



Leading in the Age of Artificial Intelligence: How AI Adoption Transforms Managerial Work, Competencies, and Practices

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Abstract

Title: Leading in the Age of Artificial Intelligence: How AI Adoption Transforms Managerial Work, Competencies, and Practices

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The increasing adoption of artificial intelligence (AI) in organizations has changed the workplace. While research focuses primarily on technical implementation or employee acceptance, the managerial dimension remains underexplored. Therefore, this thesis examines how AI adoption affects the work and competencies of managers and what management actions can support successful adoption.

To address these objectives, semi-structured interviews were conducted with 10 managers and five AI experts. The data was analyzed using inductive thematic analysis.

Findings show that AI adoption reshapes managerial work by accelerating information processing and analytical activities, leading to shorter decision cycles. Managerial value creation increasingly shifts toward interpretation, prioritization, and sense-making for employees. As a result, AI adoption rebalances competency requirements, as contextual judgement, critical evaluation, learning orientation, and human-centered leadership gain importance. Successful AI adoption is associated with managerial actions that legitimize AI use, foster psychological safety, enable experimentation, and provide governance and support structures.

Taken together, this thesis shows that AI adoption does not fundamentally redefine managerial roles formally but rather changes the work in practice by shifting responsibilities and competency demands. Overall, managers must navigate the tension between technical acceleration and human-centered guidance.

Key Words: AI Adoption, Managerial Work, AI-enabled Management, Managerial Competencies

Sumário

Título: Liderança na era da inteligência artificial: como a adoção da IA transforma o trabalho, as competências e as práticas gerenciais

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A crescente adoção da inteligência artificial (IA) nas organizações tem alterado o trabalho. Embora a investigação se concentre principalmente na implementação técnica ou na aceitação pelos funcionários, a dimensão de gestão permanece pouco explorada. Portanto, esta tese examina como a adoção da IA afeta o trabalho e as competências dos gestores e que ações dos gestores podem apoiar a adoção bem-sucedida.

Para abordar esses objetivos, foram realizadas entrevistas semi-estruturadas com 10 gestores e cinco especialistas em IA. Os dados foram analisados utilizando análise temática indutiva.

Os resultados mostram que a adoção da IA remodela o trabalho de gestão, acelerando o processamento de informações e as atividades analíticas, levando a ciclos de decisão mais curtos. A criação de valor de gestão muda cada vez mais para a interpretação, priorização e criação de sentido nos funcionários. Como resultado, a adoção da IA reequilibra os requisitos de competência, à medida que o julgamento contextual, a avaliação crítica, a orientação para a aprendizagem e a liderança centrada no ser humano ganham importância. A adoção bem-sucedida da IA está associada a ações de gestão que legitimam o uso da IA, promovem a segurança psicológica, permitem a experimentação e fornecem estruturas de governança e apoio.

No geral, esta tese mostra que a adoção da IA não redefine fundamentalmente as funções gerenciais de forma formal, mas sim altera o trabalho na prática, mudando responsabilidades e exigências de competência. Em geral, os gestores devem navegar a tensão entre a aceleração técnica e a orientação centrada no ser humano.

Palavras-chave: Adoção da IA, Trabalho de Gestão, Gestão habilitada por IA, Competências dos Gestores

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List of Abbreviations

AI	Artificial Intelligence
RQ	Research Question
KSA(O)	Knowledge, skills, abilities, and other characteristics
KRA	Key result areas
EM	Expert Manager
EAI	Expert AI
UTAUT	Unified Theory of Acceptance and Use of Technology

1 Introduction

“AI Won’t Replace Humans — But Humans With AI Will Replace Humans Without AI”

(Lakhani, 2023)

Since the public introduction of OpenAI's generative artificial intelligence (AI) ChatGPT in 2022, AI has become accessible and visible to the general public, including managers and employees. Companies have recognized this development as well. According to a report published by McKinsey (2025), 92% of companies plan to increase their investment in AI in the coming years. Additionally, in a study conducted in 2023, 70% of global CEOs stated that generative AI is their top priority (Statista, 2025). Global companies hope to achieve the following key benefits from using AI in descending order: 1) improve efficiency and productivity, 2) reduce costs, and 3) improve existing products and services (Statista, 2024). Industries that can best utilize AI are seeing three times higher revenue growth per employee (PwC, 2025). However, the implementation of AI leads to significant organizational changes. According to the World Economic Forum (2025), workers can expect 39% of their skill sets to become transformed or outdated in the next five years. This development entails shifts in managerial competencies, raising the question of which skills can be considered relevant and how leadership can support successful AI implementation and employee adoption. As AI becomes integrated into organizational processes, it reshapes how work is coordinated, how decisions are made, and how responsibilities are assigned (Berente et al., 2021; Raisch & Krakowski, 2021). This puts managers at the center of AI adoption, because their competencies can influence the effectiveness of AI usage in organizations (Cascio & Aguinis, 2011; Armstrong & Taylor, 2014; Kolbjørnsrud et al., 2016). AI adoption covers the organizational introduction of AI systems (Cooper & Zmud, 1990) as well as the willingness of individual employees to use them (Venkatesh et al., 2003). Successful AI adoption therefore depends not only on technical integration but also on the trust and positive perceptions of users towards AI (Campion et al., 2011; Dwivedi et al., 2019; Burton et al., 2020). At the managerial level, adoption further involves coordinating the alignment of AI with existing structures and workflows (Kolbjørnsrud et al., 2016; Berente et al., 2021). Overall, managers play a central role in shaping the integration of AI as it becomes increasingly embedded in organizations. Their competencies and behaviors influence how AI is used and accepted.

1.1 Relevance and Objective

Despite the growing adoption of AI in companies, research on the managerial dimensions of this transformation remains limited. Existing literature mainly focuses on technical challenges or employee-level factors such as trust or acceptance. Models such as the Technology Acceptance Model (Davis, 1986; Davis, 1989) or the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) are often used to explain individual technology adoption (Venkatesh et al., 2003; Williams et al., 2015). However, less attention has been paid to the managerial side of AI implementation and to the competencies that enable managers to guide successful AI adoption. Furthermore, empirical insights from industry experts and managers remain limited. This gap is particularly important as management research shows that managers play a key role in shaping organizational outcomes through their skills, knowledge, and behavior (Adner & Helfat, 2003; Cascio & Aguinis, 2011; Armstrong & Taylor, 2014).

In order to explore how AI adoption affects managerial work, this thesis investigates how AI integration is viewed and managed from expert and managerial perspectives. It analyzes resulting shifts in tasks, responsibilities, perceived competency requirements, and related managerial actions, drawing on qualitative insights. Therefore, this thesis addresses the following main research question (RQ): How do experts view the impact of AI adoption on managerial competencies and which skills do they consider essential for successful leading implementation and employee adoption?

This RQ is supported by the following three sub-questions:

RQ1: How does AI adoption change managerial work tasks, responsibilities, and value creation?

RQ2: Which competencies and skills enable managers to successfully implement AI at the organizational level?

RQ3: Through which managerial actions are these competencies translated into successful AI adoption outcomes?

This investigation is relevant for both managers and organizations. As AI adoption continues to expand across industries, organizations increasingly integrate AI into processes and decision-making (McKinsey, 2025; Eurostat, 2025; Berente et al., 2021). Managers therefore face the challenge of aligning AI systems with organizational goals and work practices. For

organizations, understanding the managerial dimension of AI adoption is essential for supporting role development, capability building, and the design of structures that enable responsible use (Berente et al., 2021; European Parliament and the European Council, 2024).

Beyond its practical value, this thesis also contributes academically by providing a qualitative perspective grounded in both AI expert and managerial insights. While existing research has primarily examined technological and employee-level aspects of AI use (Davis, 1989; Venkatesh et al., 2003; Dwivedi et al., 2019), this thesis offers practice-based insights. In doing so, it extends current literature on AI-enabled management and enhances the theoretical understanding of managerial work in AI-enabled environments.

1.2 Course of Investigation

In order to answer the research questions, this thesis is structured as follows. After an initial introduction, Chapter 2 presents the literature review that lays out the conceptual foundation. It links findings from existing research on managerial responsibilities and competencies with the adoption of AI. Chapter 3 then outlines the methodical approach. It explains the exploratory qualitative design and the use of semi-structured expert interviews as the main data source, including the interviewee profiles. It further describes the development of the interview guide with a flexible design to capture new insights. Moreover, Chapter 3 explains the data analysis procedure, which is based on an inductive thematic analysis following Braun and Clarke (2006). Chapter 4 presents the results of the thematic analysis, outlining the main themes and key findings from the interviews. Finally, Chapter 5 provides answers to the research questions by discussing the findings in relation to the existing research from Chapter 2. It concludes with implications, limitations, and potential suggestions for future research.

2 Literature Review

The review focuses primarily on established management theories, supplemented mainly by recent publications (\leq five years), as the area of AI is a rapidly evolving field (Gatrell et al., 2024). It introduces central definitions of AI and outlines its organizational relevance, followed by key perspectives on adoption processes. The role of managers and the organizational variables they influence are reviewed. This approach provides a conceptual basis for understanding how AI may affect managerial work.

2.1 AI Adoption

2.1.1 Definition and Characteristics of AI

The European Parliament and the European Council (2024) define an AI system as a machine-based system that is able to work with different levels of autonomy. This system can learn or change after deployment and uses data input in order to create outputs that affect physical or virtual environments. Outputs exist in different formats, for example, predictions, content, and recommendations (European Parliament and the European Council, 2024). For terminology precision, ISO 22989:2022 describes AI as an engineered system that produces outputs based on a set of objectives defined by humans (International Organization for Standardization, 2022). These definitions emphasize that AI systems can act with varying degrees of autonomy based on human-defined objectives. In line with this increasing autonomy, emerging regulatory frameworks require that AI systems are used under proper human supervision (European Parliament and the European Council, 2024; National Institute of Standards and Technology, 2023). AI is not a single, clearly defined technology but a broad and constantly evolving set of digital capabilities (Berente et al., 2021). In management research, AI is therefore viewed mainly in terms of how it automates and augments human work, rather than by distinguishing between specific technical subtypes (Raisch & Krakowski, 2021). In line with this perspective, this thesis adopts a general understanding of AI, focusing on its implications for managerial work.

2.1.2 Organizational Relevance and Adoption Trends

In 2024, 13.5% of enterprises in the EU used AI; for large-scale enterprises, adoption already reached 41.2% (Eurostat, 2025). However, a global McKinsey survey reported significantly higher adoption rates of 72% for AI in at least one business function, with large companies leading in adoption (McKinsey, 2025). Even though figures vary by measurement and sample, they both show a rapidly increasing trend in organizational AI adoption. Furthermore, empirical evidence indicates that AI can provide productivity advantages in various work settings, contributing to its growing relevance in organizations: According to a productivity experiment conducted by Noy and Zhang (2023), using ChatGPT reduced writing time by around 40% and increased output quality by around 18%. Their findings also show that inequality between workers decreased, as lower-performing participants benefited most from AI support. In customer support, AI was able to increase resolved issues per hour by a 15% average, also especially improving the speed of workers with less experience or a low skill level

(Brynjolfsson et al., 2025). Given the documented productivity effects, today using AI can be an advantage. Moreover, not using AI turns into a competitive disadvantage over time (Kergroach & H eritier, 2025).

