How Managers Make Sense of AI Versus Human Advice:
A Qualitative Study on Trust and Justification in Decision-Making

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Abstract

Artificial intelligence (AI) is increasingly used to support managerial decision-making, yet it remains unclear how managers interpret and integrate AI-generated advice compared to advice from human advisors. This thesis examines how managers make sense of AI-based advice in decision contexts and how trust, perceived control, and justification requirements shape the evaluation and use of such advice. The study follows a qualitative research design based on eleven semi-structured online interviews with managers conducted in February 2026. The data were analysed using thematic analysis.

The findings show that managers primarily interpret AI as a cognitive and preparatory support tool than as a decision authority. AI is used to structure thinking, generate options, and accelerate early-stage analysis, while final decision responsibility remains human. Trust in AI advice is conditional, task-specific, and reversible: reliance is higher for routine and well-structured tasks and lower for strategic, high-stakes, or socially complex decisions. Perceived control is maintained through verification practices, the ability to override AI recommendations, and input control via careful prompting and contextualization. Justification requirements strongly influence AI advice use, as managers emphasize human ownership, accountability and translate AI outputs into human-centred rationales to ensure social legitimacy, particularly in visible decision contexts.

Overall, the results suggest complementary roles: AI enhances efficiency and analytic support, while human advisors remain essential where contextual judgment, tacit knowledge, empathy, and credibility matter. The thesis contributes by highlighting how managers calibrate reliance on AI and by identifying justification and legitimacy as key mechanisms shaping AI advice integration and disclosure in organizations.

Resumo

A inteligência artificial (IA) é cada vez mais utilizada para apoiar a tomada de decisão, mas ainda não é claro como os gestores interpretam e integram conselhos gerados por IA em comparação com conselhos de consultores humanos. Esta dissertação analisa como os gestores atribuem sentido ao aconselhamento baseado em IA e como a confiança, o controlo percecionado e as exigências de justificação influenciam a sua utilização. O estudo adota um desenho qualitativo com onze entrevistas a gestores, realizadas em fevereiro de 2026 e analisadas através de análise temática.

Os resultados mostram que os gestores veem a IA sobretudo como apoio cognitivo e de preparação, e não como autoridade decisória. A IA é usada para estruturar o raciocínio, gerar opções e acelerar a análise inicial, mantendo-se a responsabilidade final da decisão do lado humano. A confiança na IA é condicional e específica à tarefa: a dependência é maior em tarefas rotineiras e bem estruturadas e menor em decisões estratégicas, de alto risco ou socialmente complexas. O controlo percecionado é mantido através de verificação, possibilidade de rejeitar recomendações e controlo do input por meio de prompting e contextualização. As exigências de justificação influenciam o uso da IA, pois os gestores enfatizam a responsabilidade humana e traduzem outputs em racionalizações centradas no humano para garantir legitimidade, sobretudo em decisões visíveis.

Em síntese, IA e aconselhamento humano desempenham papéis complementares: a IA aumenta a eficiência e o apoio analítico, enquanto consultores humanos permanecem essenciais quando são necessários julgamento contextual, conhecimento tácito, empatia e credibilidade.

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Keywords

artificial intelligence; generative AI; managerial decision-making; advice-taking; sensemaking; trust; perceived control; justification; qualitative research; accountability; AI disclosure

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List of Abbreviations

AI	Artificial Intelligence
B2B	Business-to-Business
CEO	Chief Executive Officer
CFO	Chief Financial Officer
GenAI	Generative Artificial Intelligence
HR	Human Resources
INT	Interview (e.g., INT1–INT11)
IT	Information Technology
JAS	Judge–Advisor System
OBHDP	Organizational Behavior and Human Decision Processes
RQ	Research Question

1 Introduction

This chapter introduces the topic of how managers make sense of AI-generated versus human advice in strategic decision-making. It begins by outlining the growing importance of artificial intelligence in managerial contexts and the paradox of its widespread use yet limited trust. The chapter then presents the theoretical foundation based on Sensemaking Theory, explains the research problem and objectives, and highlights the study's academic and managerial relevance. Finally, it provides an overview of the dissertation's structure.

1.1 Background and Topic Overview

According to McKinsey's State of AI in Early 2024 report, 65% of organizations now report regular use of generative AI, and more than 70% have adopted AI in at least one business function (Singla et al., 2024). Despite this widespread diffusion, few organizations have developed clear strategies for integrating AI into managerial decision-making. While the technical implementation of AI systems advances rapidly, the human side of adoption particularly how managers interpret and respond to algorithmic recommendations remains less understood.

Decision-support systems are designed to improve the quality and efficiency of managerial judgments, but their effectiveness ultimately depends on whether managers trust and act upon them. Understanding how managers interpret, evaluate, and integrate AI advice is therefore essential for organizations seeking to make AI-supported decision-making a reality rather than a theoretical promise.

In organizational behaviour research, advice-taking is defined as "the extent to which individuals incorporate external input into their own judgments" (Bonaccio & Dalal, 2006). Historically, this line of research has focused on how decision makers weigh and integrate advice from other humans, examining factors such as expertise, justification, and accountability. However, the rapid adoption of AI introduces a new type of advisor. One that lacks human characteristics like empathy or perceived benevolence. This shift raises a central question: how do managers respond when advice is generated by an AI system rather than by a human colleague?

1.2 Sensemaking Perspective

In this dissertation, the expression *"make sense of"* refers to the process through which managers interpret, understand, and assign meaning to AI-generated versus human advice. This conceptualization draws on Sensemaking Theory, which views decision-making not merely as rational analysis but as a process of constructing meaning from complex and ambiguous information. Managers operate in environments characterized by uncertainty, time pressure, and incomplete data. Sensemaking emphasizes how they extract cues, build narratives, and justify their interpretations to themselves and others (Weick et al., 2005). By applying this interpretive lens, the dissertation explores how managers perceive, evaluate, and justify advice from both human and AI sources, focusing on their subjective experiences rather than measurable behavioural outcomes.

1.3 Research Problem and Objective

While quantitative research has identified patterns such as algorithm aversion (Dietvorst et al., 2018) and algorithm appreciation (Logg et al., 2019), these studies reveal little about why such attitudes arise in managerial contexts. They provide limited insight into how managers describe their reasoning, doubts, and trust when dealing with AI advisors.

This qualitative study addresses that gap by examining how managers make sense of AI-generated and human advice within real or realistic decision contexts. Specifically, it aims to explore:

- How managers perceive the trustworthiness of AI versus human advisors.
- How justification style (analytic vs. intuitive) influences these perceptions.
- How contextual factors such as accountability, uncertainty, and prior AI experience shape their interpretations.

1.4 Relevance for Research and Practice

From an academic perspective, this study contributes to the growing literature on advice-taking by extending it into AI-supported managerial decisions. It combines established constructs such as trust and justification with the interpretive framework of sensemaking, offering new insights into how managerial judgment is shaped in technologically mediated environments.

From a practical standpoint, understanding how managers make sense of AI advice can help organizations design systems that align better with human reasoning and improving trust, transparency, and adoption of AI-based decision support in practice.

1.5 Structure of the Thesis

The dissertation is structured as follows. Chapter 2 reviews the relevant literature on advice-taking, trust, justification, AI, and managerial sensemaking, culminating in the research questions. Chapter 3 outlines the qualitative methodology, including the research design, participant recruitment, interview procedure, and data-analysis approach. Chapter 4 presents the results of the thematic analysis, while Chapter 5 discusses the findings considering existing theories and managerial implications. Finally, Chapter 6 concludes with key insights, limitations, and directions for future research.

