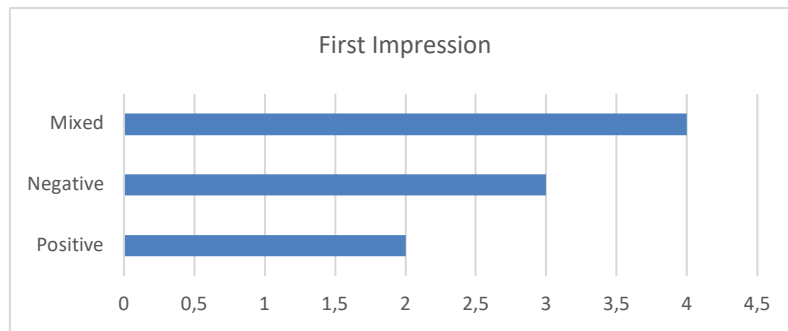
4.1.1 Initial Reactions to AI Implementation

AI tools show a range of reactions among participants, reflecting their diverse professional backgrounds and varying levels of familiarity with AI. Many approached AI with a sense of caution or skepticism, particularly in the early stages. Some perceived these tools to be overly complex and perhaps too advanced for their everyday needs at first. This sentiment is captured by one participant who described their first impression of AI as "mixed", highlighting initial intimidation that gradually subsided as they gained familiarity with the technology (Participant 1, Response to Question 1).

Similarly, other participants noted a degree of skepticism when AI tools were first introduced, driven by a perception that these tools were more a trend than lasting innovation. One participant reflected on how their skepticism was fuelled by experiences with previous technological innovations, but as AI tools matured and became more useful, the skepticism turned into cautious optimism (Participant 3, Response Question 1). Another participant said she "wasn't always convinced that AI had a place in HR," particularly given the reliance on human interaction and judgment, which AI was not ready to handle (Participant 6, Question 1).

There was a noticeable shift in perception as participants began to witness the practical benefits of AI, especially in handling labor-intensive and time-consuming tasks. One participant described how they "came around to seeing AI as a useful supplement," especially as it began to assist in making data-driven decisions more efficiently (Participant 4, Question 1). Another participant shared their surprise at how quickly and accurately AI could process large volumes of data, a task that would have been considerably more challenging without such tools (Participant 5, Question 1).

The initial skepticism often changed to a more balanced perspective. One participant, while acknowledging the impressive capabilities of AI, also recognized the technology's limitations, particularly in contexts where critical thinking was required (Participant 8, Q1). A similar approach by another participant noted the growing importance of these tools in their work and expressed a willingness to engage with them more fully as their familiarity increased (Participant 7, Q1). Over time, most participants recognized AI's value in enhancing efficiency and supporting data-driven decision-making, while some remained aware of its limitations.



4.1.2 General Acceptance and Trust in AI

As participants gained experience with AI tools, trust in these technologies increased. For many participants, trust in AI tools developed as they observed improvements in their work outcomes. One participant noted how AI enabled them to generate reports that were far more comprehensive and subtle than what could have been achieved manually, leading to a greater reliance on and trust in AI's capabilities (Participant 10, Q1). Another participant described AI as a "game-changer," especially in its ability to process large amounts of data in real-time, a crucial factor in maintaining a competitive edge in their industry (Participant 12, Q1).

Some participants maintained a degree of caution, particularly in fields where human judgment and interaction were seen as irreplaceable. One participant mentioned the benefits of AI in recruitment but expressed concerns about its impersonal nature, emphasizing the importance of maintaining a human element in decisions that impact people's careers (Participant 6, Q1). Similarly, another participant emphasized that while AI tools were valuable, there is still a need for human oversight (Participant 7, Q1).

4.2 AI as a Debiasing Tool

Awareness of cognitive biases within organizations varied among the participants, influencing how AI was perceived and used. While some had a strong awareness of the biases in question, others noted that their awareness was not deeply integrated into organizational culture. One participant noted, "I'd say we're somewhat aware of cognitive biases, but it's not something we actively think about unless someone points it out" (Participant 1, Q1). Another participant mentioned that while there is a general awareness of biases, "it's easy to overlook them in the rush of daily tasks" (Participant 2, Q2).

One participant highlighted that in their organization, there is a general awareness of cognitive biases among the management team, especially when it comes to evaluating people's performance (Participant 5, Q2). However, even in these cases, the practical application of this awareness varied. Participant 3 mentioned that being influenced by biases happens especially when "you're under pressure to make quick decisions" (Participant 3, Q2).

4.2.1 Instances of Bias Mitigation

Participants highlighted several instances where AI effectively reduced cognitive biases. For example, AI was instrumental in processing data objectively, helping reduce availability bias by highlighting insights based on actual data rather than subjective preferences (Participant 5, Q2).

Another participant observed that AI had helped reduce confirmation bias in financial forecasting by generating scenarios based on data rather than human intuition or preconceptions. They explained that AI's ability to present recommendations based on data "rather than what comes to mind first" was particularly valuable in avoiding decisions that are influenced by initial impressions or

preferences (Participant 2, Q2). Another participant mentioned that AI's capacity to provide a "second opinion that's free from the influence of human bias" had been useful in challenging their assumptions during the decision-making process (Participant 3, Q2).

One participant highlighted how AI helped to "focus on a broader range of consideration" and reduce the temptation to "only consider evidence that supports a preconceived idea" (Participant 6, Q2), which was seen as a significant advantage of using AI tools.

4.2.2 Limitations in Bias Mitigation

One participant cautioned that AI "does not get tired, but it also does not get creative" (Participant 4, Q2). This perspective highlights the potential drawback of AI tools being inflexible, which might prevent them from effectively dealing with complex decision-making situations where human intuition plays a critical role.

Another participant raised concerns about the quality of the data AI systems work with, noting that "if the data is biased or incomplete, then the AI's recommendations will be too" (Participant 7, Q2). This reflects a broader issue with AI as a debiasing tool and its effectiveness is directly tied to the quality of the input data.

Additionally, some participants stressed the importance of using AI as a supportive tool rather than the final decision-maker, emphasizing the need for human interpretation of AI-generated insights (Participant 6, Q2).

Lastly, there were concerns about over-reliance on AI, with one participant pointing out that "it is tempting to just go with what AI suggests because it's quick and easy" (Participant 1, Q4). This highlights the potential risk of decision-makers becoming too dependent on AI tools, which might increase accepting AI-generated outputs without critical thinking.

4.3 Impact of AI on Decision-Making Outcomes

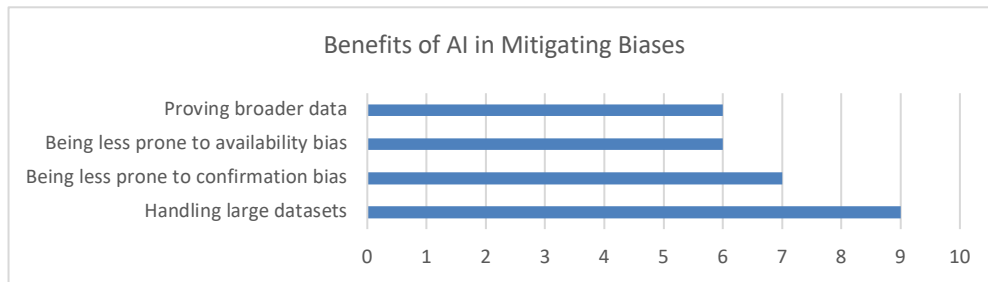
4.3.1 Positive Outcomes

Participants emphasized AI's positive impact on decision-making, particularly in reducing biases and improving decision quality. Participant 5 noted that AI tools have been instrumental in "highlighting insights based on what is there, not what we want to see," which has helped reduce the biases in question (Participant 5, in response to Question 2). Similarly, Participant 6 emphasized that AI tools support "evaluating choices rationally without being biased" (Participant 6, in response to Question 2), indicating that AI's objective approach allows decision-makers to consider a broader range of information.