2.1.3 Concept of AI Adoption

A widely used model on technology implementation by Cooper and Zmud (1990) specifies six process stages: initiation, adoption, adaptation, acceptance, routinization, and infusion. These stages describe how a technological innovation moves from initial consideration to full integration into organizational practices. In contrast to this, the widely used umbrella term AI adoption is rather understood as a complex and multifaceted process of organizational change and adaptation (Tursunbayeva & Gal, 2024; Berente et al., 2021). Comparing it to the adoption stage of the traditional process, marking the formal decision to proceed and secure resources (Cooper & Zmud, 1990), AI adoption extends this classical definition and needs to be understood on a wider level (Tursunbayeva & Gal, 2024). On the managerial level, AI adoption describes how managers oversee and coordinate the use of AI within organizational structures and processes (Berente et al., 2021). It includes the integration of AI systems into existing workflows but also the establishment of new mechanisms to ensure effective and appropriate use (Kolbj ornsrud et al., 2016; Berente et al., 2021). As this thesis particularly focuses on the managerial perspective, this level will be further discussed in later sections. On the individual level, AI adoption addresses employee acceptance and the use of AI-based tools, which aligns with classical technology-acceptance research such as the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003). According to the model, four core determinants shape an individual's intention to use technology: performance expectancy, effort expectancy, social influence, and facilitating conditions. Furthermore, the strength of the key determinants varies based on the four key moderators: gender, age, experience, and voluntariness of use (Venkatesh et al., 2003; Williams et al., 2015). For emerging technologies such as AI, prior research emphasizes that trust plays a crucial role in shaping the acceptance of data-driven systems (Dwivedi et al., 2019; Dwivedi et al., 2020). Furthermore, AI governance frameworks underline similar aspects such as transparency, explainability, or accountability as conditions for uptake (European Parliament and the European Council, 2024; National Institute of Standards and Technology, 2023; European Commission, 2019). This thesis uses the described individual level determinants as a conceptual background to make sense of which perceptions managers can influence to improve AI adoption.

2.2 Management

2.2.1 Definition and Nature of Managerial Work

Classically, management describes different functions, such as planning, coordinating, or controlling, through which work is structured within organizations (Fayol, 1949). Mintzberg (1990) builds on this view by acknowledging the formal responsibility of managers. At the same time, he emphasizes that in practice, managerial work is more dynamic than assumed. Managers work at a constant, fast pace with varying and short tasks, often less than 30 minutes, as they are interrupted regularly by new scenarios. Moreover, most managerial work involves social interaction and communication (Mintzberg, 1990). Complementing this perspective, a more recent perspective emphasizes that managers draw on dynamic capabilities such as combining and adapting resources in changing environments (Adner & Helfat, 2003). Understanding what managers do in practice provides the basis to understand how their work is formally described and evaluated in organizations (Mintzberg, 1990). Together, these perspectives provide a starting point for understanding potential developments in leadership roles.

2.2.2 Job Analysis and Competency Modeling

The formal description of managerial work is typically captured through job analysis and competency modeling (Cascio & Aguinis, 2011; Campion et al., 2011). These approaches are central frameworks in HR research for describing the content and expectations for a role (Cascio & Aguinis, 2011). While job analysis provides a structured approach to identifying the tasks and duties that make a job (Cascio & Aguinis, 2011), competency modeling expands this view by focusing on the knowledge, skills, abilities, and other characteristics – KSA(O) associated with successful execution (Campion et al., 2011).

In this context, a task is a clearly defined work activity with a specified purpose, whereas duties describe a broader area of work composed of multiple tasks (Cascio & Aguinis, 2011). These terms serve as the basis for the job description, which summarizes the main activities of a role (Armstrong & Taylor, 2014). In addition, modern work design reviews further emphasize the difference between what people do (activities) and their outcomes, especially in terms of technological and remote transformation (Fraccaroli et al., 2024). This is in alignment with the job vs. role principle: while a job refers to a defined set of tasks or duties, a role describes how individuals adapt these tasks to achieve an expected outcome (Armstrong & Taylor, 2014).

These expected outcomes are often captured through key result areas (KRA), also described as accountability (Armstrong & Taylor, 2014; Cascio & Aguinis, 2011).

Beyond describing work activities, HR frameworks also specify individual requirements. These are captured through knowledge, skills, abilities (and other characteristics) - KSA(O) (Armstrong & Taylor, 2014). Skills represent trainable “able to do” capabilities and determine the level of performance that is needed in a role (Armstrong & Taylor, 2014). Competencies represent broader bundles that combine knowledge, skills, and abilities (Campion et al., 2011; Cascio & Aguinis, 2011). They are typically separated into behavioral competencies and technical or work-based competencies. Behavioral competencies describe observable patterns of actions, whereas technical or work-based competencies capture job-specific knowledge and skills (Armstrong & Taylor, 2014; Campion et al., 2011). Competency models are closely connected to organizational strategy, as they specify the capabilities that enable effective performance (Campion et al., 2011). Together with job analysis, they offer a foundation for describing managerial work, linking role expectations with capabilities required for organizational effectiveness (Armstrong & Taylor, 2014; Cascio & Aguinis, 2011).

2.2.3 Managerial Roles: Formal Expectations and Areas of Influence

While job analysis and competency modeling clarify the formal expectations associated with managerial roles (Cascio & Aguinis, 2011; Campion et al., 2011), management research further shows how managers can influence organizational outcomes through their actions (Mintzberg, 1990). Prior studies highlight several domains in which managers shape work, employee behavior, coordination, and the social environment (Hackman & Oldham, 1976; Lawrence & Lorsch, 1967; Schneider et al., 2013). These domains provide a basis for examining managerial tasks, responsibilities, and required competencies in practice.

Work Design & Tasks. A central group of variables that managers can influence relates to the design of the work itself (Hackman & Oldham, 1976; Morgeson & Humphrey, 2006). Managers influence work by structuring tasks and job characteristics such as autonomy, skill variety, and task significance (Hackman & Oldham, 1976). Furthermore, managers decide how responsibilities are organized (Hackman & Oldham, 1976; Hackman, 1980). In addition, they define the scope and boundaries of work through task variety, interdependence, or feedback (Hackman & Oldham, 1976; Morgeson & Humphrey, 2006). Work design research further extends this view, showing that work has structural, cognitive, social, and contextual

dimensions (Morgeson & Humphrey, 2006; Humphrey et al., 2007). Managers can modify these characteristics through job enrichment or job redesign to improve individual or team performance (Hackman & Oldham, 1976; Hackman, 1980). By modifying task complexity or interdependence, they can influence the competencies employees must apply (Campion et al., 2011). In summary, managers shape the structure of a job by defining tasks, boundaries, and work characteristics.

Motivation & Employee Responses. Moreover, managers influence employee motivation by shaping how employees feel about their work. As described in the job characteristics model by Hackman & Oldham (1976), features such as autonomy, skill variety, and feedback create a sense of responsibility and knowledge of results. These factors can foster intrinsic motivation (Hackman & Oldham, 1976; Hackman, 1980). Managers can further enhance motivation by creating a basis for commitment or effort: they can achieve this by setting clear goals and supporting employees in overcoming obstacles and linking efforts to rewards (House, 1971). Motivation is also shaped through fairness, trust, and respectful behavior (Yukl & Gardner, 2019). Finally, employees must feel capable of doing the work assigned (Bandura, 1977). Based on this, managers influence perceptions of fairness, meaning, and confidence.

Structure & Coordination Processes. Managers can influence organizations through structure and processes. Structure is shaped by authority and communication, which guide how activities are administered and coordinated (Chandler, 1962; Mintzberg, 1989). Managers can adjust these elements to align with strategic goals (Chandler, 1962). In addition, they coordinate specialization and integration of subunits to ensure effective collaboration (Lawrence & Lorsch, 1967). Furthermore, they are responsible for the overall fit of tasks, people, structure, and culture (Nadler & Tushman, 1997). Managers therefore influence the formal systems and relationships impacting the company's success and effectiveness.

Organizational Climate. Managers also shape the social environment and the performance of a company. In this context, climate reflects the shared perception of rules, practices, and norms guiding employees in their daily work (Schneider et al., 2013). It is influenced through the actions and communication of managers, as well as expectation management (Schneider et al., 2013). A key aspect of a positive company climate is the safety to speak up, share ideas, and make mistakes (Edmondson, 1999; Schneider et al., 2013). Safety can be created through openness, support, and fairness (Edmondson, 1999). In addition, consistency shapes shared

perceptions that support cooperation and effectiveness (Schneider et al., 2013). Structured management practices such as feedback, people management, and clear performance targets are also linked to a stronger company productivity (Bloom & van Reenen, 2007). In summary, managers influence collective perceptions and interaction patterns, directly linked to organizational performance.

2.2.4 Managerial Competencies

While managerial tasks describe what managers are expected to do, competencies (KSA(O)) describe what enables them to perform their tasks successfully (Campion et al., 2011; Cascio & Aguinis, 2011). Prior research shows that combinations of cognitive, social, leadership-related, and task-related behavioral competencies are strongly associated with managerial effectiveness and performance (Bartram, 2005; Boyatzis, 2008). To specify competency requirements more precisely, occupational classification systems offer empirically grounded descriptions of relevant KSA(O). The U.S. Department of Labor's (2025) O*NET database outlines competency requirements across occupations, including those relevant to managerial roles.

Knowledge. For general and operations managers, O*NET identifies knowledge of administration and management as the primary area of knowledge, complemented by customer and personal service, language requirements (captured in O*NET as English Language), production and processing, and mathematics (U.S. Department of Labor, 2025).

Skills. While knowledge is domain-specific and abilities are relatively stable individual characteristics, skills are viewed as the most developable component of KSA(O), which is why they are described in greater detail (Boyatzis, 2008; Campion et al., 2011; Cascio & Aguinis, 2011). O*NET highlights a broad set of interpersonal and analytical capabilities. Highly rated skills include active listening, monitoring, reading comprehension, speaking, and coordination, followed by critical thinking, management of personnel resources including motivating and developing, social perceptiveness, active learning, and complex problem solving (U.S. Department of Labor, 2025).

Abilities. O*NET further emphasizes several, mainly cognitive, abilities required for general and operations managers. They include oral comprehension, oral expression, written comprehension, and written expression, as well as deductive reasoning (U.S. Department of Labor, 2025).

Taken together, these competency profiles provide a baseline for understanding what effective management requires. With that, they provide a foundation for analyzing how AI adoption may shift the importance of specific competencies or introduce additional requirements.