2 Literature Review

This chapter reviews the existing body of research relevant to understanding how managers make sense of AI-generated versus human advice in decision-making contexts. It begins by outlining the theoretical foundations of advice-taking, emphasizing its role in managerial judgment and the impact of justification on decision acceptance. The chapter then explores how trust and justification interact within organizational settings and how these dynamics evolve when the source of advice shifts from human to algorithmic. Building on this, it introduces AI as a novel source of advice, reviewing empirical findings on algorithm aversion and appreciation. Finally, the chapter discusses Sensemaking Theory as a conceptual lens for interpreting how managers perceive and assign meaning to advice from both human and AI systems, concluding with the conceptual framework and research questions guiding this dissertation.

2.1 Decision Making in Managerial Context

Decision-making has long been a central focus of management and organizational research. Early work described decision-making as a rational process of evaluating alternatives and maximizing outcomes (Simon, 1955). This classical view evolved through the concept of bounded rationality, which recognizes that individuals make decisions under cognitive and informational limitations (Kahneman & Tversky, 1979). In practice, managerial decisions often deviate from this rational ideal, as they are shaped by uncertainty, time constraints, and the social context in which managers operate.

Empirical research has shown that managerial decision processes are rarely linear or purely rational. Instead, they are iterative, political, and socially embedded, reflecting the complexity of organizational realities (Mintzberg et al., 1976). Later work synthesized these behavioural and strategic perspectives, describing decision-making as a multifaceted interplay of rational analysis, intuition, and power dynamics (Eisenhardt & Zbaracki, 1992). Recent studies further emphasize reflection and sensemaking as key processes through which managers interpret and respond to uncertain or dynamic environments (Hodgkinson & Healey, 2011).

Taken together, these perspectives highlight that managerial decision-making combines analytical reasoning with interpretive and socially constructed processes. This conceptual foundation helps to understand advice-taking as a mechanism through which managers interpret and act upon external input, whether such advice originates from human or artificial intelligence sources.

2.2 Advice Taking in Managerial Decision Making

Advice-taking refers to the process by which individuals incorporate external input into their own judgments and decisions (Bonaccio & Dalal, 2006). Within organizational settings, advice functions as both a cognitive aid and a social tool that supports decision quality, reduces uncertainty, and provides legitimacy. The Judge–Advisor System conceptualizes advice-taking as an interactive process between a decision maker and one or more advisors, where the recipient evaluates the advice and decides whether to adjust their initial judgment accordingly (Sniezek & Buckley, 1995).

A consistent finding in the literature is that individuals tend to underutilize advice, often giving greater weight to their own opinions than to external input, even when the advisor's expertise is comparable or superior. This phenomenon, known as egocentric discounting, reflects a systematic bias in favour of one's own perspective (Yaniv, 2004). In managerial contexts, such bias may be reinforced by accountability pressures, confidence in one's experience, and concerns about preserving authority.

The degree to which advice is accepted depends strongly on the perceived justification behind it. Analytically justified advice which is supported by data, models, or structured reasoning is typically regarded as more credible and defensible than intuitive advice based on experience or instinct (Bonaccio & Dalal, 2006).

Recent research has extended advice-taking theory to the managerial domain, showing that analytically justified advice is more likely to be followed than intuitively justified advice, regardless of advisor characteristics such as gender (Ribeiro et al., 2019). These findings highlight that managers not only seek accuracy in advice but also favour recommendations that enhance the defensibility of their decisions.

More recently, studies have begun to examine how advice-taking processes change when the source of advice is no longer human but artificial. Evidence indicates that managers still display a preference for human-generated advice, even when AI provides equivalent or superior information quality. However, this preference is moderated by social and psychological factors, such as social comparison orientation and the perceived neutrality of AI as an advisor (Rizzo et al., 2024). This growing body of research suggests that advice-taking remains shaped by social interpretation and identity concerns, even when the advisor is non-human.

In sum, advice-taking in management is shaped by both cognitive and social considerations. It enables managers to balance confidence in their own judgment with the need for legitimacy and accountability. As organizations increasingly integrate artificial intelligence into decision processes, understanding these dynamics becomes essential for examining how managers interpret and act upon advice generated by algorithmic systems.

2.3 Trust and Justification in Organizational Contexts

Trust is central to managerial decision-making and strongly influences whether advice is accepted. It can be defined as the willingness to rely on another party based on perceived competence, integrity, and benevolence (Mayer et al., 1995). In organizations, trust reduces uncertainty and facilitates collaboration, enabling managers to incorporate advice into their judgments.

Two dimensions of trust are particularly relevant. Cognitive trust is grounded in assessments of ability and reliability, whereas affective trust reflects emotional connection and perceived goodwill. Analytically justified advice supported by data and transparent reasoning tends to strengthen cognitive trust by signalling competence and objectivity, while intuitive advice relies more on relational confidence and affective trust (Bonaccio & Dalal, 2006). Because managerial decisions must often be justified to stakeholders, managers tend to favour options that can be easily defended (Tetlock, 1985). Empirical findings show that analytically justified advice is more frequently adopted than intuitive advice, independent of who provides it (Ribeiro et al., 2019).

As artificial intelligence becomes part of managerial contexts, trust extends from interpersonal to human–machine relationships. Research indicates that trust in AI depends on transparency, reliability, and familiarity, alongside classical dimensions of ability, integrity, and benevolence (Glikson & Woolley, 2020). Meta-analytic evidence identifies reliability and feedback as key mechanisms for calibrating trust in automation (Schaefer et al., 2016). Managers are more willing to rely on AI when they understand how it functions and retain control over the final decision, while emotional resistance and fear of losing autonomy decrease acceptance (Brink et al., 2024; Longoni et al., 2019).

In summary, trust and justification jointly determine how managers interpret and use advice. Trust provides psychological confidence in the source, while justification ensures that decisions remain socially and organizationally defensible. These mechanisms form the foundation for understanding how managers make sense of both human and AI-generated advice in complex organizational environments.

2.4 Sensemaking and Managerial Decision Making

Sensemaking describes how individuals interpret complex or ambiguous situations to create shared understanding and guide action. In organizational settings, it refers to the process through which managers give meaning to information, experiences, and advice under uncertainty. Later work refined the concept as a multidimensional process involving cognition, emotion, and social interaction that enables individuals to construct meaning under changing conditions (Brink et al., 2024; Longoni et al., 2019). Recent research confirms that sensemaking remains central to how organizations and managers navigate uncertainty and technological change (Turner et al., 2023).

Managerial decision-making is increasingly understood as a behavioural and interpretive process rather than a purely rational one. Managers operate under bounded rationality, using perception, heuristics, and contextual judgment when facing complex or ambiguous environments (Aharoni et al., 2011). Under these conditions, sensemaking serves as the mechanism through which they transform incomplete information into actionable understanding. The process is both retrospective and social: managers extract cues from unfolding events, relate them to existing mental frames, and justify their interpretations to others (Weick et al., 2005).

Sensemaking also helps explain how managers engage with advice from both human and artificial sources. Advice functions as an informational cue that must be interpreted within the organization's social and structural context. Whether advice is accepted depends on how well it aligns with existing narratives of competence, control, and accountability. When managers can trust the source and justify their reliance on it, advice becomes part of a coherent sensemaking process that enhances collective understanding.

Recent research emphasizes that sensemaking is a critical managerial capability for reducing complexity in dynamic environments. Managers continuously interpret, evaluate, and act upon cues to maintain coherence and direction, a process described as evolutionary sensemaking (Kulkarni et al., 2024). This approach highlights that effective sensemaking requires metacognitive awareness and adaptability skills that become increasingly important as organizations adopt AI systems. Trust in AI thus emerges not only from its performance but also from the meanings and roles managers assign to it, whether as a supportive partner or a threat to professional autonomy (Brink et al., 2024).