Several participants also underscored AI's ability to process vast amounts of data quickly and efficiently. Participant 3 pointed out that AI's capacity to handle large datasets and analyse them in ways that would be impossible for humans alone has led to more informed and accurate decisions (Participant 8, in response to Question 3), as well as making decision-making more efficient and precise (Participant 5, in response to Question 1).

Participant 8 remarked that "AI tools are useful in maintaining a standard approach to decision-making across different scenarios, reducing variability in outcomes" (Participant 8, in response to Question 3), aligning with organizational goals and standards, and minimizing the risks associated with human error. Participant 3 added that AI's ability to bring "statistical objectivity" to the process has been crucial in achieving more reliable outcomes (Participant 3, in response to Question 3).

Additionally, Participant 6 mentioned that AI tools have enabled managers to consider a broader range of factors before making a decision, which has been crucial in strategic planning and long-term forecasting (Participant 6, in response to Question 3). This broader perspective allows organizations to anticipate market trends better, respond to changes faster, and make more proactive decisions. This provides a more "rounded view of the opportunity" (Participant 9, in response to Question 1), making strategic decisions more comprehensive and well-informed.



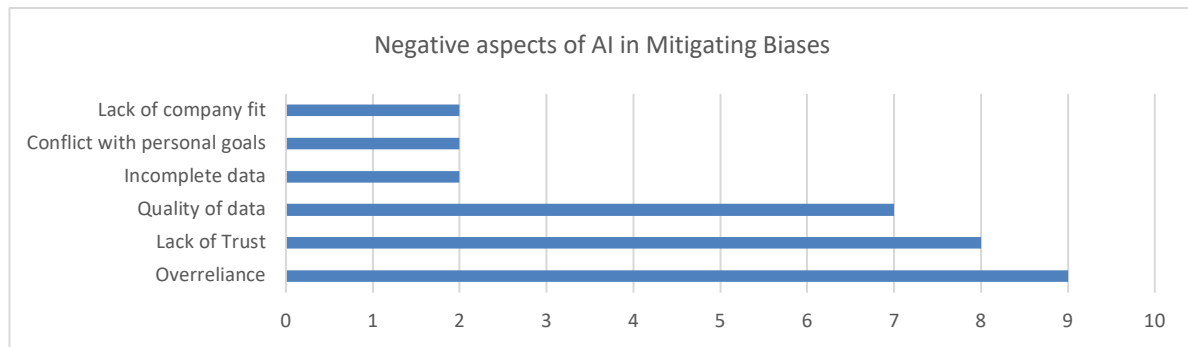
4.3.2 Negative Outcomes and Challenges

Despite these benefits, participants identified challenges associated with AI in decision-making processes. One of the most significant concerns was the potential for over-reliance on AI tools. Participant 1 warned that using AI suggestions “can be dangerous if we stop questioning the results” (Participant 1, in response to Question 4). This concern was shared by Participants 2 and 4, who stressed the importance of maintaining a critical perspective and not becoming too dependent on AI-generated outputs (Participant 2 and Participant 4, in response to Question 4).

The quality and reliability of data used by AI systems were also highlighted as major concerns, as flawed data could lead to biased or inaccurate outputs (Participant 6, in response to Question 4). This concern was repeated by Participant 2, who emphasized that AI systems need to be continuously fed with "diverse and up-to-date data" to avoid reinforcing biases or making inaccurate predictions (Participant 2, in response to Question 4). Participant 2 added that ensuring the quality of data is a significant challenge that requires ongoing attention (Participant 8, in response to Question 4).

Furthermore, AI's limitations in handling complex decisions that require an understanding of interpersonal dynamics or cultural contexts were noted, since AI doesn't understand the context of certain decisions (Participant 4, in response to Question 4). This sentiment was shared by Participant 10, who pointed out that AI tools can't fully grasp the “cultural fit between companies” or the potential impact of upcoming legislation (Participant 10, in response to Question 4).

Finally, some participants pointed out that the integration of AI into decision-making processes can lead to resistance within organizations. Participant 9 explained that there is always some resistance to change, which might also be driven by concerns about job replacement (Participant 9, in response to Question 4; Participant 11, Q6). This resistance can hinder the effective implementation of AI tools, as employees may perceive AI as threatening or difficult to understand. Participant 12 noted that not everyone is comfortable with AI, and the "resistance to change" needs to be carefully managed (Participant 12, in response to Question 4).



4.4 Obstacles to Successful AI integration

4.4.1 Technical and Operational Challenges

One of the most significant obstacles highlighted by participants is the quality of data used to train AI systems. Participant 6 emphasized that "AI's output is only as good as the data it's trained on, and if that data has any biases or gaps, the AI can end up reinforcing those biases instead of mitigating them" (Participant 1, in response to Question 4). Similarly, Participant 8 stressed the importance of continuously feeding AI systems with "diverse and up-to-date data" to ensure accurate and unbiased decision-making (Participant 8, in response to Question 4).

Another technical challenge mentioned by participants is the need for AI systems to be tailored to the specific needs of the organization. Participant 2 noted that "ensuring that the AI models are trained on data relevant to the specific context of the organization is crucial, but it's also a significant challenge" (Participant 2, in response to Question 4). This sentiment was shared by Participant 8, who pointed out that "the biggest risk, especially in a corporate context, is that we should continuously feed the systems with material from the external environment" (Participant 8, in response to Question 4). Failure to do so can lead to AI tools making decisions based on incomplete or outdated information, which can be a big risk to the organization.

System integration was also cited as a significant challenge. Participant 11 mentioned that "realistic integration into everyday working life" is important, emphasizing that the successful adoption of AI requires careful planning and alignment with existing systems and processes (Participant 11, in response to Question 4). Participant 10 added the importance of a cultural fit since "not everyone is comfortable relying on a machine to do work that they have been handling manually for years" (Participant 10, in response to Question 4). This highlights the need for a gradual and well-supported integration process to ensure that AI tools are seamlessly integrated into the organization's workflow.

4.4.2 Organisational and Cultural Barriers

In addition to cultural resistance (Participant 10, in response to Question 4) and resistance to change (Participant 12, in response to Question 4), the need for ongoing training and education was highlighted as a critical factor in overcoming resistance and ensuring successful AI integration. Participant 3 emphasized that "it's important to educate the team on what AI can and cannot do" (Participant 4, in response to Question 5). This point was reinforced by Participant 5, who mentioned that "teams need to be equipped with the knowledge and skills to use AI tools effectively" (Participant 5, in response to Question 5).

Transparency and clear communication play a vital role in overcoming organizational barriers to AI adoption. Participant 1 noted that "the more we understand how the AI is making its

recommendations, the more likely we are to trust it”, which makes it “easier to see whether it’s catching something we missed or if there is a reason to be cautious” (Participant 1, in response to Question 5). Participant 4 stressed the importance of maintaining a "healthy balance between relying on data and trusting our judgment" (Participant 4, in response to Question 6). Ensuring that AI tools are seen as partners in the decision-making process, rather than as replacements for human expertise, is mandatory in building acceptance and trust.

Finally, the need to align AI tools with the specific goals and values of the organization was identified as a key challenge. Participant 8 pointed out that "the data being fed into the system must be relevant to the specific needs of the company," as this ensures that the AI’s recommendations are aligned with organizational objectives (Participant 8, in response to Question 4). Failure to do so can lead to AI tools making decisions that may be technically correct but are not in line with the broader strategic goals of the organization.

4.5 Strategies for Successful AI Integration

4.5.1 Key Success Factors

Effective AI integration requires a strategic approach that balances technical and human factors. High-quality data, ongoing training, and transparency were identified as critical components of success.