2.3 Management and AI Adoption

2.3.1 How AI Adoption Intersects with Managerial Responsibilities

As AI becomes more embedded in organizational decision-making, the managerial role and responsibilities evolve, since AI can change how decisions are made and controlled in organizations (Kolbjørnsrud et al., 2016). Managerial influence plays an important role in shaping organizational practices, as reflected in upper echelons theory, which suggests that organizational outcomes reflect the characteristics of top management (Hambrick & Mason, 1984). Bertrand and Schoar (2003) underline this effect, stating that company policies move with a manager if the manager changes the company. Hambrick and Quigley (2014) further show that CEOs have a strong influence on company outcomes, which is increased with more freedom to act. But not only CEOs or top management directly influence companies. Research shows that qualitative everyday management is linked to higher productivity and profitability (Bloom & van Reenen, 2007). Furthermore, the involvement of middle managers connecting across departments influences organizational performance (Floyd & Wooldridge, 1997). In times of change, middle managers who support initiatives and innovation can support adaptation successfully (Huy, 2002). Taken together, these insights show that managers have a significant influence on organizational outcomes, suggesting that their role is central in how AI is introduced and perceived.

Furthermore, AI adoption affects how work is structured and coordinated in organizations (Berente et al., 2021; Raisch & Krakowski, 2021). This directly intersects with core managerial responsibilities, as managers plan, coordinate, and control work (Fayol, 1949). Managers are therefore essential for linking new technologies to existing structures and processes. Research on technology implementation shows that managerial actions are central for aligning new technologies with organizational goals (Klein & Sorra, 1996). Managers also play a key role in embedding innovations into existing workflows (Cooper & Zmud, 1990).

In the context of AI, managers decide how tasks are automated, how decision authority is distributed, and how employees are supported during these changes (Kolbjørnsrud et al., 2016; Berente et al., 2021). Furthermore, AI adoption requires oversight, introducing new challenges

regarding monitoring and responsibility (European Parliament and the European Council, 2024; National Institute of Standards and Technology, 2023). These responsibilities also fall within the managerial domain, as managers oversee performance and allocate responsibilities (Mintzberg, 1990).

In summary, prior research shows that AI adoption is not only a technical process but also a managerial one (Berente et al., 2021). Managers shape how AI is integrated into organizational workflows (Kolbjørnsrud et al., 2016), how employees engage with new systems (Burton et al., 2020), and how risks and system use are supervised (Lee & See, 2004; National Institute of Standards and Technology, 2023).

2.3.2 Empirical Evidence on How AI Changes Managerial Work

Research on AI adoption increasingly analyzes how managerial work changes when organizations integrate AI into their processes. Studies highlight that AI adoption changes how work is coordinated and overseen (Revilla et al., 2023). AI systems can take over routine monitoring, and managers can focus on handling exceptional circumstances and coordination (Stelmaszak et al., 2025). Managers need to determine the balance between automation and augmentation (Raisch & Krakowski, 2021). They need to decide which tasks should be standardized and which tasks need human oversight, particularly for risky decisions (Revilla et al., 2023). This redistribution of tasks introduces challenges related to transparency and accountability in decision processes (Kellogg et al., 2020). Moreover, experimental evidence shows that AI can increase efficiency in various knowledge-intensive tasks, for example, writing (Noy & Zhang, 2023), customer support issue resolution (Brynjolfsson et al., 2025), or software development (Ziegler et al., 2024). These findings suggest that AI may shift how work is divided within teams, with more routine tasks supported by AI, directly influencing the managerial area of responsibility (Kolbjørnsrud et al., 2016). However, these studies remain limited to specific roles, leaving open questions about the generalization across different job groups (Noy & Zhang, 2023; Brynjolfsson et al., 2025; Ziegler et al., 2024).

Furthermore, research analyzes how AI adoption affects employees and how managers support them throughout the change. With integrating systems in daily work, managers face new requirements in guiding employee expectations (Burton et al., 2020), building trust (Dietvorst et al., 2015; Georganta & Ulfert, 2024), and addressing reactions such as stress (Kellogg et al., 2020). According to Burton et al. (2020), employees' prior expectations towards AI influence

how they engage with the system. This highlights the importance of clear communication about the purpose and contribution of AI. Managers are also responsible for recognizing and mitigating negative emotional responses (Kellogg et al., 2020). To handle these challenges, they require skills in risk management and oversight (Berente et al., 2021). Furthermore, AI adoption can affect employee motivation, which may decline when a system is seen as controlling or restricting the employee's autonomy (Kellogg et al., 2020). However, if AI enables employees to learn and enhance their skills, it can foster motivation (Berente et al., 2021). Managers therefore need to preserve a sense of autonomy (Burton et al., 2020; Lee et al., 2023). Research shows that human-AI teams rely on similar foundations as traditional teams, such as clear roles or open communication (Georganta & Ulfert, 2024). In summary, AI does not replace traditional functions in the people management dimension but rather amplifies their complexity. Managers must place greater emphasis on transparent communication, motivation, oversight, and the calibration of trust between humans and AI.

Moreover, AI adoption changes the coordination, decision-making, and delegation of managers. Traditionally, these activities were shaped by authority, communication, and coordination (Chandler, 1962; Mintzberg, 1989). Today, they increasingly involve interaction between humans and AI (Kellogg et al., 2020; Kim et al., 2023). Managers need to reconsider how decision authority is distributed, as algorithms handle analytical tasks that were once performed by humans (Kellogg et al., 2020; Kim et al., 2023). Also, there is a shift toward integrating AI insights into organizational processes and ensuring goal alignment (Berente et al., 2021; Lee et al., 2023). Furthermore, users tend to overuse or underuse AI systems, either relying too much on them or avoiding them (Burton et al., 2020). Structured decision processes are therefore needed to ensure efficient use (Lee & See, 2004; Dietvorst et al., 2015). Lastly, they are responsible for escalation and risk management (Stelmaszak et al., 2025). Overall, the literature shows that AI adoption influences expectations towards managers, as the coordination of a human-AI system requires stronger analytical oversight.

In addition, AI adoption expands managerial responsibilities by adding requirements for responsible system use. Companies need to ensure unbiasedness and responsibility (Boussioux et al., 2024). There is a risk of AI-based models including systematic bias in decision-making processes (Kliegr et al., 2021; Boussioux et al., 2024). In addition to bias, AI raises broader ethical issues such as fairness, justice, and discrimination (Fjeld et al., 2020), as well as legal aspects such as accountability, regulation, and data privacy, including customer and employee

data (Berente et al., 2021). Managers are involved in these AI-related challenges because they oversee the work in which AI systems are used (Berente et al., 2021). Although they do not verify each output themselves, managers need to establish supervision processes and clarify AI-output responsibilities (Kolbjørnsrud et al., 2016; Kakatkar et al., 2020). As a result, ethical and regulatory considerations become increasingly integrated as a part of managerial responsibility.

2.3.3 Research Gap and Implications for the Empirical Study

Overall, the existing literature provides relevant insights into how AI adoption affects managerial tasks, coordination activities, employee responses, and oversight responsibilities (Kellogg et al., 2020; Berente et al., 2021; Raisch & Krakowski, 2021). Despite the growing interest, research on AI at work still provides a rather limited and often fragmented understanding of how AI shapes managerial work. Raisch and Krakowski (2021), for example, note that management scholars have so far offered limited insights into AI adoption. Furthermore, empirical studies often focus on specific use cases, such as AI-assisted writing, customer support, or software development, which raises the question of generalizing findings across different managerial roles (Noy & Zhang, 2023; Brynjolfsson et al., 2025; Ziegler et al., 2024). In addition, recent publications indicate that, while AI-related shifts in managerial work are acknowledged, the implications for the specific competencies required for managers remain insufficient (Berente et al., 2021). Established managerial competencies, as identified in O*NET, provide an important baseline for understanding how managerial requirements may shift in AI-enabled work environments (U.S. Department of Labor, 2025). To address these gaps, the empirical part of this thesis adopts an exploratory qualitative design.

3 Methods

This thesis uses an exploratory qualitative approach based on expert interviews in order to gain in-depth and practice-oriented insights that are still limited in existing research. Qualitative research provides access to practice-oriented knowledge (Edmondson & McManus, 2007; von Krogh, 2018). It is particularly suitable when relevant expertise is not fully captured in written sources or existing theory (Bogner et al., 2009; Patton, 2002) and when new insights need to be developed (Stebbins, 2011). Even though the interview guides were informed by the broad areas of research identified as affected by AI, these areas serve only as an orientation. They were not used as predefined categories. Inductive thematic analysis was applied to allow patterns to emerge directly from the experts' perspectives (Stebbins, 2011; Edmondson & McManus, 2007; Braun & Clarke, 2006). Semi-structured interviews with managers and AI experts created

practice-based insights that are not yet fully reflected in written sources (Edmondson & McManus, 2007; Patton, 2002).

3.1 Selection of Participants

A total of 15 managers and experts were interviewed, including 10 managers on different levels and five AI experts. They were recruited via professional networks. Interviewees were chosen using purposeful sampling to ensure that all had relevant experience and knowledge of the study topic (Patton, 2002; Palinkas et al., 2015). Selection criteria were that the people interviewed either 1) held a managerial position in companies already adopting AI or 2) had recognized expertise in AI implementation or AI management (e.g., through research in this field). Individuals meeting the first criterion are referred to as managers, while individuals meeting the second criterion are referred to as AI experts to clearly distinguish the two groups. Both groups meet the general definition of experts by Meuser and Nagel (2009), who define experts as individuals who have specialized, context-bound knowledge. Furthermore, managers were chosen based on criterion sampling, and AI experts were chosen based on key informant sampling (expert sampling) (Patton, 2002). Recruitment of new interviewees ended once additional interviews did not generate substantially new themes but rather confirmed topics already identified. This follows the principle of thematic saturation, defined as the point at which no new relevant themes or insights emerge from further interviews (Bowen, 2008). Prior research shows that saturation is often achieved after a limited number of interviews in focused and relatively homogeneous samples (Guest et al., 2006; Mason, 2010). In this thesis, saturation was achieved after 13 interviews. In line with Hennink and Kaiser (2022), two additional interviews were conducted to confirm that no new information emerged. The sample consisted of 40% female and 60% male participants. Participants varied in seniority, ranging from project and team leads to top executives and senior industry and AI experts. Professional experience was on average high, with most participants having more than 10 years of work experience and several exceeding 20 years. Given the recent emergence of AI in practice, this experience reflects general managerial or technical expertise rather than AI-specific work. Ages ranged from the mid-20s to the 60s. An overview of the interviewees is provided in Appendix 1.

3.2 Materials and Procedures

Interviews were conducted in a semi-structured format. This method allows the researcher to explore participants' experiences and opinions in depth while ensuring that all key topics are addressed across interviews (Patton, 2002). Interviews were conducted based on an interview

guide that focuses on certain topics and allows spontaneous follow-up questions (Brinkmann & Kvale, 2014). Based on this, two interview guides, one for managers and one for AI experts, were developed in alignment with the group's perspective and position. In alignment with the semi-structured approach and thematic organization of the interview (Braun & Clarke, 2006), questions were structured around five different blocks for flexible but systematic coverage. The structure and content of the guides were closely aligned with the earlier defined research questions and the influential dimensions of AI adoption. The following five areas were covered in both guides: (A) background and context, (B) shifts in managerial tasks and responsibilities, (C) competencies and skills required for effective AI implementation, (D) managerial actions that contribute to successful AI integration, and (E) reflection and outlook. The full guides can be found in Appendix 2 (Interview Guide Managers) and Appendix 3 (Interview Guide AI Experts).