In summary, sensemaking provides a valuable framework for understanding how managers interpret advice and construct meaning in uncertain, technology-mediated contexts. It bridges cognitive, emotional, and social perspectives, explaining why trust, justification, and perceived control are central to managerial acceptance of AI-supported decision-making.

2.5 Conceptual Framework and Research Questions

The reviewed literature shows that managerial decision-making is not a purely rational process but a behavioural and interpretive one. Managers construct meaning under uncertainty by combining analytical reasoning with social and emotional interpretation. Advice-taking plays a central role in this process, as it allows managers to access external perspectives while balancing confidence in their own judgment with accountability to others. The degree to which advice is accepted depends on perceived trustworthiness and the ability to justify its use.

Trust and justification together form the foundation of managerial advice-taking. Trust determines whether advice is viewed as credible and legitimate, while justification ensures that its use can be defended within the organization. These mechanisms apply not only to human interactions but also to advice generated by artificial intelligence. However, as AI systems increasingly enter managerial decision processes, new challenges emerge. Managers must make sense of advice that is technically reliable but lacks human intention or empathy. The literature suggests that emotional trust, perceived control, and accountability concern strongly influence how managers interpret and adopt AI recommendations.

Sensemaking provides a suitable theoretical lens to integrate these insights. It explains how managers interpret advice, assign meaning to it, and justify their decisions in socially acceptable ways. The framework connects psychological constructs such as trust with organizational concepts like legitimacy and defensibility. From this perspective, advice-taking becomes an interpretive act shaped by individual cognition and social context.

Based on the reviewed literature, this dissertation explores how managers make sense of advice from human and AI sources in decision-making. The conceptual framework focuses on three interrelated dimensions: trust (how credible advice is perceived to be), justification (how defensible its use appears), and sensemaking (how managers interpret and integrate advice within their decision process).

The literature reviewed highlights that while the concepts of trust, justification, and sensemaking have been studied separately, their interaction in the context of AI-supported managerial decision-making remains underexplored. Previous research has primarily adopted quantitative approaches to examine behavioural patterns, offering limited insight into how managers interpret and justify advice from AI systems compared to human sources. This study therefore adopts a qualitative perspective to explore how managers make sense of algorithmic and human advice and how trust, perceived control, and justification shape this process. Based on these objectives, the following research questions guide the investigation:

RQ1: *How do managers make sense of advice from artificial intelligence compared to human advisors in their decision-making processes?*

RQ2: *How do trust and perceived control influence managerial interpretations of AI-generated advice?*

RQ3: *How do justification requirements shape the way managers evaluate and integrate advice from AI-systems?*

3 Methodology

This chapter describes the methodological approach used to investigate how managers make sense of advice from artificial intelligence compared to human advisors. It outlines the qualitative research design, the interview-based data collection strategy, and the sampling approach adopted for the study. In addition, the chapter explains the procedures for data analysis and discusses measures to ensure research quality, ethical integrity, and transparency.

3.1 Research Design and Approach

This study adopts a qualitative research design to explore how managers make sense of advice from artificial intelligence compared to human advisors in organizational decision-making contexts. The research addresses interpretive processes such as sensemaking, trust, perceived control, and justification, which are difficult to capture through purely quantitative methods. A qualitative approach is therefore appropriate, as it allows for an in-depth examination of subjective interpretations, meanings, and experiences (Creswell & Poth, 2018).

The study follows an exploratory and interpretive research logic. Prior research on advice-taking and AI-supported decision-making has predominantly relied on experimental and survey-based designs, focusing on behavioural outcomes rather than the underlying cognitive and social processes. While these approaches provide valuable insights into general patterns, they offer limited understanding of how managers interpret, rationalize, and justify advice in real-world contexts. This research seeks to address this gap by focusing on how meaning is constructed in managerial decision-making rather than on measuring predefined causal relationships (Saunders et al., 2019).

Sensemaking serves as the central theoretical lens guiding the research design. From this perspective, decision-making is understood as an ongoing process of interpretation in which managers extract cues from their environment, relate them to existing frames of reference, and justify their actions within a social and organizational context. This lens aligns closely with the study's research questions, which emphasize interpretation, trust, and justification rather than prediction or outcome optimization.

Accordingly, the study does not aim to test hypotheses or establish generalizable causal effects. Instead, it seeks to generate rich, contextualized insights into how managers experience and interpret advice from AI systems relative to human advisors. The qualitative research design is therefore well suited to capturing the complexity and nuance of managerial sensemaking in AI-supported decision-making environments.

3.2 Research Strategy: Qualitative Interviews

This study employs semi-structured qualitative interviews as the primary research strategy to investigate how managers make sense of advice from artificial intelligence compared to human advisors. Semi-structured interviews are particularly suitable for exploring interpretive processes such as trust, perceived control, and justification, as they allow participants to reflect on their experiences while providing sufficient structure to ensure comparability across interviews (DeJonckheere & Vaughn, 2019; Kallio et al., 2016).

Alternative research strategies, such as surveys or experiments, were considered but deemed less appropriate for the objectives of this study. While quantitative approaches are effective for measuring predefined variables and testing hypotheses, they offer limited flexibility in capturing evolving interpretations and context-dependent meanings. Qualitative interviews allow researchers to adapt questions during the interaction and explore unexpected themes as they emerge, making them particularly suitable for exploratory research on managerial sensemaking (Adhabi & Anozie, 2017).

A semi-structured interview format was chosen to balance flexibility and consistency. An interview guide was used to ensure that all participants address core topics related to AI-based and human advice, trust, perceived control, and justification. At the same time, the semi-structured design allows for follow-up questions and probing, enabling deeper exploration of individual perspectives and decision rationales (Kallio et al., 2016).

All interviews are conducted online using video-conferencing tools such as Microsoft Teams or Zoom. Online interviewing has become an established method in qualitative research, particularly when participants are geographically dispersed or hold time-constrained professional roles (Deakin & Wakefield, 2014). The online format increases accessibility and feasibility while reducing logistical barriers for managerial participants.

Moreover, research indicates that online interviews can generate data of comparable depth and quality to face-to-face interviews, especially when discussing professional experiences and reflective decision-making processes. Studies suggest that online settings may even encourage openness by reducing perceived social pressure, provided that interviews are carefully prepared and conducted (Deakin & Wakefield, 2014).

In summary, semi-structured online interviews represent a methodologically appropriate and practical research strategy for examining managerial sensemaking in AI-supported decision-making contexts. This approach enables the collection of rich, contextualized data while remaining aligned with the exploratory and interpretive nature of the research design.

3.3 Sampling Strategy and Participants

The study employs a purposive sampling strategy to select participants who can provide relevant and informed insights into managerial decision-making involving advice from artificial intelligence and human sources. Purposive sampling is appropriate for qualitative research when the objective is to gain in-depth understanding from individuals with specific experience rather than to achieve statistical representativeness.

The target population consists of managers with decision-making responsibilities in organizational contexts. For this study, managers are defined as individuals who hold roles involving responsibility for evaluating information, making recommendations, or taking decisions that affect teams, projects, or organizational outcomes. This includes team leaders and middle managers across different industries. Senior executives are not explicitly excluded; however, the primary focus lies on managers who are directly involved in day-to-day decision-making processes.

Participants are required to have exposure to AI-supported decision-making tools or processes. Direct hands-on use of AI systems is not mandatory; rather, experience with decision contexts in which AI-generated recommendations, analytics, or decision support outputs are considered sufficient. This criterion ensures that participants can reflect meaningfully on AI-based advice while maintaining feasibility in participant recruitment.