As Participant 1 emphasized, "People need to understand both the strengths and limitations of AI, and also be aware of their own biases" (Participant 1, in response to Question 5). This understanding is important because AI tools are only as effective as the data they are trained on. Participant 4 added that "ensuring that the data you are feeding into the AI is accurate, diverse, and up-to-date" is essential for making informed decisions (Participant 4, in response to Question 5). The consensus among participants is that the foundation of any successful AI system lies in the quality and relevance of the data it processes.

Training and education emerged as critical components of successful AI integration. Participant 3 pointed out that "ongoing training and education about how AI works, what its limitations are, and how it can be used effectively to complement human judgment" are key to building confidence in AI tools (Participant 3, in response to Question 5). According to Participant 8, this includes "training teams on how to formulate prompts” and “understand what AI can and cannot do” (Participant 8, in response to Question 5).

Participant 1 highlighted the importance of "understanding how the AI is making its recommendations" and ensuring that the process is transparent (Participant 1, in response to Question 5). This allows decision-makers to see the logic behind AI-generated recommendations. Participant 8 noted that "while the AI can process millions of data points, perhaps only 10 to 50 variables are truly significant for an 80% decision-making process" (Participant 8, in response to Question 6). This insight underscores the importance of transparency in helping users understand which factors are most relevant in each context.

Another key strategy is integrating AI as a partner rather than as a replacement for human judgment (Participant 3, in response to Question 5). This approach ensures that AI is used to enhance, rather than undermine, human expertise. Participant 5 added that "organizations can learn how to effectively integrate AI without overwhelming the team" by balancing AI insights with human expertise

(Participant 5, in response to Question 5). This balance is critical to maximizing the benefits of AI while minimizing potential risks.



4.5.2 Recommendation for Future AI Use

Looking ahead, participants provided several recommendations for organizations planning to implement AI tools in their decision-making processes. Participant 8 suggested that "developers need to consider whether all available information is even relevant for the decision-making process" and to incorporate a "logical pre-filtering process" to enhance AI effectiveness (Participant 8, in response to Question 6). This recommendation highlights the need for AI systems to be tailored to the specific needs of the organization, ensuring that only the most relevant data is considered.

Moreover, Participant 12 states that "ensuring that AI development teams are diverse" and that the data used is "representative of different perspectives" (Participant 12, in response to Question 6). This recommendation underscores the need for inclusivity in AI development to ensure that AI systems are robust and free from inherent biases.

Finally, Participant 3 encouraged organizations to "stay curious and open-minded about AI's potential" and to continuously explore new ways to leverage AI as technology advances (Participant 3, in response to Question 6). This forward-looking approach will help organizations stay ahead of the curve and maximize the benefits of AI in decision-making.

5. Discussion

This chapter discusses the key findings from the interviews, comparing them with existing literature and addressing the research questions. The analysis is divided into three main sections. First, the effectiveness of AI in reducing cognitive biases is examined, highlighting both the strengths and limitations identified by participants. Next, the broader impact of AI on managerial decision-making is considered, exploring both positive outcomes and challenges. Finally, strategies for successful AI integration are discussed, including practical recommendations.

5.1 Interpretation of the Results

5.1.1 Effectiveness of AI in Reducing Cognitive Biases

AI's ability to process and analyze large datasets objectively is one of its most frequently mentioned strengths in mitigating cognitive biases. Participants highlighted that AI can quickly work through large amounts of data, identifying patterns and insights that may not be immediately present to human analysts (Participant 3, in response to Question 2). This aligns with findings from Binns (2018), who suggests that AI handles extensive datasets without cognitive limitations, which can reduce biases such as the availability heuristic.

For instance, one participant mentioned how AI's structured analysis helped "consider a wider range of possibilities" by presenting options that might not have been considered (Participant 7, in response to Question 3). This capability of AI is well-supported by literature. Dietvorst, Simmons, and Massey (2015) argue that AI's systematic approach to data evaluation can reduce confirmation bias by challenging decision-makers to consider data that challenges their pre-existing beliefs.

Moreover, AI's capacity to continuously learn and improve its models based on new data was mentioned as a critical factor in its debiasing effectiveness. Participants noted that AI tools can adapt to changing environments with every new input and reduce the risk of falling into biased patterns (Participant 8, in response to Question 2). This dynamic learning process is supported by research from Silver (2012), arguing that machine learning algorithms, particularly those that integrate feedback loops, can identify, and adjust for biases that might otherwise be overlooked by human decision-makers.

AI's strength in this context is particularly evident in scenarios with multiple, complex variables. For example, several participants pointed out that in strategic decision-making, AI tools provided data-driven insights that helped avoid heuristic shortcuts that often happen under pressure (Participant 3, in response to Question 2). This observation was also analyzed in the work of Batarseh and Freeman (2020), who highlight how AI can assist by offering a structured analysis that reduces the influence of cognitive biases, particularly when decisions are complex.

Another participant mentioned that AI's ability to process and integrate information from various sources without the influence of recent events or emotional influences is a key advantage in maintaining objectivity (Participant 7, in response to Question 3). A similar thesis was developed by Kleinberg et al. (2018), emphasizing that AI systems can help neutralize the emotional and situational biases that often influence human judgment.

The interviews revealed that AI tools excel in data-rich environments where decision criteria can be clearly defined and quantified. In these contexts, AI's ability to process and analyze large volumes of data can significantly help decision-makers with minimizing biases (Participant 7, in response to Question 3). This observation is supported by Araujo et al. (2020), who found that AI is particularly effective in domains where decision-making is heavily data-driven and where biases are a result of information overload or selective attention.

5.1.2 Limitations of AI as a Debiasing Tool

One of the most significant challenges, as highlighted by the participants, is the quality of the data AI systems work with. If the data is biased, incomplete, or outdated, the AI's outputs will likely reflect these biases (Participant 5, in response to Question 4). This concern is widely acknowledged in the literature, with Barocas, Hardt, and Narayanan (2019) stating that AI systems can even perpetuate existing biases if not properly managed.

Moreover, several participants pointed out that AI might struggle in situations requiring human judgment or an understanding of context-specific factors. For instance, decisions that involve interpersonal dynamics require a depth of understanding that AI may not be able to replicate (Participant 4, in response to Question 2). Mittelstadt et al. (2016) support the view that while AI can improve decision-making by providing objective data analysis, it cannot fully replace the experiential knowledge and intuition that humans have.

Another limitation discussed is the potential for over-reliance on AI tools. Some expressed concern that depending too much on AI-generated recommendations could lead to a reduction in critical

thinking (Participant 7, in response to Question 4). This is supported by Jarrahi (2018), who warns that over-reliance on AI can make decision-makers fail to question or verify AI outputs, potentially leading to flawed decisions.

Furthermore, AI's effectiveness in reducing biases depends on its proper integration into the decision-making process. For instance, one participant emphasized that while AI can provide valuable insights, it is ultimately the human decision-makers who must interpret these insights within the broader context of their organization's goals and values (Participant 10, in response to Question 3) which was supported by Wilson and Daugherty (2018). They argue that the best outcomes are achieved when AI is used as a complement to human judgment instead of a replacement.

In summary, while AI offers great potential as a tool for reducing cognitive biases in decision-making, its effectiveness highly depends on several factors, including the quality of the data it processes, the context in which it is applied, and to which extent human oversight is maintained.

5.2 Impact of AI on Managerial Decision-Making

5.2.1 Positive Outcomes

The interviews revealed that one of the most significant advantages of AI in managerial decision-making is its ability to maintain objectivity. This capability helps reduce the influence of individual biases, which are often driven by subjective judgment (Participant 3, in response to Question 3). Research supports this view, stating that AI tools can help managers make more data-driven decisions, thereby reducing the reliance on intuition and potentially biased heuristics (Dietvorst, Simmons, & Massey, 2015; Kahneman, 2011).