Interviews were conducted with each interviewee individually to obtain personal views and to encourage openness (Adams, 2015; Solarino & Aguinis, 2021). All interviews were conducted virtually via Microsoft Teams. Interviewees were asked to choose a quiet and undisturbed place for the interview, which is recommended to minimize distractions and interruptions (Patton, 2002). Before the interview, participants were informed about the study purpose and usage of data. In addition, they were asked to provide consent for audio recording. This reflects standard practice in qualitative management research (Bryman & Bell, 2011). The automatic transcription feature from Microsoft Teams was used to generate transcripts. The transcripts were then manually checked and corrected to ensure accuracy (McMullin, 2021).

Some interviews were conducted in the interviewees' mother tongue (i.e., German) to allow participants to express themselves naturally and more precisely. As recommended by Temple and Young (2004), translation was not only technical but also interpretive, following guidance on cross-language research. The focus was on conveying meaning rather than word-for-word production (Temple & Young, 2004). Machine translation was used to increase efficiency and consistency in the translation. However, the output was manually reviewed to ensure accuracy and nuance. This is in line with the latest recommendations on AI-assisted translations (Blohm et al., 2025; Chidlow et al., 2014). This approach ensures the credibility, dependability, and confirmability of the data, following the established quality criteria of qualitative research (Lincoln & Guba, 1985).

The interviews lasted on average 50 minutes and 9 seconds (recorded duration). A brief summary of the main topic of the thesis, along with guiding questions, was used in PowerPoint format to support the interview flow. Interview questions were displayed sequentially using animations so that only the current topic was visible. Questions already addressed earlier in the interview were skipped, and spontaneous follow-up questions were asked to explore relevant themes in more depth. This approach supported systematic and comprehensive interviewing (Patton, 2002), as well as focused discussion, and enhanced the participants' understanding of key topics through visualization (Speer, 2008). The PowerPoint support slides can be found in Appendix 4.

3.3 Thematic Analysis

The interview data was analyzed following the thematic analysis proposed by Braun and Clarke (2006). Their methodology offers a systematic but flexible approach to identify patterns in qualitative data sets and is well suited for expert interviews (Braun & Clarke, 2013). The analysis follows a six-phase framework proposed by Braun and Clarke (2006), including 1) familiarizing yourself with your data, 2) generating initial codes, 3) searching for themes, 4) reviewing themes, 5) defining and naming themes, and 6) producing the report. In the first phase, all interviews are transcribed and translated according to earlier discussed standards. In addition, transcripts are read repeatedly for familiarization with the material and initial notes and ideas are recorded. In the second phase, relevant text segments are systematically coded in meaningful units, capturing all aspects relevant to the research questions. If applicable, each segment can be assigned to more than one code. In the third phase, the generated codes are organized into broader patterns to define themes based on similar codes, resulting in a framework for analysis. In the next phase, earlier defined themes are reviewed and refined to ensure coherence across the dataset. Based on this, a thematic map is created to illustrate the relation between themes. Fifth, each theme is examined in more depth to understand its role within the overall narrative of the data. Every theme is clearly defined, named, and described with a short definition. Finally, the sixth phase involves producing an analysis and report, which includes relevant quotes and meaning. Thus, it creates an overview of key findings from the data set.

Based on Braun and Clarke's (2006) distinction between inductive and theoretical thematic analysis, this thesis adopts an inductive approach. Codes and themes were created based on the interview data itself rather than from pre-existing literature. This approach allows new aspects to emerge beyond existing literature (Braun & Clarke, 2006) and without any constraints of

predefined structures (Thomas, 2006). This approach is particularly useful when existing theory provides limited guidance (Gioia et al., 2013). In addition, the analysis was conducted at a semantic level, focusing on explicit meanings expressed by the experts rather than underlying assumptions (Braun & Clarke, 2006).

3.4 Analytical Procedure

The coding and analysis of the interview data were conducted using MAXQDA (VERBI Software, 2025) and followed the six phases of thematic analysis outlined by Braun and Clarke (2006). Although the software supported the systematic organization and comparison of material, all analytical decisions and interpretations were made by the researcher. After transcription and familiarization, all interviews were imported into MAXQDA. In line with the first phase, transcripts were read multiple times to gain a holistic understanding of the material. During Phase 2, initial codes were generated inductively and applied systematically across all interviews, using semantic coding and focusing on explicit meanings. If necessary, passages were assigned to multiple codes. Across the full dataset, this resulted in 2017 coded segments and 471 distinct codes, reflecting the exploratory nature of the study and the aim to capture a broad range of perspectives in a nascent area (Edmondson & McManus, 2007). In the third phase, codes were organized into preliminary clusters using MAXQDA's creative coding function (VERBI Software, 2025). A picture of the preliminary coding structure can be found in Appendix 5. During Phase 4, these clusters were reviewed and refined to ensure conceptual clarity. Due to the number of codes, separate maps were created for each theme to visualize relationships between codes and subthemes. The theme maps are included in Appendix 6. In the fifth phase, each theme was clearly defined and described, resulting in five themes, including 26 sub-themes. This thematic structure is provided in Appendix 7 (Table of Themes & Sub-Themes) and reflects the structure used in the analysis. The final list of all codes is included in Appendix 8. The final stage consisted of producing the report. Illustrative quotations were selected in order to support the analytic narrative. Selections were made based on their relevance and clarity.

4 Results

Across interviews, a relatively coherent picture emerged of how AI is reshaping managerial work, competencies, and practices associated with successful AI adoption. The results are structured according to the five themes identified through the thematic analysis (Braun & Clarke, 2006). The first theme captures perceived advantages and attitudes towards AI and

serves to contextualize the organizational setting in which AI adoption takes place. Building on this background, the second theme examines how AI transforms managerial work and responsibilities, addressing changes in tasks, roles, and value creation (RQ1). The third theme focuses on the competencies managers require to operate effectively in AI-supported environments (RQ2). Complementing these findings, the fourth theme outlines risks and barriers that may influence how managers engage with AI in practice. The fifth theme describes leadership practices that the interviewees associate with successful AI adoption, addressing RQ3. To distinguish between the two interviewee groups, interview quotes are labeled as EM (Expert Manager) and EAI (AI Expert), followed by the individual interviewee number.

4.1 Perceived Advantages and Attitudes Towards AI

Interviewees described a predominantly positive attitude toward AI (EM1; EM2; EM5; EM8; EM9; EM10; EAI1; EAI2; EAI3; EAI5). Several managers and experts emphasized that AI offers new possibilities, with one manager stating, “I experience artificial intelligence as a strong enrichment” (EM1, P72). Many interviewees also pointed out that the capabilities of AI are rapidly improving, reinforcing expectations of continuous technological progress (EM1; EM2; EM3; EM4; EM5; EM7; EAI1). This dynamic was illustrated by one manager who said, “It is a technology that develops incredibly quickly. What did not work three weeks ago may work very well three weeks later” (EM5, P48).

In addition to these generally positive attitudes, the interviewees described noticeable differences in how employees approach AI. Younger employees were often perceived as more intuitive and open, whereas older employees tended to be more cautious or hesitant (EM1; EM2; EM3; EM4; EM5; EM6; EM7; EM8; EM9; EAI2; EAI3; EAI4; EAI5). This was illustrated by contrasting statements such as “younger generations are noticeably smarter and more skilled in this regard” (EM6, P42) versus a manager describing a typical reaction of an older employee “Leave me out of it; I don’t want to change” (EM2, P54).

Furthermore, interviewees described that AI simplifies various aspects of daily work. They mentioned reductions in administrative burdens (EM5; EAI4) and a general ease in routine activities (EM4; EM7; EM8; EM9; EM10). Beyond simplification, the interviewees emphasized that AI improves the informational basis for managerial decision-making by increasing the amount, speed, and structure of accessible information (EM1; EM2; EM4; EM9; EM10; EAI3; EAI4; EAI5). One manager explained that AI could soon enable her team to have

“one hundred percent, actively in view [instead of] around thirty percent [today]” in a decision-making process (EM9, P18).

Finally, many interviewees associated AI with efficiency gains and time savings (EM1; EM2; EM3; EM5; EM7; EM8; EM10; EAI1; EAI3; EAI4; EAI5). They described noticeable acceleration in their work, with one manager noting that “where I used to say, ‘Give me a week to get back to you,’ I now just write a prompt myself and get an answer within two minutes” (EM2, P19).

4.2 How AI Transforms Managerial Work and Responsibilities

Throughout the interviews, both managers and AI experts described how AI increasingly takes over a broad range of operational, analytical, and preparatory tasks. Interviewees reported that AI performs simple data processing tasks and preliminary analytical steps that would formerly require manual effort or staff support (EM8; EM10; EAI1; EAI2; EAI3; EAI5). Managers further highlighted that AI enables faster information retrieval and pre-filtering of content, resulting in time savings on searching, scanning, or compiling materials (EM1; EM5; EM6; EM10; EAI1; EAI5). In addition, AI supports the creation of summaries and condensed briefings that allow managers to make decisions with a stronger and more accessible information base than before (EM1; EM3; EM4; EM5; EM6; EM8; EM9; EM10; EAI4; EAI5). Similar shifts were described for general meeting structures, with AI supporting the structuring of topics, generating briefing notes, or consolidating dispersed materials. Administrative and low-value tasks such as drafting routine emails, preparing initial text versions, or adapting documents, as well as creating initial layouts, were further mentioned (EM1; EM2; EM3; EM5; EM6; EM7; EM8; EM9; EM10; EAI1; EAI2; EAI3; EAI4; EAI5). Moreover, several interviewees noted that AI supports early analytical steps, simple forecasting, and preliminary data interpretation, allowing managers to focus more on reviewing these materials (EM1; EM2; EM3; EM8; EM10; EAI3; EAI4; EAI5). Even if managers did not previously perform every task themselves, AI changes how they coordinate with their teams, brief themselves, and access information, for example, “by summarizing information much faster than a human can” (EM10, P24).

As these tasks are automated, managers rely more heavily on AI materials, which introduces new responsibilities around oversight and quality control. Interviewees emphasized that AI outputs require careful validation and plausibility checks (EM1; EM2; EM3; EM4; EM5; EM7; EM8; EM9; EM10; EAI1; EAI2; EAI3; EAI4; EAI5), with one manager stating the need to

“check the quality and accuracy of everything” (EM8, P36). Responsibility for the correctness and relevance of outputs remains with managers who cannot delegate accountability to the system (EM1; EM2; EM4; EM7; EM9; EM10; EAI3; EAI5). This responsibility is linked both to legal liability, for example, when “a human signs a solution” (EM4, P38) or “if AI-based decisions cause losses for the bank, that’s considered an organizational fault that we, as management, would be held personally responsible for” (EM2, P66), but also the broader responsibility inherent in the managerial role (EAI5). Consequently, managers increasingly focus on reviewing, refining, and supervising AI-supported work, including monitoring how AI is used within their team and acting as safeguards for responsible and ethical use (EM2; EM3; EM4; EAI2; EAI4; EAI5).