The study aims to conduct approximately 10 to 12 interviews. This range is considered appropriate for qualitative research seeking thematic saturation while allowing for in-depth analysis of individual perspectives. The final number of interviews was guided by the principle of data saturation, defined as the point at which additional interviews no longer yield substantively new insights relevant to the research questions.

Participants were recruited through the researcher's professional and personal network, as well as through targeted outreach via professional platforms such as LinkedIn. Leveraging existing networks is a common and accepted approach in qualitative research, particularly when studying managerial populations that are otherwise difficult to access. This strategy increases the likelihood of securing experienced participants while maintaining relevance to the research objectives.

3.4 Data Collection Procedure

Data collection was conducted through semi-structured online interviews with managerial participants. Each interview is expected to last approximately 20 to 45 minutes, which is considered sufficient to explore participants' experiences and interpretations while respecting the time constraints of managerial roles.

Prior to the interviews, participants received an information sheet outlining the purpose of the study, the voluntary nature of participation, and the intended use of the data. Informed consent was obtained before the start of each interview. Participants were informed that they may withdraw from the study at any time without providing a reason.

All interviews were conducted via video-conferencing platforms such as Microsoft Teams or Zoom. With participants' permission, interviews were audio-recorded to ensure accurate data capture. Recordings were stored securely and used exclusively for research purposes.
Following data collection, interviews were transcribed in a lightly edited form, focusing on the accurate representation of content while removing filler words and non-essential repetitions. This approach supports clarity during analysis while preserving the meaning and intent of participants' statements. All transcripts were anonymized by removing identifying information, such as names of individuals or organizations.

Data was stored securely in accordance with data protection requirements. Only the researcher will have access to the raw data, and all materials will be deleted after the completion of the thesis.

3.5 Data Analysis and Method

The collected interview data was analysed using thematic analysis, a flexible qualitative method for identifying, analysing, and interpreting patterns of meaning within textual data. Thematic analysis is particularly suitable for exploratory research that aims to understand how individuals interpret experiences and construct meaning, rather than to test predefined hypotheses.

The analysis will follow an iterative and systematic process. First, all interview transcripts were read repeatedly to achieve familiarization with the data. Initial codes will then be generated by identifying meaningful segments of text related to the research questions, such as perceptions of AI-based advice, trust, perceived control, and justification practices. Coding was conducted in a data-driven manner while being informed by the theoretical concepts discussed in the literature review.
In the next step, related codes were examined and grouped into broader themes that capture recurring patterns across participants. These themes were reviewed, refined, and clearly defined to ensure internal coherence and distinctiveness. Throughout the analysis, attention was paid to similarities and differences between participants' accounts, particularly regarding how advice from artificial intelligence is interpreted in comparison to advice from human advisors.

Thematic analysis allows for both inductive and deductive elements. While themes are primarily derived from the data, the analysis is sensitized by theoretical concepts such as sensemaking, trust, perceived control, and justification. This approach supports a structured yet flexible interpretation of the data, enabling a nuanced understanding of managerial sensemaking in AI-supported decision-making contexts.

To enhance transparency and rigor, coding decisions and theme development was documented throughout the analysis process. This ensures that analytical interpretations can be traced back to the original data and that the research process remains systematic and coherent. The final codebook, the theme development overview, and selected illustrative excerpts are provided in the appendix (Appendix 1–3). Coding and theme development were supported using a structured coding table in Microsoft Excel and Microsoft Word. Interview excerpts were translated into English for reporting purposes; translations were kept meaning-faithful and minimally edited for readability.

3.6 Research Quality and Trustworthiness

In qualitative research, quality is assessed through criteria that differ from the concepts of validity and reliability commonly used in quantitative studies. To ensure the trustworthiness of the findings, this study follows established qualitative quality criteria, including credibility, dependability, and reflexivity.

Credibility refers to the extent to which the findings accurately represent participants' perspectives. This study enhances credibility using semi-structured interviews, which allow participants to describe their experiences in their own words. The systematic application of thematic analysis and the use of direct quotations in the results chapter further support a transparent link between the data and the interpretations.

Dependability relates to the consistency and transparency of the research process. To address this criterion, all steps of data collection and analysis are documented in detail, including interview procedures, coding decisions, and theme development. This documentation ensures that the analytical process is traceable and logically coherent.

Reflexivity is particularly important in interpretive research. The researcher acknowledges that personal assumptions and prior knowledge may influence data interpretation. To mitigate this, reflective notes were maintained throughout the research process, and analytical decisions was grounded in the data rather than in preconceived expectations. These measures contribute to a balanced and transparent interpretation of the findings.

3.7 Ethical Consideration

Ethical considerations are addressed throughout all stages of the research process. Participation in the study is entirely voluntary, and all participants were informed about the purpose of the research, the procedures involved, and the intended use of the data prior to participation.

Informed consent was obtained before each interview. Participants were informed of their right to withdraw from the study at any time without negative consequences. To ensure confidentiality, all interview data was anonymized by removing identifying information such as names, job titles, and organizational affiliations.

Interview recordings and transcripts were stored securely and accessed only by the researcher. Data was used exclusively for academic purposes and will be deleted after the completion of the thesis, in accordance with institutional data protection guidelines.

3.8 Methodological Limitations

Despite careful design, this study has methodological limitations that should be acknowledged. First, the qualitative research design and relatively small sample size limit the generalizability of the findings. The aim of the study is not statistical representativeness but an in-depth understanding of managerial sensemaking in AI-supported decision-making contexts.

Second, participants are recruited through the researcher’s professional network and online platforms, which may introduce selection bias. Managers who are more open to discussing AI or reflective about their decision-making may be more likely to participate. This limitation is partially mitigated by the diversity of managerial roles and organizational contexts included in the sample.

Third, the study relies on self-reported accounts of decision-making. While interviews provide valuable insights into interpretations and justifications, they may be influenced by recall bias or social desirability. Nevertheless, self-reported narratives are central to understanding sensemaking processes and are therefore appropriate for the objectives of this research.

Acknowledging these limitations allows for a cautious interpretation of the findings and highlights opportunities for future research, such as comparative studies using mixed-method approaches or larger samples.

4 Findings

4.1 AI as Cognitive and Preparatory Support, Not Decision Authority

Across all interviews, managers consistently described artificial intelligence as a tool that supports thinking and preparation rather than as a source of final decisions. AI was frequently framed as an assistant or sparring partner that helps structure ideas, generate options, or challenge initial assumptions. At the same time, interviewees emphasized that decision authority and responsibility remain firmly with humans.

Many participants reported using AI primarily in the early or intermediate stages of decision-making. In these stages, AI was seen as helpful for exploring alternatives, summarizing information, or preparing inputs for further discussion. One manager explained that AI is mainly used "on the way to a solution" (INT9), while the final judgment is made independently. Similarly, another interviewee described AI as an additional voice that improves efficiency and preparation quality but stressed that "in the end, I decide" (INT1).

The distinction between preparation and authority was particularly salient in decisions perceived as complex or consequential. While AI was considered useful for drafting concepts, conducting preliminary analyses, or generating ideas, participants were clear that final decisions especially those involving strategic direction, accountability, or people-related consequences were not delegated to AI systems. As one interviewee noted, AI can significantly reduce preparation time, but decisions with long-term implications remain a human responsibility.

Overall, the findings indicate that managers integrate AI into their decision-making processes as a cognitive support tool rather than as a decision-maker. AI contributes to efficiency, reflection, and analytical depth, but it does not replace human judgment or accountability. This pattern was consistent across all interviews, regardless of differences in managerial role, industry, or level of AI experience.

4.2 Conditional Trust in AI Advice

Across interviews, managers consistently described their trust in AI-based advice as conditional rather than absolute. Trust was not expressed as a general belief in the technology, but as something that depended on the task at hand, the perceived quality of the output, and the manager's ability to assess or verify the advice. Participants emphasized that AI advice could be useful and reliable in certain contexts, while remaining inappropriate or insufficient in others.