Several participants identified AI's ability to improve decision-making efficiency. By automating data collection and analysis, AI tools can reduce the time required to make decisions, allowing managers to focus on higher-level strategic tasks (Participant 5, in response to Question 3). AI is often credited with streamlining decision-making processes, particularly in data-intensive environments (Wilson & Daugherty, 2018). This ultimately leads to quicker, more informed decisions, and enhances organizational agility (Binns, 2018).

Moreover, AI's capacity to handle and integrate diverse data sources was seen as a critical factor in supporting better decision-making. Participants observed that AI tools help in gathering information from various departments, thereby providing a broader view of the business context (Participant 7, in response to Question 3). This wider perspective is especially important where decisions are based on multiple variables and where the integration of different data streams can reveal insights that might otherwise be overlooked (Araujo et al., 2020).

5.2.2 Negative Outcomes

The interviews revealed several challenges and negative outcomes associated with AI in decision-making. As mentioned, one main factor was the risk of over-reliance on AI tools, which can lead to a reduction in critical thinking and human oversight. Participants expressed concern that in some cases, managers might become too dependent on AI-generated recommendations and ignore contextual factors that the AI might not fully understand (Participant 4, in response to Question 4). The risk of an over-reliance on AI can lead to a deskilling of human decision-makers and a lack of accountability (Jarrahi, 2018; Mittelstadt et al., 2016).

Another significant issue is AI's potential to increase the impact of existing biases if the data it is trained on is biased. Several participants mentioned that AI tools could replicate the biases present in

historical data, leading to skewed decisions (Participant 6, in response to Question 4). This concern is supported by research, particularly in areas like human resources, where historical data may reflect societal inequalities (Barocas, Hardt, & Narayanan, 2019).

Another theme that was captured was that in cases where decisions involve complex interpersonal dynamics, AI's reliance on data and algorithms may not capture the full scope of the issue (Participant 8, in response to Question 4). This has been discussed in previous literature, pointing out that AI still lacks the emotional intelligence and ethical reasoning that humans bring to decision-making (Mittelstadt et al., 2016; Wilson & Daugherty, 2018).

Finally, a few participants raised concerns about the integration of AI into existing organizational cultures. They mentioned that successful AI adoption requires not only technical integration but also a cultural shift within the organization. Resistance to change, lack of trust in AI tools, and inadequate training were cited as significant barriers to effective AI implementation (Participant 6, in response to Question 5). These challenges are well-supported by the literature, which emphasizes the importance of organizational readiness and the need for a supportive culture when introducing AI technologies (Binns, 2018; Davenport & Ronanki, 2018).

5.2.3 Organisational and Cultural Factors

The interviews highlighted that organizational culture plays a critical role in determining the success of AI adoption. Participants noted that in organizations with a culture of innovation and openness to new technologies, AI tools are more likely to be embraced and used more effectively (Participant 5, in response to Question 5). This observation was also mentioned in the work of Davenport and Ronanki (2018), who argue that a supportive organizational culture is essential for successful AI integration.

That also means that in organizations where there is resistance to change or a lack of trust in AI, the benefits of AI tools may not be fully effective. Participants pointed out that in such environments, AI initiatives often face pushback, leading to underutilization and sometimes even rejection of the technology (Participant 6, in response to Question 4). Several studies indicate similar findings, stating that organizational resistance is a major barrier to AI adoption, often driven by fear of job displacement and a lack of understanding of AI's capabilities (Wilson & Daugherty, 2018; Binns, 2018).

Another factor to consider is that if organizational leaders actively master AI initiatives and demonstrate a commitment to integrating AI into decision-making processes, it sends a strong message to the rest of the organization. This helps to build trust and reduce resistance (Participant 7, in response to Question 5). Davenport and Kirby (2016) support this aspect, highlighting the role of leadership in supporting a culture that is receptive to AI and other disruptive technologies.

All the mentioned factors depend on a large offer of continuous training and education to ensure that employees are equipped to work effectively with AI tools. Participants mentioned that without proper training, employees might lack the confidence or skills needed to fully understand AI and how the tools work most efficiently (Participant 4, in response to Question 5). This observation is supported by Wilson and Daugherty (2018), who argue that ongoing education and skill development are critical for maximizing the benefits of AI in organizations.

In conclusion, while AI offers significant potential to enhance managerial decision-making, the impact is mainly dependent on how it is integrated within the organization. The benefits of AI must

be balanced against the risks, and the organizational and cultural context plays a crucial role in the success of AI adoption.

5.3 Strategies for Effective AI Integration

5.3.1 Best Practices and Lessons Learned

Aligning AI initiatives with organizational goals and values was one of the key practices identified by participants. AI projects tend to be more successful when they are closely linked to the strategic objectives of the organization and clear communication about how AI will support these goals (Participant 8, in response to Question 5). This aligns with research by Agrawal, Gans, and Goldfarb (2018), who argue that AI should be viewed as a tool for enhancing core business strategies, and if AI's integration is aligned with them, it is more likely to be accepted and utilized effectively by employees.

This can be achieved by a phased approach to AI implementation, beginning with pilot projects. Participants emphasized that starting with smaller-scale projects allows organizations to test AI tools, identify potential challenges, and refine their processes before broader deployment (Participant 5, in response to Question 5). This approach is well-supported by existing literature, for example, Brynjolfsson and McAfee (2017) argue that such projects are essential in understanding how AI can be tailored to meet specific organizational needs while managing uncertainties.

This aligns with the need for ongoing training, not only to help develop the necessary skills to work with AI tools but also to support a deeper understanding of the technology's potential and limitations (Participant 3, in response to Question 5). Wilson, Daugherty, and Morini-Bianzino (2017) emphasize that continuous learning is crucial for ensuring that AI tools are used effectively and ethically. They suggest that organizations should invest in both technical training and education on the broader implications of AI, equipping employees with a skillset to leverage AI's capabilities to a great extent. During the process, Participants noted that for AI to be trusted and effectively utilized, decision-makers need to understand how AI algorithms work and what factors influence their recommendations (Participant 4, in response to Question 6). This need for transparency is mentioned in several works, including the work of Doshi-Velez and Kim (2017), particularly in complex decision-making scenarios. They argue that when decision-makers understand the rationale behind AI outputs, they are more likely to use these tools responsibly and effectively.

Furthermore, it is important to involve employees in the AI adoption process. Involving staff in the design and implementation of AI systems can help reduce resistance and increase buy-in (Participant 8, in response to Question 5). This approach is supported by the work of Edmondson and Lei (2014), who found that when employees feel comfortable expressing their concerns and contributing ideas, the chances of successful technology adoption are much higher. By doing so, organizations can support a sense of ownership and reduce the fear that often accompanies technological change.

5.3.2 Implications for Future AI Use

Some participants suggested that organizations must remain adaptable and forward-thinking in their approach to AI. Monitoring and evaluation of AI systems are important to ensure that these tools remain effective and relevant as business environments evolve (Participant 10, in response to Question 6). This perspective is reinforced by Rai, Constantinides, and Sarker (2019), who argue that AI systems should be viewed as dynamic entities that require ongoing adjustment and refinement.

Feedback loops and iterative development processes to continually improve AI performance are important to address emerging challenges.

Furthermore, Participants noted that organizations should encourage employees to explore new ways of leveraging AI to solve arising problems on the way (Participant 4, in response to Question 5). This culture of innovation is essential for maintaining a competitive edge in an increasingly AI-driven world. Research by Gawer and Cusumano (2014) supports this view, emphasizing that organizations that embrace experimentation and continuous innovation are better positioned to benefit from the opportunities presented by AI.