The broader data access allows managers to work with more structured information and take a more strategic and interpretive approach, rather than an intuitive one when guiding their teams (EM4; EM9). Experts reported that providing orientation and direction, as well as giving employees a sense of purpose, becomes increasingly more important in the context of AI (EAI2; EAI4). Overall, interviewees also mentioned that human-centered leadership gains relevance as employees work with changing processes and tools (EM1; EM2; EM3; EM5; EAI3; EAI4; EAI5). This was particularly emphasized by two AI experts stating that future leaders “will become radically more human” (EAI4, P46) and be “responsible for people and more of a coach on a human level” (EAI5, P22). Interviewees also mentioned a future-oriented view in which AI might be perceived as a team member, indicating an emerging way of collaboration (EM5; EAI2).

Moreover, interviewees described organizational and structural changes connected to the growing adoption of AI. They noted that job profiles need to evolve, as some activities lose relevance while new expectations emerge (EM5; EM7; EM10; EAI1; EAI2). One AI expert stated, “I think the change in job profiles is quite central” (EAI2, P18). At the same time, interviewees emphasized that their formal and contractual responsibilities are often unchanged, even though their content shifts in practice (EM1; EM5; EM6; EM7; EM9; EAI1). One interviewee explained, “It falls under leadership as a responsibility, and leadership itself has not shifted, but content-wise it is something completely different” (EM7, P40). In relation to this, interviewees described growing expectations for upskilling and continuous learning of their employees, as well as AI-related assistance (EM1; EM5; EM7; EM8; EAI4). This leads to increased workloads, as managers spend more time exploring AI tools, participating in training activities, and supporting their employees in use (EM5; EM7; EM8; EM10; EAI4; EAI5). As

one expert observed, “[Managers] suddenly find [themselves] responsible for upskilling” (EAI4, P18). Furthermore, the increasing adoption of AI may lead to workflow and process adjustments (EM1; EM2; EM5; EM6; EM8; EAI1; EAI2; EAI5). Interviewees mentioned an organizational move toward more process-oriented structures to align work with AI-supported activities (EM9; EAI2). Overall, they noted the need for future adjustments in how work is formally structured (EM5; EM7; EM10; EAI1; EAI2). Even though none of the interviewees mentioned full managerial substitution, several pointed to the possibility that routine or entry-level tasks may disappear in the future (EM2; EM3; EM5; EM6; EM8; EAI1; EAI2).

Interviewees further mentioned that AI changes how managerial value is created (EM2; EM6; EAI2; EAI3), increasingly stemming from strategic and communication-focused activities that shape AI-supported content into direction and clarity (EM1; EM2; EM8; EM9; EAI3; EAI4). For example, one manager stated, “[I] simply save time that I can actually invest in strategic thinking” (EM2, P23). In this context, interviewees emphasized a broader shift from producing inputs toward interpreting results (EM6; EM7; EM9; EM10; EAI4). Human judgement remains central, particularly in recognizing patterns and connecting information to organizational goals, as managers “are paid to see patterns and connections that no software can detect” (EAI4, P10). One expert further mentioned that she perceives the value of managerial work mainly in innovation, strategic orientation, and forward-looking decision-making (EAI2).

4.3 Competencies and Skills Required for Effective Implementation

The interviews revealed a distinct set of competencies that interviewees considered essential for effectively adopting and navigating AI-supported work environments. They highlighted the importance of critical evaluation and particularly the ability to validate AI outputs (EM1; EM3; EM4; EM5; EM7; EM8; EM9; EM10; EAI2; EAI3; EAI4). As one AI expert stated, “We must never accept AI outputs as unquestionable truth but always evaluate them against our own experience and values” (EAI4, P36). This evaluative work relies on domain knowledge and expert judgement to detect inconsistencies or errors that AI may overlook (EM2; EM6; EM7; EM9; EAI2; EAI3). Interviewees further emphasized the importance of maintaining non-AI operational competencies to ensure holistic oversight despite automation (EM3; EM4; EM5; EAI2). Ethical awareness, including bias sensitivity, responsibility, and risk awareness in AI use, was also highlighted as a core competence (EM1; EM2; EM3; EM4; EM6; EAI1; EAI4; EAI5).

For facilitating the practical use of AI, a baseline technological competence and digital intuition were mentioned (EM1; EM5; EM7; EM9; EAI1; EAI2; EAI4; EAI5). Furthermore, interviewees emphasized the relevance of understanding AI's functionalities, as well as its constraints (EM1; EM2; EM3; EM4; EM6; EM9; EAI1; EAI2; EAI3; EAI4; EAI5). Effective AI use further depends on interaction competencies such as the ability to formulate precise instructions, which was also mentioned as prompting, or giving context (EM1; EM2; EM3; EM4; EM5; EM6; EM9; EM10; EAI3; EAI4; EAI5). As one expert stated, “You need to know how to ask the right questions” (EAI4, P20). Interviewees explained that prompting has become more intuitive overall, as systems increasingly understand natural language (EM6; EAI2). As tools differ in how they need to be used, multi-tool proficiency, the ability to select appropriate tools, and a general understanding of functions are needed in order to work efficiently with AI (EM1; EM6; EM7; EM8; EM10; EAI2; EAI3; EAI5). Depending on the role, support in solution finding and deeper practical AI proficiency may be relevant (EM7; EM8; EM10; EAI1; EAI2; EAI3; EAI4; EAI5).

Interviewees also described the growing importance of interpersonal and human-centered leadership skills in AI-supported environments (EM1; EM2; EM3; EM4; EM5; EM9; EM10; EAI1; EAI3; EAI4; EAI5). Managers need to be able to reduce AI-related fears through empathetic leadership (EM1; EM2; EM9; EAI4) and show emotional intelligence in AI-related conversations (EM10; EAI1; EAI4). Furthermore, psychological awareness of team heterogeneity and the need to address diverse needs, particularly across different age groups (EM1; EM2; EM4; EM7; EAI2; EAI5), were mentioned. These competencies were described as more critical than technical expertise (EM1; EAI2), as not all employees adopt AI at the same pace. Interviewees further pointed out the need for motivational abilities (EM2; EAI1) and the competence to create meaning and help individuals navigate uncertainty (EAI2, EAI4). In this context, the ability to act as human counterparts based on empathy-driven leadership was mentioned (EM2; EAI1; EAI3; EAI4), with one expert stating an example of an employee feeling like “I am supposed to control something that in my feeling is better than I am” (EAI1, P44). Overall, interviewees emphasized that human interaction and self-reflective leadership become increasingly central as AI reshapes established work routines (EM1; EM5; EM8; EM10; EAI2; EAI4).

Furthermore, an increasing relevance of strategic and creative competencies was highlighted. While control, communication, and strategic thinking remain important (EAI1), interviewees emphasized that structural and strategic judgement will be required more deliberately to guide

decision-making and maintain direction in increasingly AI-mediated contexts (EM3; EM8; EM10; EAI1). AI experts also described a growing need for strategic creativity and imagination (EAI1; EAI2), as AI often provides starting points that require human conceptualization. Additionally, the experts mentioned the relevance of increased solution orientation (EM7), abstraction ability (EAI3), and problem-solving competence (EAI3), as AI outputs require managers' interpretations to turn them into choices, and concrete next steps. One manager emphasized, “AI can propose actions very well, but deciding if they are the right actions, that is where the human comes in” (EM7, P78).

Interviewees also emphasized a broad set of learning- and change-related competencies that have become increasingly important in AI-supported work environments. They highlighted the need for a flexible and adaptive mindset (EM1; EM7; EM10; EAI1), as well as a high degree of openness to learning and continuous engagement in new developments (EM1; EM2; EM3; EM5; EM6; EM7; EM8; EM9; EM10; EAI1; EAI3; EAI4), in order to keep pace with the perceived rapid evolution of AI (EM5; EM10; EAI4). These capabilities were closely linked to proactiveness (EM7; EAI4), the ability to operate effectively under uncertainty (EM5; EM10; EAI4), and broader change-leadership competences (EM1; EM2; EM5; EM7; EM9; EM10; EAI1; EAI3; EAI4). Interviewees further stressed the relevance of fostering a learning culture (EM2; EM7; EM8) and maintaining persistence in iterative problem-solving, for example, “staying persistent until you build solutions that really create value” (EM7, P68). One manager summarized this shift, stating that “Success depends less on experience or hierarchy and more on willingness to learn, adaptability, and courageous experimentation” (EM1, P70).

4.4 Barriers and Risks to AI Adoption

Across interviews, interviewees mentioned several risks and barriers associated with AI adoption and managerial engagement, which frame and constrain changes in managerial work and competencies. In relation to managerial responsibilities, interviewees frequently mentioned ethical, legal, and compliance-related uncertainties, including concerns that employees “might input confidential data into an external AI” (EM8, P54). They particularly pointed out data protection concerns and confidential information leakage into external systems (EM1; EM2; EM3; EM4; EM5; EM6; EM8; EM9; EAI1; EAI4; EAI5). Legal restrictions and regulatory frameworks, such as the EU AI Act were further mentioned (EM2; EM4; EM6; EAI3; EAI5), often linked to the concern of uncontrolled private tools (EM2; EM3; EM4; EM5; EAI1; EAI5). Beyond compliance-related aspects, interviewees raised concerns about unreliable outputs and ethical ambiguity (EM1; EM2; EM3; EM6; EAI1; EAI4; EAI5). These challenges were

described as complicating managerial decision-making, directly affecting how managers fulfill their responsibilities in AI-supported environments (RQ1).

Interviewees also identified barriers to skill development. They referred to limited availability for engaging with AI tools (EM7) and uneven learning dynamics across employee groups and generations (EM1; EM2; EM4; EM5; EM7; EM9; EAI2; EAI3). AI experts further mentioned that the use of AI often remains superficial due to limited understanding or an underestimation of its capabilities (EAI2; EAI3). Some experts expressed concerns regarding the increasing complexity of AI systems. In particular, they noted that individuals may lack the capability to effectively oversee complex AI-supported processes or struggle with the shift toward more abstract and conceptual tasks (EAI1; EAI2). In addition, several interviewees mentioned the risk that AI usage may reduce opportunities for junior employees to develop foundational skills, which they viewed as problematic due to potential skill loss and future expertise development (EM2; EM3; EM4; EM7; EM10; EAI1; EAI2). These barriers explain the need and basis for certain competencies and skills identified earlier (RQ2).