A recurring pattern was that trust in AI varied strongly by task type and decision scope. Managers reported higher trust in AI when dealing with routine, analytical, or well-structured tasks, such as summarizing information, drafting initial concepts, or supporting operational decisions. In contrast, trust declined when decisions involved strategic direction, long-term consequences, or people-related considerations. As one interviewee explained, AI can be helpful "on a high level," but reliance decreases when deeper judgment or contextual understanding is required (INT7).

Another important condition for trust concerned the ability to understand how AI-generated advice was produced. Several managers stated that they trusted AI outputs only when they could follow the underlying reasoning or logic. Advice that appeared opaque or unsupported was treated with scepticism. One participant noted that trust increased when the AI's suggestions aligned with their own way of thinking, whereas unexplained outputs were rarely accepted without further scrutiny (INT5).

Trust was also described as fragile and reversible. Past experiences with incorrect or fabricated information reduced confidence in AI advice, even when the technology performed well in other situations. Managers emphasized that a single error could lead to increased caution in future interactions, reinforcing the need for continuous critical evaluation. As a result, trust was not seen as a stable state but as something that had to be continually reassessed (INT2).

Overall, the findings indicate that managers do not treat AI as an inherently trustworthy or untrustworthy source of advice. Instead, trust is negotiated situationally, shaped by task characteristics, transparency, and prior experience. This conditional approach to trust was evident across all interviews and formed a central aspect of how managers make sense of AI-based advice.

4.3 Maintaining Control Through Verification and Override

Across interviews, managers emphasized that the use of AI in decision-making did not imply a loss of control. Instead, participants described a range of practices through which they actively maintained control over AI-generated advice. Central to these practices were verification, critical evaluation, and the explicit retention of decision authority.

A dominant pattern across interviews was the use of verification and double-checking. Managers consistently reported that AI outputs were rarely accepted at face value. Instead, AI-generated suggestions were treated as provisional inputs that required validation through additional sources, personal expertise, or consultation with colleagues. One interviewee explained that AI results were always reviewed critically and compared with existing knowledge before being considered further (INT4). This verification process was described as essential for ensuring reliability and avoiding overreliance on potentially incorrect or incomplete information.

Closely related to verification was the importance of retaining the ability to override AI advice. Managers repeatedly emphasized that AI recommendations did not carry binding force and could be ignored or rejected if they conflicted with personal judgment or contextual considerations. Several participants stated explicitly that the final decision always remained with them, regardless of how convincing the AI output appeared (INT2). This ability to override AI advice was central to maintaining a sense of autonomy and responsibility in decision-making.

Control was also exercised through the way managers interacted with AI systems, particularly through careful formulation of inputs and prompts. Interviewees highlighted that the quality and relevance of AI advice depended strongly on how questions were framed and how much contextual information was provided. One manager summarized this relationship by noting that poorly specified inputs lead to poor outputs, whereas detailed and context-rich prompts enabled more useful results (INT5). By shaping the input, managers positioned themselves as active drivers of the interaction rather than passive recipients of AI advice.

Together, these practices illustrate that control in AI-supported decision-making is not relinquished but actively managed. Verification, override, and input control functioned as mechanisms through which managers safeguarded their autonomy and accountability. Rather than perceiving AI as a threat to control, participants described it as a tool that could be integrated into decision-making while preserving human authority and responsibility.

4.4 Justifying Decisions: Human Ownership and Social Legitimacy

Across interviews, managers consistently emphasized that decision-making did not end with choosing an option but also involved justifying that decision to others. This justification process was described as a crucial part of managerial work and strongly shaped how AI-generated advice was evaluated and used. While AI was widely accepted as a support tool, participants made clear distinctions regarding its role in justification and accountability.

A recurring pattern was that final responsibility and ownership of decisions were understood as inherently human. Managers emphasized that, regardless of whether AI contributed to the decision process, they remained personally accountable for outcomes. Several interviewees stated explicitly that responsibility could not be delegated to an AI system, particularly in cases where decisions had strategic, financial, or personnel-related consequences (INT1; INT6; INT9). This sense of ownership was closely tied to managerial identity and role expectations.

Justification was also described as a social process, shaped by audiences such as superiors, colleagues, clients, or external stakeholders. In this context, participants expressed reservations about explicitly referencing AI as the basis for a decision. Some managers indicated that AI involvement was not always viewed as a legitimate or convincing justification, especially in high-stakes or strategic situations. One interviewee explained that they would avoid stating that a decision was based on AI advice and instead present the outcome as the result of human analysis and experience (INT1).

Rather than the source of advice, managers emphasized the importance of the quality of reasoning used to justify decisions. Several participants noted that arguments needed to be coherent, plausible, and aligned with organizational expectations, regardless of whether AI had been involved in generating them. AI-generated insights were considered acceptable when they could be translated into convincing human arguments, but insufficient when they stood alone without interpretive framing (INT3).

The findings also show that managers differentiated between contexts in which AI use could be openly acknowledged and those in which it was strategically downplayed. For routine or administrative tasks, AI involvement was often seen as unproblematic and could be disclosed without concern. In contrast, for strategic decisions or advisory contexts, managers preferred to emphasize human judgment and expertise to maintain credibility and social legitimacy (INT6).

Overall, the findings indicate that justification plays a central role in shaping how managers make sense of AI-based advice. While AI can contribute to the reasoning behind decisions, legitimacy and accountability remain tied to human ownership. Managers therefore integrate AI outputs selectively, translating them into human-centred justifications that align with social and organizational expectations.

4.5 The Enduring Role of Human Advice

Across interviews, managers consistently highlighted the continued importance of human advice in their decision-making processes. While AI was widely used as a supportive tool, participants emphasized that human advisors played a distinct and irreplaceable role, particularly in situations involving complexity, uncertainty, or interpersonal considerations. Human advice was valued not only for its content, but also for the relational and contextual qualities embedded in it.

A recurring theme was the significance of experience-based and tacit knowledge. Managers described human advisors as capable of drawing on prior experiences, organizational history, and situational awareness that AI systems could not fully replicate. Several interviewees noted that human advisors were better able to prioritize information, recognize subtle signals, and adapt recommendations to the specific context of the organization or decision situation (INT3). This contextual sensitivity was viewed as especially important in strategic decisions with long-term implications.

Participants also emphasized the role of empathy and relational understanding in human advice. In contrast to AI-generated outputs, human advisors were perceived as capable of understanding emotions, organizational dynamics, and interpersonal sensitivities. One manager explained that advice involving people, leadership, or change processes required an understanding of human reactions and relationships that could not be reduced to analytical input alone (INT6). As a result, human advice was considered essential in situations where trust, credibility, or emotional intelligence mattered.

Another important aspect of human advice concerned social legitimacy and credibility. Managers described human advisors as providing not only guidance but also a form of social validation for decisions. Consulting colleagues, experts, or trusted partners helped managers feel more confident in their choices and made decisions easier to justify to others. In comparison, AI advice lacked this relational dimension and was therefore less effective as a source of reassurance or legitimacy in socially visible decision contexts (INT1).

Overall, the findings indicate that AI and human advice serve fundamentally different roles in managerial decision-making. While AI contributes efficiency, analytical support, and idea generation, human advisors remain central where judgment, context, empathy, and social legitimacy are required. Rather than replacing human advice, AI is integrated alongside it, reinforcing the enduring importance of human interaction in managerial sensemaking.