The balance between AI-driven insights and human judgment was emphasized throughout the interviews as critical for effective decision-making. Human input is essential for interpreting these insights within the broader organizational context, especially when it comes to decisions more prone to being influenced by cognitive biases (Participant 8, in response to Question 5). This balanced approach is discussed by Jarrahi (2018), who argues that the most effective decision-making processes are those that integrate AI with human expertise, ensuring that AI supports rather than replaces human judgment.

5.4 Relevance for Management and Practice

5.4.1 Practical Implications for Managers

To maximize AI's potential, managers should prioritize the alignment of AI tools with organizational objectives. AI's ability to process and analyze large datasets can directly be used to address biases such as confirmation and availability bias (Dietvorst, Simmons, & Massey, 2015). Managers should focus on deploying AI in areas where these biases are most prevalent, ensuring that AI tools are designed to challenge existing assumptions and broaden decision-making perspectives. While AI can provide valuable data-driven recommendations, it is nevertheless essential that managers use their expertise to interpret these insights to maintain a balance between AI recommendations and human judgment.

Additionally, it is their responsibility to support a culture of continuous learning and innovation within their teams. This can be achieved by continuously investing in training programs for their employees that not only focus on the technical aspects of AI but also the transparency of such tools to both employees and stakeholders, which builds trust in AI tools and helps mitigate concerns about algorithmic bias or data misuse (Doshi-Velez & Kim, 2017). By clearly communicating how AI tools function and what data they use, managers can support greater acceptance and responsible use of AI within their organizations.

5.4.2 Recommendations for Organisational Policy

Effective AI implementation requires collaboration across various organizational functions and the involvement of diverse teams. By doing so, organizations can better identify potential biases and tailor AI tools to meet specific needs (Holstein et al., 2019). This approach also promotes broader acceptance and more effective use of AI tools across the organization.

Furthermore, organizations should implement continuous monitoring and evaluation of AI systems. Policies and feedback loops can help ensure that AI systems remain aligned with organizational goals and do not result in unintended consequences.

Therefore, it is important to invest in AI education and training across all levels of the organization. As AI becomes increasingly integrated into business processes, all employees must understand the basics of AI and its implications for their work. This broad-based AI literacy can help minimize resistance to AI adoption and ensure that employees are equipped to work effectively with new technologies (Wilson & Daugherty, 2018).

5.5 Limitations and Future Research

5.5.1 Study Limitations

While this study provides insights into the role of AI in mitigating cognitive biases within managerial decision-making, several limitations must be mentioned to fully understand the scope and implications of the findings.

This research is limited to the results retrieved from the sample size and composition. Although efforts were made to include participants from diverse backgrounds, the sample may not fully capture the wide range of perspectives necessary to generalize the findings across different industries, organizational sizes, or cultural contexts. Most participants shared similar professional roles and levels of experience with AI, which could result in a narrow perspective on the broader application of AI in decision-making. While the findings are relevant to the specific contexts studied, they may not be entirely generalizable to other settings where AI integration might operate under different conditions.

The scope of the interview questions is also limited, as they were designed to focus on specific aspects of AI's impact on cognitive biases. This targeted approach may have excluded other important factors that influence AI's effectiveness in mitigating bias influence. Moreover, the complexity of cognitive biases and their interplay with AI tools might not have been fully captured, potentially limiting the depth of the analysis. Cognitive biases are deeply embedded in human decision-making processes, and their subtle or unconscious nature makes them challenging to measure accurately. The study attempted to assess the impact of AI on these biases, but not all nuances of human-AI interaction might be fully explored, especially given the interplay between different biases.

The qualitative nature of this research introduces a degree of subjectivity in the interpretation and categorization of participant responses. Despite rigorous efforts to maintain objectivity, the thematic analysis may have resulted in the oversimplification of complex ideas or the merging of distinct concepts. This subjectivity could affect the depth and accuracy of the findings, as personal biases might have influenced how the data was analyzed. Additionally, the study relied heavily on personal perceptions. Participants may have emphasized certain aspects of their experiences while downplaying others, leading to a skewed understanding of AI's role in decision-making. Moreover, providing participants with the interview questions beforehand, although intended to help them prepare, may have influenced their responses, leading to answers that align with perceived expectations rather than their true experiences.

Another important limitation is the temporal relevance of the findings. AI technology is rapidly evolving, and what is true about AI integration today may change significantly soon as new advancements emerge. This study captures a specific moment in time, and the findings may become outdated as organizations continue to adapt to technological developments. The long-term effects of

AI on decision-making processes are not fully understood from the data collected, emphasizing the need for ongoing research in this area.

The study's focus on certain industries or regions may limit the generalizability of the results to other contexts. The effectiveness and challenges of AI integration could vary significantly across different cultural or economic settings, which may not be fully reflected in this research. This limitation underscores the importance of considering the unique characteristics of each context when applying the study's findings to different organizational environments.

5.5.2 Directions for Future Research

Given these limitations, several possibilities for future research emerge. Expanding the sample size and diversity of participants would provide a more comprehensive understanding of AI's role in mitigating cognitive biases across various industries and cultural contexts. Future studies could include participants from different organizational levels, regions, and sectors to explore how these factors influence AI integration and its effectiveness in decision-making.

Further research is also needed to delve deeper into the full complexity of cognitive biases and their interaction with AI tools. This includes investigating biases not covered in this study and examining how multiple biases may interact to affect decision outcomes. Such research could lead to the development of more nuanced AI systems that are better equipped to address a wider range of biases. In addition, future studies could adopt a mixed-methods approach, combining qualitative interviews with quantitative measures to provide a more robust analysis of AI's impact on decision-making. This approach would help validate self-reported data and offer a more objective assessment of AI's effectiveness in reducing cognitive biases.

Finally, as AI technology continues to evolve, ongoing research will be necessary to monitor its long-term impact on decision-making processes. This includes tracking how AI systems are adapted over time, how organizations respond to new ethical and practical challenges, and how the relationship between AI and human judgment develops as technology advances.

6. Conclusion

This master thesis investigated the role of AI tools in mitigating confirmation bias and availability bias in a managerial decision-making context. Through qualitative interviews with participants across various industries and backgrounds, the study concludes that while AI tools have a high potential to reduce these biases by processing large datasets and providing objective, data-driven insights, their effectiveness is influenced by several important factors. These include the quality and diversity of the data, the context in which AI is applied, and the extent of human oversight.

The findings indicate that AI is particularly effective in addressing availability bias. AI's capacity to process and analyze large datasets objectively can help overcome this bias by highlighting data that might otherwise be overlooked. However, the research also shows that confirmation bias, which is more motivational in nature, poses a different challenge. While AI can present counterevidence and alternative perspectives, its success in mitigating confirmation bias is less certain and often requires active human engagement to overcome personal motivations.

In conclusion, this thesis provides important insights into the role of AI in mitigating different types of cognitive biases in decision-making processes. It offers practical recommendations for organizations on how to effectively integrate AI while recognizing its limitations. The findings emphasize the need for a balanced approach where AI enhances decision-making by supporting,

rather than replacing, human judgment. As AI technology continues to develop, organizations must remain proactive in adapting their strategies to ensure that AI is used effectively to support unbiased, data-driven decisions.

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Appendix

Appendix A: Interview Guide

Interview Protocol

Johannes Stephan Lamprecht

Topic of Thesis:

The Role of AI in Mitigating Cognitive Biases in Managerial Decision-Making Processes

In the following, I present the script for my interview. I chose a semi-structured approach with 5 questions and sub-questions (follow-up). For general structure, I followed the guidelines by Taherdoost (2022). One advantage of this method is that it offers a fixed structure, but also allows flexibility in the treatment and order of the topics. This flexibility makes it possible to react spontaneously to topics (Misoch, 2019).

Below the script, I developed an analysis plan of my interviews and the given answers.