Beyond these implications, interviewees emphasized risks and barriers that directly shape how managers need to act to enable effective AI adoption in practice. At the organizational level, they pointed to insufficient preparation, limited access to appropriate tools, and fragmented or outdated technical infrastructures (EM2; EM4; EM6; EM7; EM8; EM9; EAI1; EAI2; EAI3; EAI5). These conditions were described as constraints on effective AI use, which depends strongly on data quality and availability (EM9; EAI3). Inconsistent communication from upper management and a lack of clear guidance regarding AI use were further described as hindering (EM1; EM5; EM6; EM8; EM9), as one manager noted, “I have not seen that our top management said: Attention, AI is our future, please engage with it. That is one aspect, the official go to deal with it” (EM4, P78). In addition, uncertainty about measurable AI impact and the absence of clear performance metrics were described as barriers that undermine confidence (EM1; EM5; EM7; EM9; EM10; EAI4; EAI5). Interviewees also referred to technological limitations of AI systems, such as hallucinations (EM2; EM5; EM6; EM8; EM10; EAI2; EAI5), inaccurate or unreliable output (EM2; EM3; EM4; EM6; EM8; EM9; EM10; EAI2), and difficulties in handling more complex tasks (EM2; EM3; EM5; EM8; EAI1; EAI2). One manager addressed the risk of missing out on something “that is wrong because of hallucinations or a wrong result” (EM5, P60). Some also pointed to model limitations, such as biases or missing bias detection (EM1; EM3; EM6). Moreover, interviewees highlighted psychological and emotional barriers that managers need to address through leadership

practices. These include fears related to job security, uncertainty about AI use within areas of responsibility (EM1; EM2; EM3; EM7; EM9; EAI1; EAI3; EAI4; EAI5), emotional strains resulting from rapid change, intensified expectations (EM1; EAI1), or increased monitoring (EM10; EAI2; EAI4; EAI5). Several managers further mentioned that persistence in established routines can slow AI adoption (EM1; EM2; EM3; EM4; EM6; EM8; EM10). AI experts raised concerns about the loss of professional identity, particularly when employees feel displaced or reduced in their role through AI (EAI1; EAI2). These barriers were described as shaping how managers engage with AI in practice, influencing the leadership actions through which AI adoption is addressed (RQ3).

4.5 Leadership Practices Enabling Successful AI Adoption

Interviewees described a range of leadership practices they consider essential for supporting successful AI adoption, such as communication and conditions that encourage engagement, learning, and responsible use. More specifically, interviewees emphasized that employees need active encouragement to engage with AI tools (EM1; EM2; EM3; EM5; EM6; EM7; EM8; EM10; EAI1). Managers were seen as responsible for motivating and legitimizing AI use, as one top manager noted, “Their task is to spread the topic within their team, to motivate colleagues, and to encourage use. Ultimately, it’s also a leadership responsibility” (EM2, P50). Furthermore, creating psychological safety and reassuring employees that experimentation is permitted and welcomed were highlighted as key leadership actions (EM2; EM3; EM4; EM5; EM10; EAI1). Transparent communication, such as openly addressing uncertainties and clarifying expectations, was further described as essential for reducing fears and building trust (EM1; EM2; EM6; EM9; EM10; EAI3; EAI4; EAI5). Creating an environment in which errors are treated as part of the learning process is also important (EM3; EM5; EM6; EM10).

In addition, interviewees outlined leadership practices that support a learning-oriented AI culture. In particular, they mentioned that managers should play a central role in organizing access to structured training and upskilling opportunities (EM1; EM5; EM7; EM8; EM9; EM10; EAI1; EAI2; EAI3; EAI4; EAI5), such as technical introductions (EM1; EM2; EM3; EM6; EM8; EM10), prompting training (EM2; EM6; EM8), and compliance-related sessions (EM1; EM2; EM8; EAI5). Encouraging continuous learning and fostering a balanced understanding of the possibilities and limitations of AI were emphasized as important (EM1; EM6; EM8; EM9; EM10), as one expert summarized, “You don’t need to be a programmer, but you must understand what the technology can do, where its limits are” (EAI4).

Interviewees also described practices that foster an AI-supportive team culture. These include visibly endorsing AI, encouraging bottom-up ideas and practical use cases (EM2; EM4; EM6; EM7; EM8; EM9; EM10; EAI4; EAI5). Furthermore, managers should recognize contributions and make progress visible to strengthen motivation and engagement (EM2; EM4; EM5; EM7). Managers were advised to actively balance different adoption speeds within the team to maintain engagement and prevent disengagement or overuse (EM2; EM4; EAI1; EAI2; EAI4; EAI5).

Beyond cultural aspects, interviewees highlighted structural and enabling actions that support AI adoption in practice. These include providing secure and reliable AI tools that meet internal standards to avoid uncontrolled usage (EM1; EM2; EM5; EAI1; EAI5), as one expert warned, “If the technology exists employees may use it illegally and that is a bigger risk” (EAI5, P44). Moreover, establishing clear contact points for AI-related questions was mentioned (EM8; EAI3). Interviewees further emphasized the role of internal AI experts (EM2; EM5; EM6; EM8; EAI1; EAI3) or dedicated teams to support employees and consolidate expertise (EM2; EM4; EM7; EAI1; EAI3; EAI5). Centralized structures for coordinating and evaluating AI use cases were also mentioned as helpful for aligning activities across the organization (EM2; EAI4).

Interviewees further emphasized that clear governance rules (EM1; EM2; EM6; EAI1; EAI3; EAI5) and compliance boundaries are essential to guide responsible AI use (EM1; EM2; EM6; EAI3; EAI4; EAI5). They also mentioned the value of a problem-first approach to ensure that AI is only applied where it provides clear organizational benefits (EM1; EM5; EM7; EM9; EM10; EAI4; EAI5), as one manager shared: “If AI is useful for achieving this goal, then we use it, but not as an end in itself to advertise or to measure ourselves by it” (EM5, P68). In addition, linking AI initiatives to measurable outcomes was highlighted to guide prioritization (EM1; EM2; EM3; EM8; EM10; EAI4; EAI5). In addition, formal authorization by top management (EM1; EM3; EM4; EM6; EM8; EM10; EAI3) and cross-functional perspectives were mentioned as important for enabling coordinated and accepted AI adoption (EM1; EM2; EM6).

Finally, interviewees highlighted the importance of enabling safe and low-threshold experimentation with AI. They referred to the value of protected testing environments (EM1; EM2; EM3; EM5; EM6; EM10; EAI4; EAI5) and early success stories to build confidence and demonstrate practical benefits (EM1; EM3; EM5; EM6; EM7; EAI3; EAI4). As one manager noted, “Only when the benefit is clearly visible does the willingness to use it increase” (EM1,

P52). In addition, opportunities for regular exchange, informal knowledge sharing, and structured exploration formats such as workshops (EAI3), hackathons (EM7; EM8), or other staged testing environments were described as supporting engagement and learning (EM1; EM4; EM5; EAI5). Furthermore, some interviewees mentioned that incentives of different formats can help lower barriers and motivate employees to use AI (EM1; EM2; EM7; EM8).

In summary, interviewees described the following leadership actions as enabling for effective AI adoption:

- Legitimizing AI use through active encouragement, role modeling, and visible support from managers (EM1; EM2; EM3; EM4; EM5; EM6; EM7; EM8; EM9; EM10; EAI1; EAI5)
- Transparent communication and clarification of expectations regarding the use of AI (EM1; EM2; EM6; EM9; EM10; EAI3; EAI4; EAI5)
- Creating psychological safety and openly addressing fears and uncertainties related to AI (EM2; EM3; EM4; EM5; EM6; EM10; EAI1)
- Providing access to structured training, and continuous learning opportunities (EM1; EM2; EM3; EM5; EM6; EM7; EM8; EM9; EM10; EAI1; EAI2; EAI3; EAI4; EAI5)
- Enabling low-risk experimentation through pilot projects, workshops, hackathons, and other testing formats in protected environments (EM1; EM2; EM3; EM4; EM5; EM6; EM7; EM8; EM10; EAI3; EAI4; EAI5)
- Normalizing AI use in everyday work through recognition, visibility of progress, and mutual learning (EM1; EM2; EM4; EM5; EM6; EM7; EM8; EM9; EM10; EAI3; EAI4; EAI5)
- Providing secure AI tools, internal experts, and contact persons (EM1; EM2; EM4; EM5; EM6; EM7; EM8; EAI1; EAI3; EAI5)
- Establishing governance rules and compliance boundaries (EM1; EM2; EM6; EAI1; EAI3; EAI4; EAI5)
- Adopting a problem-first approach to the use of AI, including the definition of measurable outcomes (EM1; EM2; EM3; EM5; EM7; EM8; EM9; EM10; EAI4; EAI5)

5 Discussion

5.1 Interpretation of Findings

In this section, the three research questions of this thesis are discussed and answered on the basis of the interview results in relation to the existing literature. Both prior research and interview findings indicate that AI adoption leads to changes in managerial work. Interview findings reinforce the perspective that managers function as central actors in integrating new technologies into organizations (Cooper & Zmud, 1990; Berente et al., 2021). In contrast to classical implementation frameworks (Cooper & Zmud, 1990; Tursunbayeva & Gal, 2024) that describe AI adoption as a formal and staged process, interviewees experienced AI implementation in reality more as a gradual development through everyday work.

Shifts in managerial work, responsibilities, and value creation. A central change mentioned in the interviews concerns the flow of managerial work. Prior to AI adoption, managers often depended on the timing, availability, and quality of their stakeholders' work when tasks were delegated. AI reduces these dependencies by enabling direct and immediate access to information and preliminary analyses through centralized data sources. As a result, managers can engage with decision material earlier and more continuously. This aligns with research describing AI as a technology that supports and augments organizational work processes (Berente et al., 2021; Raisch & Krakowski, 2021). However, the interviews add a new layer, as this temporal dimension has received limited attention so far, with prior studies focusing on individual productivity in specific areas (Noy & Zhang, 2023; Brynjolfsson et al., 2025; Ziegler et al., 2024). For managers, rather than reducing involvement, AI is perceived to intensify decision cycles. In this sense, AI reinforces classical characteristics of managerial work as fast-paced and fragmented (Mintzberg, 1990), while increasing the immediacy of decision-making.

In parallel, formal managerial responsibility structures remain unchanged. Managers continue to be responsible for outcomes within their area of responsibility (Fayol, 1949). However, the interviews indicate that the focus of responsibility is expanding. Instead of evaluating human-generated work, managers increasingly oversee AI-supported outputs, including their accuracy and appropriate use. This highlights a gap between stable formal job descriptions and evolving practical expectations. From a job analysis perspective, this shift reflects a reconfiguration of how managerial KRAs (Armstrong & Taylor, 2014) are enacted. Interviewees further emphasized that responsibility cannot be delegated to the system itself, increasing the importance of validation and supervision. Managers were more likely to view accountability as

a personal obligation, while AI experts emphasized it as a structural governance level. These differing perspectives align with prior research highlighting accountability challenges and oversight requirements in AI-supported work contexts (Kolbjørnsrud et al., 2016; Kellogg et al., 2020). In practice, this expansion of responsibility often takes place without established reference points, making managers responsible for how AI is used and interpreted within their teams. For example, interviewees noted that managers are increasingly expected to support learning, upskilling, and responsible experimentation. As AI adoption progresses, these activities become central, contributing to a paradox in which efficiency gains coexist with expanding developmental responsibilities. Classical job analysis (Armstrong & Taylor, 2014; Cascio & Aguinis, 2011) provides the basis for role definitions, but is often too static to capture these evolving demands due to AI.