5 Discussion

This chapter interprets the findings in relation to the research questions and the literature on managerial decision-making, advice-taking, and AI-supported decision processes. It discusses how managers make sense of AI-generated versus human advice, and how trust, perceived control, and justification shape the interpretation and use of AI-based recommendations. Empirical evidence is referenced using interview identifiers (INT1–INT11). Interpretation of the findings is linked to prior research through academic citations placed at the end of sentences.

5.1 Discussion of Findings by Research Question

RQ1: How do managers make sense of advice from artificial intelligence compared to human advisors in their decision-making processes?

The findings suggest that managers make sense of AI-generated advice primarily as a cognitive and preparatory resource rather than as a decision authority. AI was described as supporting ideation, structuring, and early-stage analysis, while the final decision was consistently framed as a human responsibility across interviews (INT1–INT11). This pattern reinforces a view of decision-making as an interpretive process in which managers integrate cues and inputs to construct plausible understandings that guide action rather than simply selecting from a fully known set of alternatives (Maitlis & Christianson, 2014).

Managers' accounts further indicate that AI is incorporated into managerial sensemaking as an additional input that enables iteration, reflection, and alternative framing. AI outputs were typically treated as prompts that challenge assumptions or provide structure, rather than as definitive recommendations to follow (INT1–INT11). This interpretation aligns with the insight that managerial decision processes are often iterative and socially embedded rather than linear and purely analytical (Mintzberg et al., 1976).

In contrast, managers made sense of human advice through relational and contextual frames. Human advisors were valued for tacit knowledge, situational awareness, and sensitivity to organizational culture and interpersonal dynamics (INT3–INT7). These qualities were repeatedly described as decisive in ambiguous, complex, or socially delicate situations, where "good advice" depends not only on analytic content but also on contextual calibration and interpersonal understanding (INT3–INT7).

Overall, the results indicate that AI and human advice are not perceived as interchangeable sources. AI is integrated as an efficiency- and structure-enhancing input, whereas human advice remains central where context, credibility, and relational understanding are required (INT1–INT11).

RQ2: How do trust and perceived control influence managerial interpretations of AI-generated advice?

A central finding is that trust in AI advice is conditional, task-specific, and reversible. Managers described trust as dependent on whether AI seemed appropriate for a specific task and whether outputs could be checked or validated (INT2–INT11). This is consistent with the idea that trust reflects a willingness to rely under uncertainty and depends on perceived competence and reliability rather than unconditional acceptance (Mayer et al., 1995).

Transparency and comprehensibility were repeatedly described as prerequisites for trusting AI outputs. Trust increased when managers could follow the logic behind an AI output or verify it through additional sources and cross-checking (INT3–INT11). This pattern is consistent with research emphasizing transparency and explainability as important antecedents of trust in AI systems (Glikson & Woolley, 2020).

Perceived control emerged as equally influential in shaping interpretations of AI advice. Managers maintained control through three recurring practices: verification, override, and input control. Verification ensured that AI outputs remained provisional and subject to review (INT2–INT11). Override preserved autonomy by positioning managers as final arbiters even when AI suggestions appeared convincing (INT1–INT3, INT5–INT11). Input control was enacted through careful prompting and the provision of relevant context, reflecting a belief that output quality depends on the quality of the input (INT2, INT4–INT11). These findings align with research suggesting that acceptance of AI advice depends not only on perceived system performance but also on users' sense of control and ability to intervene (Berger et al., 2021; Brink et al., 2024).

Overall, the study suggests that managers interpret AI advice through a calibrated reliance lens in which AI is used when it can be understood, checked, and integrated without reducing managerial autonomy or accountability (INT1–INT11).

RQ3: How do justification requirements shape the way managers evaluate and integrate advice from AI systems?

The findings show that justification requirements strongly shape how managers integrate AI advice into decision-making. Managers consistently emphasized that decision-making includes not only choosing an action but also being able to explain and defend that choice to relevant audiences (INT1–INT11). This is consistent with the view that judgment and choice are embedded in accountability contexts in which decision-makers anticipate evaluation by others (Tetlock, 1985).

A recurring pattern was that AI was widely accepted as an internal support tool but rarely treated as an acceptable standalone justification in high-stakes or socially visible settings. Some managers described avoiding explicit references to AI when presenting decisions to superiors or external stakeholders, instead framing decisions as the result of human analysis and expertise (INT1, INT6). Beyond social legitimacy concerns, the findings indicate that disclosure can also be shaped by commercial considerations. In particular, one manager described concealing AI use in client work to protect perceived value and billing models, suggesting that justification practices may reflect not only accountability pressures but also economic incentives (INT8).

At the same time, several interviewees emphasized that what ultimately matters is the strength of the reasoning used to justify a decision, not whether AI or a human produced the initial input (INT2–INT7). In practice, AI advice was integrated when managers could translate it into coherent and defensible rationales that they could personally "own" and communicate credibly (INT2–INT11).

The findings therefore suggest that AI advice is filtered through legitimacy considerations that vary across audiences and decision contexts. AI contributes arguments, options, and structure, but legitimacy remains tied to human ownership of decisions and the manager's ability to craft a defensible narrative (INT1–INT11). This complements advice-taking research by highlighting that beyond uncertainty and trust, justification and audience expectations meaningfully shape reliance and disclosure strategies (Ribeiro et al., 2019; Tetlock, 1985).

5.2 One-Sentence Answers to the Research Questions

RQ1: Managers make sense of AI advice as an input that supports preparation and structured thinking, while human advice remains central for contextual judgment and socially embedded decision-making. (INT1–INT11)

RQ2: Trust in AI is calibrated situationally and is strengthened when managers can maintain control through verification, override, and input framing. (INT2–INT11)

RQ3: Justification requirements filter AI advice use by making human ownership and socially legitimate reasoning essential, particularly in strategic or high-stakes contexts. (INT1–INT11)

5.3 Theoretical Implications

This study offers three theoretical implications for research on managerial decision-making and advice-taking in AI-supported contexts.

First, the findings indicate that managers integrate AI advice primarily as a sensemaking resource rather than as an authority, suggesting that AI becomes part of interpretive work without replacing human agency (INT1–INT11). This extends sensemaking-oriented perspectives by showing that AI contributes cues and structure while meaning and commitment remain anchored in human judgment and responsibility (Maitlis & Christianson, 2014).

Second, the results suggest that trust and perceived control in AI advice-taking should be understood as enacted through practical routines rather than as purely attitudinal phenomena. Trust calibration emerged through verification practices, continued override capacity, and prompt-based input control (INT2–INT11). This supports an interactional view of trust and control in which reliance is continuously adjusted in response to task demands, transparency, and perceived risk (Berger et al., 2021; Brink et al., 2024; Glikson & Woolley, 2020).

Third, the findings highlight justification as a central mechanism shaping the integration of AI advice. AI was used most readily when managers could transform outputs into socially legitimate human justifications, whereas disclosure was more cautious when AI involvement could undermine credibility or accountability (INT1, INT6). This underscores the importance of accountability contexts for understanding not only reliance on AI advice but also disclosure and framing strategies (Tetlock, 1985).

5.4 Practical Implications

The findings have implications for organizations, managers, and AI system providers. Organizations should clarify responsibility structures for AI-supported decision-making and support managers in developing routines for verification and critical evaluation. This includes establishing norms for when AI is appropriate, how outputs should be validated, and how accountability is assigned (INT1–INT11).

Managers may gain the most value from AI when it is used as a preparatory tool that improves speed and structure while maintaining human decision authority. Risk can be reduced by applying deliberate verification routines and by translating AI-supported insights into defensible rationales that remain credible even when AI involvement is not foregrounded (INT2–INT11).

AI system designers and vendors should support explainability, traceability, and controllability to facilitate calibrated trust and reduce social risks in justification contexts. Features such as clearer reasoning pathways, source attribution, and interaction designs that help users test assumptions can support adoption in managerial environments (Brink et al., 2024; Glikson & Woolley, 2020).