I aligned the questions closely with the following research questions:

1. Why can the use of AI tools lead to a less biased decision outcome? Why not?
 2. What positive or negative impact comes with the implementation of AI tools in mitigating biases in managerial decision-making?
 3. Which actions should be taken to achieve a successful implementation?
-

Informed Consent Form (see Appendix)

Opening Question:

1. **Can you please describe your professional background and your experience with AI tools in your work and daily life?**
 - What specific AI tools have you used in your professional environment?
 - How frequently do you interact with these AI tools?
 - What were your first impressions and experiences with the implementation of AI tools in your corporate environment?

Before we proceed, here's a brief explanation of cognitive biases

- **Confirmation bias:** The tendency to search for, interpret, and remember information that confirms one's preconceptions.
- **Availability bias:** The tendency to rely on immediate examples that come to mind when evaluating a topic or decision, rather than all possible evidence.

AI as a Debiasing Tool:

2. **Do you think you and the people in your organization are generally aware of cognitive biases? In your experience, how do AI tools influence decision-making processes in your organization?**
 - Can you describe any instances where AI has helped reduce biases in decision-making?
 - Are there specific types of decisions where you find AI particularly helpful or not helpful?
 - In what situations you rather listen to (trust) AI advice, in what situations would you listen to (trust) human advice?

Benefits and Opportunities of AI Implementation:

3. **What benefits and opportunities have you observed from the implementation of AI advisors in decision-making, particularly in mitigating confirmation and availability biases?**
 - Can you provide specific examples where AI tools have improved decision-making processes by reducing these biases?
 - How have these AI tools impacted your ability to consider a broader range of information and avoid over-reliance on readily available data?

Obstacles, Risks, and Cognitive Bias Mitigation:

4. **What obstacles and risks have you encountered with the implementation of AI advisors in decision-making, especially in mitigating confirmation and availability biases?**
 - Are there specific challenges or issues that have arisen in using AI to address these biases?
 - Are there particular types of decisions where you find AI more or less effective in mitigating these biases?

Actions for Successful Implementation and Interaction:

5. **What actions should be taken to achieve the successful implementation of AI advisors in decision-making to reduce influence of confirmation and availability bias exposure?**
 - What strategies or practices have proven effective in your experience?
 - What recommendations would you make for other organizations planning to implement AI advisors?

Additional Aspects and Closing:

6. **Is there anything else you would like to add regarding the use of AI in mitigating cognitive biases or any other relevant aspect that we have not discussed?**
 - Do you have any recommendations for improving AI tools to better assist in decision-making?

After the interview, I will conclude with a Thank You Statement.

Appendix B: Interview Summary

Category: Initial impression and Experience				
Number	Frequency	Participant	Segment	Sub Code
	2	5 12	<p>When i had my first contacts with AI, I was impressed by how quickly and accurately the AI could process data that would have taken us weeks to go through manually.</p> <p>My first impressions in this setting were quite positive. The financial industry, especially in the US, is very forward-thinking when it comes to technology, and AI is seen as a game-changer. It's impressive how these tools can process vast amounts of data in real-time. However, while I appreciate the efficiency and insights that AI brings, I'm also aware of its limitations.</p>	Positive
	4	1 2 4 7	<p>My first impression of AI was, honestly, a bit mixed. I thought it was going to be this super complicated thing, but once I started using it, I realized it was more about understanding the basics and letting the tool do the heavy lifting</p> <p>When we first started implementing AI in our workflows, I was a bit skeptical. My viewpoints have changed over the last couple years.</p> <p>I've come around to seeing AI as a useful supplement. Still, I'd say my approach to AI is cautious.</p> <p>So, while I know AI is there and it's super important, I'm still in the early stages of getting comfortable with it.</p>	Mixed
	3	3 6 8	<p>When AI started gaining traction, I was initially hesitant, probably because I've seen so many tech trends come and go. But as AI matured, it became clear that it wasn't just a fad; it was something that could actually add value to our operations and decision-making processes. There was a learning curve, and some skepticism from the team.</p> <p>I wasn't always convinced that AI had a place in HR; it felt too impersonal for a field that is fundamentally about people. But I've come to appreciate its value, especially in areas like recruitment and talent analytics.</p> <p>While I use the tool frequently, I am not yet fully impressed with its current level of development. For many of my daily tasks that require critical thinking or specialized skills, ChatGPT has not yet proven to be particularly helpful.</p>	Negative

Category: General awareness of cognitive biases				
Number	Frequency	Transcript	Segment	Sub Code

		2	Yes, I believe there's a general awareness of cognitive biases within our organization, especially among those of us who deal with data analysis and client advisories. That said, I wouldn't say everyone is fully conscious of these biases at all times. It's easy to overlook them in the rush of daily tasks, which is where AI can be quite helpful.	
		3	We're all human, and it's easy to fall into the trap of confirmation or availability bias, especially when you're under pressure to make quick decisions.	
		4	Sure, it's something that's on our radar, but I wouldn't say we sit around talking about it all the time. We're more focused on getting the job done, and sometimes that means biases slip through, it's human nature.	
		5	Yes, I'd say there's a decent level of awareness about cognitive biases in my organization, but we are no experts like you are, and like with most things, awareness doesn't always translate into action.	
	9	6	there's a general awareness of cognitive biases among the team, especially in HR where we deal with people's perceptions and judgments all the time. But awareness doesn't always mean we can avoid them.	Aware
		7	I think people in my organization are generally pretty aware of cognitive biases, especially since we're all trained to think critically and challenge our assumptions. I'd say it's something we're conscious of, but sometimes you are not conscious of being exposed to them.	
		8	Yes, but i can only speak for myself. I still believe most people i work with here are very cautious on how the make unbiased decisions.	
		9	The teams i mainly work with here are aware of it, i would say. Sometimes you realise straight away that certain decisions need more attention to be as unbiased as possible.	
		11	I think, generally speaking, we all know what cognitive biases are, and I also see a growing awareness especially in relation to working with AI tools and their lack of natural human behaviour.	
	3	1	I'd say we're somewhat aware of cognitive biases. It's one of those things where you know they exist, but unless someone points it out, it's easy to just go with your gut without questioning it. We've had a few workshops about it, so it's on people's radar, but I wouldn't say we're experts or anything.	Some Awareness

		10	I would say some are aware more than others. I think our brains are not entirely capable of not being influenced by biases of all sorts.	
		12	I think we are more aware of the exposure to biases than the older generations, but i think the theories behind them are still relatively new. so books like kahneman's are a real eye-opener in terms of their presence.	

Category: Influence on decision making processes				
Number	Frequency	Transcript	Segment	Sub Code
	2	2	AI tools have played a significant role in influencing decision-making by providing a more objective lens.	Significant
		3	AI tools have played a significant role in influencing decision-making by providing a more objective lens.	
	3	5	Sometimes i find myself forced to reconsider my recommendations and consider a more balanced, long-term strategy, in some ways. In some cases, I see AI as a valuable second opinion; one that needs to be considered but not necessarily followed to the letter.	Some
		6		
		8	AI can be a tool that supports us evaluating these criteria without being biased.	
			As a company, it's clear that we can never make decisions based on a 100% evaluation of all the available information in the world. We always have to make a 'best guess' decision. AI helps us significantly expand the scope of our decisions by allowing us to process much more information in a much shorter time.	
	1	7	Since I haven't worked directly with AI tools that are designed specifically for debiasing, I can't speak from personal experience	None

Category: Benefits and Opportunities				
Number	Frequency	Transcript	Segment	Sub Code
	9	1	One benefit is that AI makes it easier to step back and look at the data objectively.	Handling large datasets
		2	Another opportunity is the ability to process and analyze vast amounts of data quickly. This is particularly useful when we're dealing with time-sensitive decisions	