In response to RQ1, this section shows that managerial contribution increasingly lies in interpreting, prioritizing, and aligning AI-supported outputs with organizational goals. Value creation is perceived to increasingly shift toward contextual judgement, strategic orientation, and ensuring coherence in decision-making processes.

Shifts in managerial competencies and skills in AI-supported work. Drawing on the managerial KSA(O) elements (Campion et al., 2011; Cascio & Aguinis, 2011) specified in O*NET (U.S. Department of Labor, 2025), the interviews indicate that AI adoption reweights and reshapes managerial competencies. For the area of knowledge, interviews suggest that managerial and domain knowledge remain central. Existing knowledge becomes even more critical as a reference point for evaluating AI-supported outputs. Interviewees repeatedly emphasized that understanding processes, content, and organizational context is necessary to detect implausible results or bias. However, as language-related knowledge is supported by AI in the form of content production or summarization, the required effort is perceived to reduce. The responsibility for these outcomes still lies with managers. Other O*NET knowledge areas, such as production or mathematical knowledge, were not directly addressed.

O*NET ranks active listening, monitoring, reading comprehension, speaking, and coordination as the most important managerial skills, followed by critical thinking, management of personnel resources (motivating and developing), social perceptiveness, active learning, and complex problem solving. The interviews indicate that highly ranked skills such as monitoring, active listening, and coordination remain central. Yet, their application shifts toward supervising AI-supported work and helping employees navigate uncertainty, hesitation, and uneven adoption.

Skills ranked a bit lower in O*NET, such as critical thinking, complex problem solving, and active learning, gain relevance as managers interpret and validate AI outputs and need to adapt continuously and rapidly to evolving systems. In contrast, skills such as reading comprehension and speaking were perceived as necessary but less performance-differentiating in the context of AI. Human-centered skills were perceived to become more critical for sustaining effective leadership during ongoing change. Furthermore, interviewees repeatedly referred to AI-specific interaction and evaluation requirements (e.g., prompting, understanding limitations, or output verification), which add a distinct AI-related skill layer.

In addition, O*NET emphasizes cognitive abilities such as oral and written comprehension and expression, as well as deductive reasoning. Interview findings indicate that these abilities remain essential and are increasingly applied under conditions of uncertainty and limited system transparency. Rather than reducing cognitive demands, AI adoption appears to increase the need for judgement, abstraction, and reasoning by translating AI outputs into decisions and actions. No decline in the relevance of core abilities was observed. Overall, these findings answer RQ2 by showing that managerial competencies are rebalanced. Judgement, interpretive skills, and human-centered leadership gain importance, complemented by new AI-related skills.

Managerial actions for successful AI adoption. The interview findings largely align with recent AI-focused research that highlights communication, trust, and the management of employee reactions as central to effective AI adoption (Burton et al., 2020; Kellogg et al., 2020; Georganta & Ulfert, 2024). They further reflect core insights from technology acceptance research (UTAUT), which states that expectations and communication shape how users engage with new systems (Venkatesh et al., 2003). The qualitative findings support existing models that view AI adoption as a process shaped by technical and social factors (Cooper & Zmud, 1990; Venkatesh et al., 2003; Berente et al., 2021). The interviewees' strong emphasis on legitimizing AI use, addressing uncertainty, and fostering psychological safety is consistent with these insights.

At the same time, the interviews offer a more practice-oriented perspective. Interviewees described specific managerial actions, including active encouragement, visible support, and transparent communication with clear expectation setting. They also emphasized that creating psychological safety and openly addressing fears and uncertainties is essential for promoting engagement and learning. Moreover, interviewees highlighted specific practices less explicitly described in existing research on managerial oversight and responsibility in AI-supported

environments (Kolbjørnsrud et al., 2016; Kellogg et al., 2020). These include training and development opportunities, as well as low-risk experimentation through pilot projects, workshops, and hackathons in protected environments. Moreover, the importance of internal contact persons, as well as the establishment of governance rules and compliance boundaries, were emphasized. Interviewees stated that AI should be used as a tool to solve organizational problems instead of adopting AI for its own sake. This includes defining measurable outcomes to support prioritization and ensure responsible use. Taken together, these findings address RQ3 by identifying specific managerial actions that translate competencies into successful AI adoption outcomes.

5.2 Theoretical Implications

The findings contribute to the conceptual understanding of AI-enabled managerial work by showing that AI does not only affect what managers do but also the temporal structure of work, for example, by shortening decision cycles. Formal job descriptions are intended to provide stable reference points for roles (Armstrong & Taylor, 2014). However, interview findings highlight a gap between stable formal role structures and AI-supported managerial work in practice, as managers increasingly validate AI outputs, support employee learning, and provide orientation in AI-related situations of uncertainty. Similarly, job analysis and competency profiles such as those provided in O*NET (U.S. Department of Labor, 2025), offer an important reference for describing managerial requirements. At the same time, the findings indicate a need for more targeted AI-specific competency profiles that capture both the new technical skills and the shifts in how existing competencies are weighted and applied in AI-supported managerial work. As AI becomes increasingly integrated into organizational processes, these requirements are likely to become relevant for a growing number of managers (McKinsey, 2025). Furthermore, the insights extend classical technology-adoption perspectives such as UTAUT (Venkatesh et al., 2003), which focus primarily on individual acceptance, by adding a managerial layer to AI adoption. Specifically, they highlight evolving competencies and responsibilities, as well as the relevance of direction setting. Overall, the interview findings suggest that existing conceptualizations of managerial work do not fully capture how responsibilities and competencies are being reshaped in AI-enabled work environments.

5.3 Practical Implications for Managers and Organizations

For managers, the findings suggest that AI adoption requires a stronger focus on interpretive, evaluative, and relational aspects of leadership compared to the traditional emphasis on

planning, coordinating, and controlling work processes (Fayol, 1949; Mintzberg, 1990). This implies a need to develop skills in contextual judgement and sense-making, accompanied by a basic understanding of AI possibilities and limitations, to guide teams through shifting work practices. Based on this, managers may also need to actively shape the introduction of AI by framing its purpose, demonstrating responsible experimentation, and supporting employees during early experimentation. Such behavior can help reduce uncertainty and strengthen effective AI engagement.

For organizations, the results indicate that existing role definitions, competency models, and development structures may need to be adjusted. Supporting managers in continuous learning, creating time and resources for upskilling and ensuring access to reliable AI tools can help guide the organization through the AI adoption shift. Organizations may also benefit from approaching AI adoption in a purpose-driven manner, rather than integrating AI for the sake of it. Aligning its use with concrete organizational goals can help ensure focused and value-adding adoption. The findings further highlight the importance of designing work environments that foster psychological safety and balanced adoption dynamics. Organizations should consider how communication, training formats, and governance structures can reduce uncertainty and enable responsible experimentation with AI.

5.4 Limitations and Future Research

While this thesis provides valuable insights into the managerial dimension of AI adoption, several limitations need to be acknowledged. Although the sampling approach followed established saturation logic, it is nevertheless possible that additional interviews would have revealed further insights. The empirical research is based on 15 qualitative interviews. No substantially new codes emerged in the last three interviews (Bowen, 2008).

Furthermore, the predominance of large organizations (80%) in managerial interviews (n=10) and the inclusion of repeated organizational context (30%) could have shaped the patterns identified. In addition, the recruitment of participants through professional and extended networks raises the possibility of selection bias, as the sample was not randomly drawn (Robinson, 2014). This raises the possibility that participants may share similar professional environments or networks. However, this approach is typical for purposeful sampling in qualitative research and appropriate when specific expertise is required (Patton, 2002).

Another limitation concerns the composition of the sample, as the study combines managerial and expert perspectives without systematic subgroup analysis. Differing viewpoints were

mentioned transparently, but the lack of structured comparison may limit conclusions about potential differences. Another relevant limitation is the absence of employee perspectives without leadership responsibility. This resulted in a predominantly top-down view of AI adoption. Prior research emphasizes that AI adoption is not only a technical implementation issue but strongly shaped by employee perceptions and acceptance (Venkatesh et al., 2003; Burton et al., 2020).

Differences across different hierarchy levels, or organizational AI maturity stages, were also not analyzed, although prior research highlights that AI adoption is context-dependent and effects may differ depending on the role or stage of integration (Berente et al., 2021; Tursunbayeva & Gal, 2024). In addition, the analysis does not differentiate between different types of AI systems or levels of AI maturity across organizations, which may influence outcomes. This reflects the capability-oriented view of this thesis (Berente et al., 2021). Furthermore, the study uses a cross-sectional design (Bryman, 2016) in a rapidly evolving technological field, which means that the findings only present a momentary snapshot. As AI and organizational practices continue to advance, managerial roles and competencies may shift further (Csaszar et al., 2024; Berente et al., 2021).

Another limitation relates to data processing. Although several interviews were conducted in the participants' native language, the translation may have produced minor losses of nuance despite careful review (Temple & Young, 2004). Additionally, all interviews were coded and analyzed by a single researcher. Single-coder thematic analysis is common and accepted (Braun & Clarke, 2006), but this procedure may increase the potential for subjectivity in analysis and limit the identification of all relevant aspects, despite systematic coding. Finally, the thesis centers on managerial perceptions and does not link these to objective indicators such as performance metrics or outcomes, which prior research associates with company-level performance (Bloom & van Reenen, 2007). These limitations should be considered when interpreting and generalizing findings.

Future research could build on the findings of this thesis by examining how managerial roles and competencies evolve over time as AI adoption progresses (Berente et al., 2021). More differentiated analyses across hierarchy levels, AI maturity stages, or specific types of AI systems would allow more detailed insights into contextual differences (Berente et al., 2021; Tursunbayeva & Gal, 2024). Future studies could also integrate the perspective of employees and compare different views (Venkatesh et al., 2003). Furthermore, linking the perceptions with

objective organizational outcomes to understand how leadership practices shape measurable effects of AI use could add value (Bloom & van Reenen, 2007). In addition, two forward-looking insights from the interviews call for deeper investigation. Interviewees occasionally described AI as a potential team member, and prior research already discusses emerging forms of human-AI teams (Georganta & Ulfert, 2024). However, in the organizations presented in this study, AI is still used primarily as a supportive tool. Future research could therefore examine how more integrated AI use would affect team dynamics and coordination. Furthermore, as routine or low-value tasks may decline, future studies could analyze how this shift influences career pathways and the distribution of responsibilities for managers.

5.5 Conclusion

AI adoption fundamentally changes managerial work by intensifying decision cycles and shifting responsibility toward the validation and contextual interpretation of AI-supported outputs. Formal roles and existing competency profiles do not yet fully reflect the competencies managers need in AI-enabled environments, in which contextual judgement, technological skills, and the ability to create psychological safety and meaning are becoming increasingly important. Successful AI adoption therefore depends on managerial actions that translate competencies into practice by supporting responsible experimentation and navigating uncertainty. In this rapidly evolving environment, managerial value lies in enabling and shaping AI use through critical judgement and human connection.