5.5 Limitations and Directions for Future Research

This study is qualitative and based on a purposive sample of managers, which limits statistical generalizability. The goal was depth of understanding rather than representativeness. Future research could test the identified mechanisms using mixed-method designs, larger samples, or comparative studies across industries, decision types, or levels of managerial seniority.

The findings rely on self-reported accounts, which may be influenced by recall bias or social desirability, particularly regarding disclosure and justification of AI use. Future studies could triangulate interview data with observational methods, decision logs, or document analysis to capture how AI advice is integrated in real-time decision settings.

Future research could also examine how organizational norms and accountability structures shape the legitimacy of AI advice over time, including how managers learn to communicate AI-supported decisions and how stakeholders respond to different disclosure strategies.

5.6 Chapter Conclusion

The discussion indicates that managers integrate AI advice as a supportive input that enhances preparation and structure, while preserving human authority, control, and accountability. Trust is calibrated situationally through transparency and verification practices, and justification requirements shape how AI outputs are framed and communicated. These insights provide the basis for the concluding chapter, which summarizes key findings, outlines actionable recommendations, and identifies opportunities for further research.

6 Conclusion

6.1 Study Purpose and Approach

This thesis examined how managers make sense of advice from artificial intelligence compared to human advisors in their decision-making processes. It further explored how trust, perceived control, and justification requirements shape managerial interpretations and use of AI-generated advice. To address these research questions, eleven semi-structured interviews with managers were conducted online in February 2026 (INT1–INT11) and analysed using thematic analysis.

6.2 Key Conclusions

The findings show that managers primarily integrate AI as a tool for cognitive support and preparation rather than as a decision authority. AI is used to structure thoughts, generate options, and accelerate early-stage analysis, while final decision responsibility remains human (INT1–INT11).

Trust in AI advice is conditional, task-specific, and reversible. Managers are more willing to rely on AI for routine or structured tasks, but become cautious for strategic, high-stakes, or socially complex decisions. Trust increases when outputs are comprehensible and verifiable and decreases sharply following perceived errors or fabricated information (INT2–INT11).

Managers maintain perceived control through verification, override, and input control. AI outputs are typically double-checked, treated as provisional inputs, and can be rejected when they conflict with contextual judgment. Control is also enacted through prompting and providing context, reflecting managers' active role in shaping the usefulness of AI advice (INT2–INT11).

Justification requirements play a central role in determining whether and how AI advice is integrated. Managers emphasized human ownership and accountability for decisions and frequently framed AI as background support rather than a visible basis for decisions. AI advice was accepted when it could be translated into defensible reasoning, while explicit reference to AI was often avoided in strategic or high-visibility contexts where legitimacy and credibility matter (INT1, INT6; INT1–INT11).

Overall, the study suggests that AI and human advice occupy complementary roles. AI contributes speed, structure, and analytical support, whereas human advisors remain essential where tacit knowledge, empathy, credibility, and organizational context shape decision-making (INT1–INT11).

6.3 Contribution to Future Research

This study contributes to research on advice-taking and AI-supported decision-making by highlighting how managers incorporate AI advice as part of an interpretive sensemaking process rather than as an authoritative recommendation. It further shows that trust and control are enacted through practical routines verification, override, and prompting indicating that reliance on AI is continuously calibrated in use. Finally, the study underscores justification and social legitimacy as central mechanisms shaping both reliance on and disclosure of AI advice in organizational contexts.

6.4 Practical Implications

For organizations, the findings suggest that AI adoption should be accompanied by clear responsibility structures and norms for verification and escalation. Managers benefit from guidance on when AI advice is appropriate, how outputs should be checked, and how final accountability is assigned.

For managers, the results indicate that the value of AI is greatest when it is used for preparation and exploration while maintaining critical judgment and explicit verification routines. Managers can reduce risk by combining AI outputs with contextual expertise and by preparing justifications that remain defensible regardless of whether AI was used in the background.

For AI designers and providers, the findings highlight the importance of explainability, traceability, and controllability. Systems that support reasoning transparency, source attribution, and interaction designs that enable users to test assumptions are more likely to be integrated into managerial decision-making practices.

6.5 Limitations

This study is based on a qualitative interview design and a purposive sample, which limits statistical generalizability. In addition, the findings rely on self-reported accounts and may reflect recall effects or social desirability, particularly in relation to how AI use is disclosed or justified. These limitations do not undermine the study’s objective, which was to develop an in-depth understanding of managerial sensemaking in AI-supported decision contexts.

6.6 Directions for Further Research

Future research could test the mechanisms identified in this study through larger samples and mixed-method designs, for example by combining interviews with surveys or experiments. Comparative studies across industries, levels of managerial seniority, or different types of AI systems could further clarify boundary conditions for trust, control, and legitimacy. Additionally, longitudinal research could examine how managers’ reliance on and disclosure of AI advice changes as organizational norms and accountability structures evolve.

6.7 Closing Statement

AI is becoming an increasingly common input to managerial decision-making, but the findings of this thesis suggest that its role is best understood as supportive rather than substitutive.

Managers integrate AI to enhance preparation and structure, while preserving human authority, accountability, and the social legitimacy required to justify decisions in organizational settings.

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8 Appendix

Appendix 1: The final dataset comprises 11 interviews (INT1–INT11). Codes were developed iteratively; each code is supported by at least one illustrative quote.

Codes	*Definition*	*Include when… / Exclude when…*	*Illustrative quote*	*Source*
AI as cognitive support and sparring partner	AI is described as supporting thinking, ideation, or preparation rather than making final decisions.	Include: sparring/assistant, structuring thoughts, preparation. Exclude: AI as decision authority.	"I would not ask AI about the important decision itself, but rather about my path towards a solution."	INT1
Human decision authority and final accountability	Managers explicitly retain the final decision and responsibility as human.	Include: "final step human," "we decide." Exclude: general AI use without decision boundary.	"We use AI as support… but we make the actual decisions ourselves as humans."	INT9
Task-contingent trust calibration	Trust in AI varies by task type, complexity, and decision scope.	Include: "depends," high-level vs deep dive, strategic vs routine. Exclude: unconditional trust statements.	"High level: all good… but for a deep dive I don't rely on the results."	INT7
Error awareness and hallucination risk	Trust is limited because AI can produce incorrect, fabricated, or impractical outputs.	Include: hallucinations, logic errors, fact concerns. Exclude: generic caution without reason.	"It happens that it starts to hallucinate and goes off track—you only notice it in the output."	INT2
Explainability-seeking and reasoning traceability	Managers seek explanations, argumentation, or process transparency to evaluate AI advice.	Include: "justify every statement," "explain process," "follow reasoning." Exclude: convenience-only use.	"I have every single statement justified by the AI so I can check how valid it is."	INT1
Verification routines and triangulation	AI outputs are cross-checked via other sources, experts, or additional tools before use.	Include: verification loop, Google check, lawyer check, second AI. Exclude: blind acceptance.	"Everything I get from it, I have it verified again—I always add another loop."	INT2
Override capacity and autonomy preservation	Managers emphasize the ability to reject AI outputs and	Include: "I can always decide differently," autonomy. Exclude:	"In the end, I can always decide differently."	INT2