		<p>3</p> <p>4</p> <p>5</p> <p>6</p> <p>7</p> <p>8</p> <p>12</p>	<p>As I was saying, AI really helps us take a step back and see the bigger picture. When reviewing past project performances, it's easy to focus on the wins and dismiss the losses as outliers. AI, however, doesn't play favorites, it highlights patterns, both good and bad, which makes it harder to ignore the full picture.</p> <p>AI helps in broadening the range of options we consider. AI can process and analyze datasets that are far too large and complex for a human to handle on their own.</p> <p>AI brings in fresh perspectives because it processes data without any preconceived notions.</p> <p>AI seems to be really good at handling the heavy lifting when it comes to processing data. highlighting trends or patterns that we might not have noticed. And all of that data is processed much faster than a human could do.</p> <p>AI seems to be really good at handling the heavy lifting when it comes to processing data. I believe the greatest advantage of AI is its ability to automate the processing, organization, and structuring of large datasets. Tasks that would take a human a long time to process—like reading or analyzing numbers—can be done much more efficiently with AI. This is a game changer, especially when dealing with lengthy texts. I can simply upload them to our integrated Teams tool and get a summary of the key points quickly. Additionally, I can perform various analyses. highlighting trends or patterns that we might not have noticed. And all of that data is processed much faster than a human could do.</p> <p>The ability of AI to process and analyze vast amounts of data in a fraction of the time it would take a human; save an enormous amount of time in some processes, especially when evaluating datasets</p>	
	6	<p>2</p> <p>3</p> <p>5</p> <p>6</p>	<p>The most significant benefit I've observed is the way AI expands our perspective. By providing access to a broader range of data and highlighting patterns that aren't immediately obvious, AI helps mitigate both confirmation and availability biases.</p> <p>AI can help us predict the impact of economic downturns or shifts in consumer behavior, giving us a more rounded view</p> <p>AI can present a wider array of possibilities</p> <p>We're able to bring in people who might not have made it through a more conventional screening process.</p>	<p>Providing Broader Data</p>

		<p>8 in terms of capabilities, AI can significantly enhance the quality of decision-making by improving the foundation on which decisions are based. You can consult AI for various decisions, including real-time production adjustments.</p> <p>12 I pay less attention to the fact that we ourselves are influenced by biases, as this objective view can now be taken over, at least in part, by AI.</p>	
	7	<p>2 AI tools also encourage us to question our assumptions. When the data contradicts our initial hypotheses, it forces us to dig deeper and consider alternative explanations. This not only reduces the risk of confirmation bias but also leads to more robust decision-making overall.</p> <p>3 It forces us to consider data points and perspectives with statistical objectivity that we might have overlooked due to our own biases. For example, when we're doing market analysis or competitive assessments, it's easy to focus on what's worked for us in the past or what's most familiar.</p> <p>5 This means we're not just seeing what's top-of-mind or what supports our pre-existing beliefs</p> <p>7 Huge amount of information and distill it down to the most relevant insights, which can definitely help avoid biases. we're less likely to just focus on the information that supports our initial ideas, and more likely to consider a wider range of possibilities</p> <p>8 AI can generate a statistical picture. For instance, we could analyze 15 studies we've purchased, these are typically the most reputable studies bought by leading companies. We can ask AI to evaluate these studies and provide us with the statistical distribution of their findings. This way, even if my opinion aligns with the three German studies, I might notice that they differ significantly from American and Chinese studies. Using AI to incorporate more sources can help create a more objective picture.</p> <p>10 AI helps us avoid confirmation bias by presenting data in its raw form, allowing us to make decisions based on the full picture rather than just what aligns with our expectations.</p> <p>11 AI can serve as a counterbalance to our natural inclinations to stick to what we know or what we think we know.</p>	Mitigate Confirmation Bias
	7	<p>2 By automating the data analysis process, we can avoid only having to rely on the most recent or most easily accessible information rather than a comprehensive dataset.</p>	Mitigate Availability Bias

		3	Helping us avoid making decisions based on incomplete or overly optimistic information.	
		4	I've also noticed that AI helps us avoid availability bias, especially when we're making decisions under time pressure. In those situations, it's easy to latch onto the most recent data or the information that's freshest in our minds. AI, by contrast, takes into account all relevant data, ensuring that we're not making decisions based on incomplete or skewed information.	
		8	AI must base its analysis on a specific dataset. In a corporate environment, you generally can't use an open AI system that's available to everyone because once you input confidential data, it gets stored in the backend, which is not permissible due to company policies. Therefore, you need a closed setting with a dedicated data pool that the AI can access.	
		8	While the AI can process millions of data points, perhaps only 10 to 50 variables are truly significant for an 80% decision-making process. It's not necessary to include all available information. This also touches on Availability Bias—developers need to consider whether all available information is even relevant for the decision-making process. An objective tool should ideally incorporate a logical pre-filtering process.	
		10	A good example that comes to my mind is that the AI tools we use can track and analyze competitor movements across various channels, including market data, social media, and even patent filings.	
		12	We would otherwise rely on the most recent or most accessible information	

Category: Obstacles and Risks				
Number	Frequency	Transcript	Segment	Sub Code
		1	One of the biggest obstacles is getting everyone to trust the AI	
		2		
	8	3	Some people feel that AI could undermine their expertise or decision-making authority, which can lead to a lack of trust in the AI's recommendations	Trust in AI
		5	There's a natural skepticism; people wonder if AI can really account for all the nuances and subtleties that human judgment can Many times we don't even know where the Data comes from	

		<p>6</p> <p>In HR, there's a natural inclination to rely on personal judgment and experience, especially when it comes to making decisions about people. Introducing AI into that mix can feel a bit threatening to some, it's like, "Is this tool going to take over my job?" So there's been a fair bit of resistance, especially from those who are more set in their ways</p> <p>10 There's a learning curve involved, and not everyone is comfortable relying on a machine to do work that they've been doing manually for years.</p> <p>11 We must not place too much trust in AI and the results, at least not blindly.</p> <p>12 We like to get a second opinion, but we are nevertheless constantly aware of the risks. different teams might have varying levels of familiarity and comfort with AI technology.</p>	
	<p>9</p>	<p>1 It's tempting to just go with what the AI suggests because it's quick and easy, but that can be dangerous if we stop questioning the results</p> <p>2 There have been instances where the AI's recommendations didn't fully align with the nuances of the situation, leading us to question the validity of its suggestions.</p> <p>3 It doesn't replace the need for human oversight. We've had to remind ourselves that AI is a tool to aid decision-making, not to make decisions for us.</p> <p>4 It's easy to get swept up in the idea that AI can do no wrong</p> <p>5 lean too heavily on AI outputs, treating them as if AI had all the knowledge they had</p> <p>7 We take AI's suggestions at face value without really thinking them through, and that can lead to issues down the line.</p> <p>10 There are often factors that AI can't fully account for, such as the cultural fit between companies or the potential impact of upcoming legislation</p> <p>11 I would say that there is still a divergence between what the different generations consider to be useful, especially in the areas of application for AI. We younger employees primarily see the great potential and how much time we can save, but sometimes forget that we should still involve the expertise of our seniors</p> <p>12 You tend to adopt some results 1 to 1 and find yourself not questioning them</p>	<p>Overreliance on AI</p>