	decide differently.	only verification without autonomy emphasis.		
Input control through prompting and contextualization	Managers shape output quality through detailed prompts, context, examples, and iterative questioning.	Include: prompting importance, "garbage in/out," rephrasing, giving context. Exclude: verification-only after output.	"Prompting is extremely important if you want to get something good out of AI."	INT2
Perceived control constraints	Managers describe control over AI as limited, even if it can be steered through interaction.	Include: "control is low," steering without control. Exclude: autonomy in final decisions (separate code).	"You can steer AI, but I don't have control over the AI."	INT9
Content-based justification logic	Decisions are justified primarily by reasoning quality and factual soundness rather than by advice source.	Include: content > source, "must be fact-based." Exclude: concealment/social risk cases.	"It shouldn't matter whether it comes from a person or an AI system—it has to be fact-based."	INT10
Stakeholder-facing legitimacy management	Managers perceive AI as weak justification externally and manage legitimacy by framing decisions as human-owned.	Include: "hard to justify chatbot told me," "AI said so isn't justification." Exclude: purely internal use.	"It's hard to justify a decision by saying: the chatbot told me that and it sounded good."	INT9
Audience-dependent disclosure strategies	Disclosure of AI use varies by context, audience, and task type (administrative vs strategic).	Include: internal vs external disclosure, audience-dependent framing. Exclude: general concealment without audience logic.	"For administrative work we can say we used AI, but for strategic consulting work we try to avoid that and say we prepared it manually."	INT6
Economic incentives for concealment	AI use is concealed partly due to commercial motives (e.g., billing models, perceived value).	Include: day-rate/price/value logic tied to AI concealment. Exclude: concealment driven only by stigma.	"We try not to communicate to the client that we work a lot with AI, so we can still sell longer day rates."	INT8

Organizational context and policy constraints	AI use is shaped or limited by organizational rules and access restrictions.	Include: restrictions on tools/data access, limited rollout. Exclude: personal preference.	“Copilot is enabled only for certain people.”	INT9
Tacit knowledge, contextual judgment, and empathy	Human advice is preferred because humans understand context, culture, and interpersonal dynamics that AI lacks.	Include: company culture, empathy, background knowledge, personal reflection. Exclude: generic “humans better” without reason.	“Every company is culturally different—and for decisions you also need empathy.”	INT4
Relationship-based credibility and ‘people business’ logic	Human advice and business decisions are tied to relationships, trust in persons, and credibility.	Include: “people buy from people,” “people business,” relationship repetition. Exclude: context/tacit knowledge only.	“People buy from people.”	INT11
Trust building through repeated performance	Trust in AI can increase gradually if it repeatedly delivers accurate results over time.	Include: trust builds slowly through experience. Exclude: immediate trust statements.	“Trust has to be built slowly… if it keeps delivering solid facts, then you start to trust it.”	INT10
Fairness concerns and bias sensitivity	Managers express concern that AI outputs may be biased or unfair due to training data and patterns.	Include: bias examples, fairness concerns. Exclude: general “AI is wrong.”	“AI can already be biased—for example, certain names might have better chances than names with a migration background.”	INT10

Appendix 2: Theme Development from Code

Theme	*Theme description*	*Supporting codes (from Appendix A)*	*Evidence interviews*
Theme 1: AI as cognitive support, not decision authority	Managers integrate AI primarily to structure thinking, generate options, and prepare decisions, while decision authority and responsibility remain human.	AI as cognitive support and sparring partner; Human decision authority and final accountability	INT1–INT11
Theme 2: Conditional and calibrated trust in AI advice	Trust in AI is task-contingent and changes depending on complexity, error risk, and the ability to evaluate outputs.	Task-contingent trust calibration; Error awareness and hallucination risk; Explainability-seeking and reasoning traceability; Trust building through repeated performance	INT1–INT9
Theme 3: Control through verification, override, and prompting	Managers preserve autonomy by verifying AI outputs, maintaining the ability to override them, and shaping outputs through careful prompting and contextualization.	Verification routines and triangulation; Override capacity and autonomy preservation; Input control through prompting and contextualization; Perceived control constraints	INT2–INT9, INT10–INT11
Theme 4: Justification, legitimacy, and disclosure management	AI advice is often treated as a background input; justification remains human-owned and is adapted to stakeholder expectations. Managers manage legitimacy through selective disclosure of AI use.	Content-based justification logic; Stakeholder-facing legitimacy management; Audience-dependent disclosure strategies; Economic incentives for concealment; Organizational context and policy constraints	INT1, INT6, INT8–INT10 (plus supporting statements across INT2, INT9)
Theme 5: Enduring value of human advice	Human advice remains essential where tacit knowledge, contextual judgment, empathy, and relationship-based credibility shape decisions and outcomes.	Tacit knowledge, contextual judgment, and empathy; Relationship-based credibility and ‘people business’ logic; Competence filter for human advice	INT3–INT4, INT6–INT9, INT11

Appendix 3: Evidence: illustrative quotations by theme

Theme 1: AI as cognitive support, not decision authority

Evidence statement	*Illustrative quote (English translation)*	*Source*
Managers use AI to support thinking and preparation rather than to decide.	"I would not ask AI about the important decision itself, but rather about my path towards a solution."	INT1
AI is treated as a supportive input, while decisions are human-owned.	"We use AI as support… but we make the actual decisions ourselves as humans."	INT9
AI helps with planning and challenging ideas, but not as final authority.	"We worked with AI to build a business plan behind it and challenged our own approach."	INT7
In strategic contexts, AI is framed as detail support rather than strategy support.	"AI is a helper in the details, not a helper in strategy."	INT11

Theme 2: Conditional and calibrated trust in AI advice

Evidence statement	*Illustrative quote (English translation)*	*Source*
Trust decreases as decisions require deeper judgment ("high-level vs deep dive").	"High level: all good… but for a deep dive I don't rely on the results."	INT7
Managers explicitly recognize hallucination risk and therefore remain cautious.	"It happens that it starts to hallucinate and goes off track—you only notice it in the output."	INT2
Trust increases when reasoning can be traced and assessed.	"I have every single statement justified by the AI so I can check how valid it is."	INT1
Trust can build gradually through repeated accurate performance over time.	"Trust has to be built slowly… if it keeps delivering solid facts, then you start to trust it."	INT10

Theme 3: Control through verification, override, and prompting

Evidence statement	*Illustrative quote (English translation)*	*Source*
Managers maintain control by adding deliberate verification loops.	"Everything I get from it, I have it verified again—I always add another loop."	INT2
Control is enacted through careful prompting and contextualization.	"Prompting is extremely important if you want to get something good out of AI."	INT2
Managers stress autonomy through the ability to override AI advice.	"In the end, I can always decide differently."	INT2
Some managers experience control as limited, even if AI can be steered.	"You can steer AI, but I don't have control over the AI."	INT9

Theme 4: Justification, legitimacy, and disclosure management

Evidence statement	*Illustrative quote (English translation)*	*Source*
AI is not perceived as a valid stakeholder-facing justification in itself.	"It's hard to justify a decision by saying: the chatbot told me that and it sounded good."	INT9
Disclosure is audience-dependent (administrative vs strategic contexts).	"For administrative work we can say we used AI, but for strategic consulting work we try to avoid that and say we prepared it manually."	INT6
Managers may strategically conceal AI use for commercial reasons.	"We try not to communicate to the client that we work a lot with AI, so we can still sell longer day rates."	INT8
Justification is often framed as human-owned even if AI contributed.	"I would never argue to my boss that I developed the solution with the help of AI."	INT1

Theme 5: Enduring value of human advice

Evidence statement	*Illustrative quote (English translation)*	*Source*
Human advice remains essential because it is embedded in culture and empathy.	"Every company is culturally different—and for decisions you also need empathy."	INT4
Human advisors contribute contextual knowledge that AI cannot easily replicate.	"A human implicitly knows what used to be important but isn't anymore—AI treats everything as equally important."	INT3
Human advice includes personal reflection and knowledge of the individual.	"A person knows me and reflects back how my decision is—AI doesn't know me."	INT9
Relationship-based credibility remains central ("people business").	"People buy from people."	INT11