	7	<p>1 AI is only as good as the data it's trained on, and if that data has any biases or gaps, the AI can end up reinforcing those biases instead of mitigating them</p> <p>2 One primary obstacle is the quality of data being fed into AI systems. if an AI tool is trained on historical data that reflects a particular market condition, it might overemphasize trends that are no longer relevant, leading to confirmation bias</p> <p>3 There are still aspects of our business that require human judgment, particularly when it comes to strategic decisions that involve a deep understanding of the company culture, client relationships, and industry dynamics.</p> <p>5 If that data is biased, outdated, or incomplete, the AI's outputs will be flawed.</p> <p>6 AI can sometimes reinforce existing biases if we're not careful about the data we're feeding into it</p> <p>7 If the data is biased or incomplete, then the AI's recommendations will be too.</p> <p>11 Realistic integration into everyday working life plays an important role here. and that often starts with understanding how the algorithm behind the programme works and functions. because it only works as well as the task guarantees. most AIs do exactly what you tell them to do, so if they give you the wrong results, it's usually because you either didn't ask the right question or the AI is using the wrong data.</p>	Quality of Data
	2	<p>2 Ensuring that the AI models are trained on diverse and up-to-date datasets is crucial, but it's also a significant challenge.</p> <p>8 The biggest risk, especially in a corporate context, is that you should continuously feed the system with material from the external environment to avoid Availability Bias. This means not just relying on the knowledge and datasets available within the company but also incorporating external sources.</p>	Need to continuously feed with external data
	2	<p>8 Every company is different. So, to some extent, you need to ensure that the data being fed into the system is relevant to the company. This might not involve considering all available data, but rather focusing on more relevant data that, however, might not be easily transferable to other companies. This is quite complex and a challenge for the developers of such tools since they need to be tailored to the specific needs of the company.</p>	Tailor to company needs

		9	From my experience, we have a few useful tools here, but most of them just simply do not get used since they do not fit to our purpose. There is still potential to align them more with our specific needs.	
	2	8	I think it could be problematic in retrospective decisions or situations where personal goals might conflict with company goals. In such cases, there's a tendency to ask questions in a way that aligns with personal objectives, making it easier to fulfill them or confirm previous decisions, thereby avoiding the need to acknowledge any mistakes	Conflict with personal goals
		12	Not everyone is comfortable using AI tools, and there can be resistance to change.	

Category: Actions for Impementation				
Number	Frequency	Transcript	Segment	Sub Code
		1	People need to understand both the strengths and limitations of AI, and also be aware of their own biases	Employee Training
		3		
		4	Provide ongoing training and education about how AI works, what its limitations are, and how it can be best utilized to complement human judgment. It is important to educate the team on what AI can and can't do, and making sure they understand that it's a tool designed to support them, not replace them	
	9	5	When people understand how the AI works, they're more likely to trust and effectively use its outputs. Teams need to be equipped with the knowledge and skills to use AI tools effectively. We've implemented regular training sessions to keep our team up-to-date with the latest AI developments and best practices.	
		6	We need to make sure that everyone understands what AI is and isn't. It's not here to replace us, but to help us make better decisions.	
		7	Our team needs to be trained and educated on the way the algorithms behind work. That starts with the prompts you put it, and evaluating the results in a objective way. it would be really helpful to have more opportunities to learn about how these tools work and how to use them effectively. This could be in the form of workshops, online courses, or even just more hands-on experience with AI tools.	

		8	It's crucial to train employees on how to formulate prompts, understand what AI can and cannot do, and ensure proper implementation. For instance, during our internal training, I learned that the AI can't differentiate between text highlighted in different colors (like yellow or red) and therefore can't summarize only the highlighted sections. It just sees the text, perhaps in italics or bold, but not in different colors. So, it's important to educate users on how to interact with AI effectively.	
		9	The team needs to understand the value AI brings and feel comfortable using it in their daily work	
		10	Resistance to new technology, especially when it's perceived as a threat to established ways of working. Providing ongoing training that not only teaches team members how to use AI tools but also explains the rationale behind their implementation can help ease this transition.	
	7	1	AI can help us see things more clearly, but it's up to us to decide what to do with that information.	Human-AI Interaction
		2	Well-integrated into the existing decision-making processes. One effective strategy is to pair AI insights with human expertise	
		3	AI should be seen as a partner in the decision-making process, not a replacement.	
		4	AI provides data, but the interpretation and final decision should always involve human insight; maintain a healthy balance between relying on data and trusting our own judgment	
		5	Organizations can learn how to integrate AI effectively without overwhelming the team or risking significant missteps. This approach allows for iterative learning and improvement, which is crucial in an area as rapidly evolving as AI.	
		7	We can make the most of what AI has to offer, while still relying on our own expertise and judgment.	
		9	We need to create a culture where AI is seen as a partner in decision-making. This means encouraging people to question the AI's recommendations and use their judgment to interpret the results.	
	4	3	I tools are well-calibrated to the specific needs and context of the organization. This means not only selecting the right tools but also feeding them with high-quality, diverse data that reflects the complexity of the business environment	Importance of extensive, high quality data

		4	Ensuring that the data you're feeding into the AI is accurate, diverse, and up-to-date.	
		8	One thing to note is the importance of having a critical mass of data, extensive data, and good quality data input. By quality, I mean both relevance and truthfulness, as the AI learns based on the data it receives. If the input data is inaccurate or based on unreliable sources, the AI will struggle to assess it correctly.	
		12	You should of course first and foremost make sure that you give the AI as large and complete a data set as possible to process in order to avoid biases.	
	5	1	The more we understand how the AI is making its recommendations, the more likely we are to trust it. If the AI can show us the data and logic behind its suggestions, it's easier to see whether it's catching something we missed or if there's a reason to be cautious.	Transparency
		2	It's crucial that the logic behind their recommendations is clear and understandable	
		4	People need to understand how AI comes to its conclusions, so that when it makes a recommendation, we can see the logic behind it.	
		5	This includes understanding the limitations of AI and knowing how to critically assess the outputs it generates.	
		11	It starts with understanding this new technology.	
		12	You first have to understand where the opportunities, risks etc. are, especially in terms of where the limitations are, and that's where cognitive biases come into play again	
	2	8	It might also be relevant to have a history or decision tracking feature. For example, an operator in a plant could make a decision based on the available data and the AI tool. Later, during a compliance check or performance review, one could theoretically look back at the decision history to see what information was available at the time. This could show that the operator made the best decision possible with the information they had.	Decision Tracking
		11	It is important to explain how you arrived at the results.	

Category: Additional remarks				
Number	Frequency	Transcript	Segment	Sub Code

	1	If AI could be more intuitive and easier to interpret, I think more people would feel comfortable relying on it for decision-making.	
	2	I believe there's a lot of potential for AI to evolve and become even more effective in helping us make better decisions. As the technology advances, we should keep exploring new ways to leverage AI.	
	5	We need to stay critical. there's a lot of potential for AI to help us in mitigating biases as previously mentioned, and i am curious how this trend will develop in the future.	
	10	What we're using today is far more advanced than what was available even a few years ago, and I expect it will continue to improve	
	11	Our everyday working lives will change drastically, and if we approach this transformation correctly, the advantages will outweigh the disadvantages. many people fear that their job could be replaced by an ai, and to some extent or for certain sectors this could be true.	
	11	I believe that this digital revolution will generate far more jobs and potentially open up opportunities that we are not yet fully aware of.	
	12	Ensuring that AI development teams are diverse and that the data used is representative of different perspectives can help mitigate some of these issues.	

Appendix: Informed Consent Form



Informed Consent Form

Welcome and thank you for participating in this interview. I, Johannes Lamprecht, am conducting this interview as part of my Master's Thesis for achieving the Master of Science in Management at Católica Lisbon School of Business and Economics, under the supervision of Ana Filipa Martinho de Almeida.

Please answer as honestly as possible. All answers will be kept strictly confidential and are anonymous. This means that there will be no way to link your responses to your identity. The information collected will be used for research purposes only. There are no expected side effects of participating in this study. If you wish, you are free to leave the interview at any point in time without providing a reason.

Do you agree to participate in this study by being interviewed by me?

Do you confirm that this interview will be recorded for research purposes only?

Hereby I agree and confirm:

Signature

Johannes Stephan Lamprecht