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Appendix 1 Overview of Interviewees

ID	Role / Position	Organizational Level	Industry
EM1	Senior executive overseeing global learning strategy in a multinational technology company	Top Management	Technology
EM2	Executive board member responsible for HR, Finance, IT, Compliance & Governance in a major financial institution	Top Management	Finance
EM3	Director for European public & governmental affairs in an international industrial company	Upper Middle Management	Industrial / Energy
EM4	Head of new development in an aerospace manufacturing organization	Upper Middle Management	Aerospace
EM5	Head of network design & planning in a multinational retail and logistics environment	Upper Middle Management	Retail / Logistics
EM6	Academic program lead and contributing to institutional project leadership	Middle Management	Education
EM7	People lead / group leader in a global e-commerce and technology company	Team Lead Level	E-Commerce / Tech
EM8	People lead / group lead in a global e-commerce and logistics organization	Team Lead Level	E-Commerce / Tech
EM9	AI project lead in a major aviation company	Project Lead Level	Aviation
EM10	AI project lead in a multinational technology & e-commerce company	Project Lead Level	E-Commerce / Tech
EAI1	AI evangelist and consultant advising on AI strategy and authoring AI publications	Expert	Independent Professional Services
EAI2	Author and consultant for career, change and leadership	Expert	Independent Professional Services
EAI3	Professor of social research & marketing, facilitating AI-related formats and workshops	Expert	Academic Sector
EAI4	AI evangelist and data analytics lead for AI adoption across corporate functions	Expert	Technical Expertise
EAI5	Data scientist acting as technical expert for AI adoption in a large enterprise	Expert	Technical Expertise

Expert Manager (EM), Expert AI (EAI)

Appendix 2 Interview Guide Managers

Background and Context

1. To begin with: Could you tell me a little about your current role and your main responsibilities?
2. In what ways is AI already part of your work or your team's daily activities?
3. How long have you been involved in AI-related initiatives, and how would you describe your personal level of engagement?

Tasks and Areas of Responsibility

1. When you think back to the time before the introduction of AI: How does a typical workday today differ from back then?
2. Thinking about your role, what has changed the most in terms of how you create value for the organization?
3. Are there specific tasks or activities that are now handled by AI (either for you personally or in terms of managing your area of responsibility)?
4. Conversely, are there things you now do more frequently since AI has been introduced?
5. How has AI influenced your decision-making process (for example, in how you gather or analyze information before making a decision)?
6. Would you say that your areas of responsibility or performance priorities have shifted in any way?

Competencies and Skills

1. Which abilities or competencies have become particularly important for working effectively with AI?
2. Have you found that you needed to develop or learn new skills (whether technical or interpersonal)?
3. Can you describe a situation in which certain skills were particularly helpful in dealing with an AI-related challenge?
4. How do you think one could best support their team in adapting to working with AI (for example through communication, training, or building trust)?

5. What do you think most prevents employees from using AI more actively or effectively?
6. How do you perceive your team members reacting to AI (and what makes it easier or more difficult for them to accept and use it)?
7. What experiences have you had with building or maintaining employees' trust in AI systems?

Implementation and Risks

1. Can you recall a specific situation in which your actions or leadership made a difference in how AI was introduced or used?
2. What do you see as the greatest advantages of using AI in your area, and what main concerns or risks do you associate with it?
3. How do you think one can reconcile the benefits of AI with the concerns or risks associated with it?
4. Have you changed anything in the processes, communication, or structure of your team or department to facilitate the integration of AI?
5. How do you ensure that AI supports your strategic goals?
6. Based on which factors would you assess whether the introduction of AI in your area has been successful?

Reflection and Outlook

1. Considering all these changes, what has been the most significant impact of AI on your work?
2. How do you think the role of leaders will evolve in the future as AI becomes even more integrated?
3. What advice would you give to other leaders preparing to work with AI in their teams or organizations?
4. Is there anything you would like to add about your experiences or views on AI that we have not yet discussed?

Appendix 3 Interview Guide AI Experts

Background and Context

1. To begin with: Could you tell me a little about your current role or profession, and your main responsibilities?
2. In what ways do you deal with the topic of artificial intelligence in your work (e.g., research, consulting, implementation, strategy)?
3. How long have you been involved in AI-related initiatives, and how would you describe your personal level of engagement?

Tasks and Areas of Responsibility

1. When you think about the time before the introduction of AI: How has the typical daily work of leaders changed, in your observation?
2. What would you say has changed most in terms of how leaders create value for their organization?
3. Which tasks or activities are, in your observation, increasingly taken over by AI today, and how does this affect the role of leaders from your perspective?
4. Are there activities that leaders, in contrast, now take on more frequently or more intensely than before (e.g., communication, oversight, strategic thinking)?
5. In your view, how has the decision-making process of leaders changed through AI (for example, how they gather, interpret, or weigh information)?
6. Do you observe a shift in the areas of responsibility or priorities of leaders as AI becomes more integrated?

Competencies and Skills

1. Which abilities or competencies do you consider particularly important for leaders to work effectively with AI?
2. To what extent do leaders, in your experience, need to develop or learn new skills (technical, analytical, or interpersonal)?
3. Can you name an example from your observation that illustrates which competencies particularly support the successful use of AI in everyday leadership?

4. In your view, how can organizations or leaders best support their teams in adapting to working with AI (e.g., through communication, training, building trust)?
5. What do you see as the biggest barriers or resistances that prevent employees from using AI more actively or effectively?
6. What reactions to AI do you typically observe among employees—and what, in your observation, facilitates or complicates their acceptance?
7. Which strategies or measures have proven helpful in your experience for building trust in AI systems among employees or leaders?

Implementation and Risks

1. What advantages and opportunities do you see in the use of AI in leadership and management contexts—and what main concerns or risks do you associate with it?
2. From your point of view, how can a balance be struck between the advantages and risks of using AI in organizations?
3. Which organizational or structural adjustments do you consider useful to facilitate the integration of AI into teams or departments?
4. How can leaders ensure, from your perspective, that the use of AI actually supports their strategic objectives?
5. Based on which criteria would you assess whether the introduction of AI in a given area has been successful?

Reflection and Outlook

1. Considering all these developments: What has been, in your view, the most significant impact of AI on the work of leaders so far?
2. How do you think the role of leaders will change in the coming years as AI becomes even more integrated?
3. What advice would you give to leaders preparing to work with AI in their teams or organizations?
4. Is there anything you would like to add from your perspective about your observations or experiences regarding the interplay between leadership and AI that we have not yet addressed?

Appendix 4 Interview Support Slides

• Consent Form



This interview will be recorded so that the content can be transcribed afterward and used for scientific analysis. The recording and the transcript will be treated confidentially and used exclusively for research purposes. All personal data will be anonymized so that no conclusions can be drawn about your identity.

Do I have your consent to record the interview?



• Introduction



Problem Statement:

The increasing use of AI is transforming leadership tasks, decision-making processes, and competency requirements, yet the concrete impacts on management remain largely unexplored.



Purpose of the Interview:

To identify the skills, challenges, and success factors that leaders experience when working with AI, and to gain practice-oriented insights from industry regarding the introduction and use of AI.



INTERVIEW QUESTIONS

● **Background and Context**

1. To begin with: Could you tell me a little about your current role and your main responsibilities?
2. In what ways is AI already part of your work or your team's daily activities?
3. How long have you been involved in AI-related initiatives, and how would you describe your personal level of engagement?



● **Tasks and Areas of Responsibility**

1. When you think back to the time before the introduction of AI: How does a typical workday today differ from back then?
2. Thinking about your role, what has changed the most in terms of how you create value for the organization?
3. Are there specific tasks or activities that are now handled by AI (either for you personally or in terms of managing your area of responsibility)?



● **Tasks and Areas of Responsibility**

4. Conversely, are there things you now do more frequently since AI has been introduced?
5. How has AI influenced your decision-making process (for example, in how you gather or analyze information before making a decision)?
6. Would you say that your areas of responsibility or performance priorities have shifted in any way?



● **Competencies and Skills**

1. Which abilities or competencies have become particularly important for working effectively with AI?
2. Have you found that you needed to develop or learn new skills (whether technical or interpersonal)?
3. Can you describe a situation in which certain skills were particularly helpful in dealing with an AI-related challenge?



● **Competencies and Skills**

4. How do you think one could best support their team in adapting to working with AI (for example through communication, training, or building trust)?
5. What do you think most prevents employees from using AI more actively or effectively?
6. How do you perceive your team members reacting to AI (and what makes it easier or more difficult for them to accept and use it)?
7. What experiences have you had with building or maintaining employees' trust in AI systems?



● **Implementation and Risks**

1. Can you recall a specific situation in which your actions or leadership made a difference in how AI was introduced or used?
2. What do you see as the greatest advantages of using AI in your area, and what main concerns or risks do you associate with it?
3. How do you think one can reconcile the benefits of AI with the concerns or risks associated with it?



● Implementation and Risks

4. Have you changed anything in the processes, communication, or structure of your team or department to facilitate the integration of AI?
5. How do you ensure that AI supports your strategic goals?
6. Based on which factors would you assess whether the introduction of AI in your area has been successful?



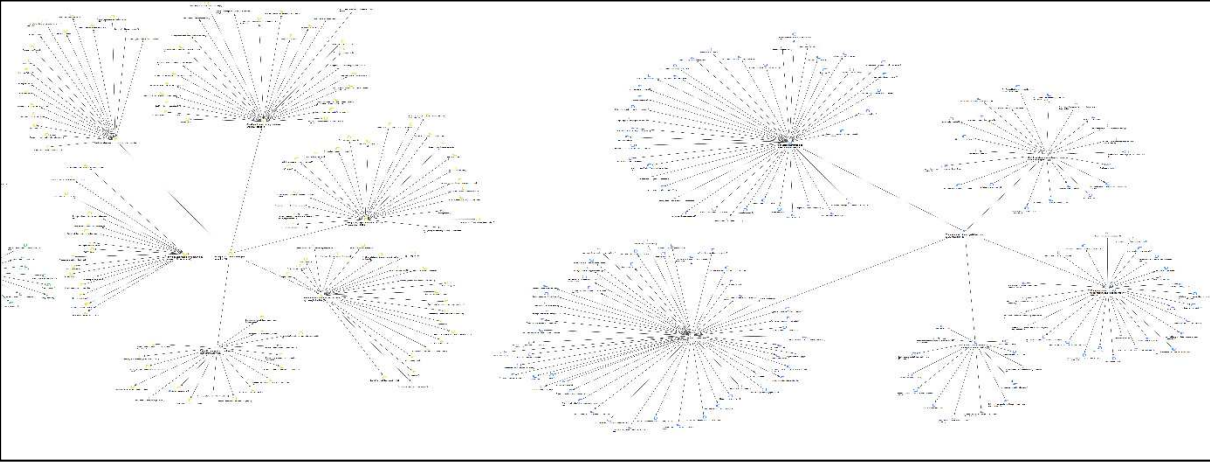
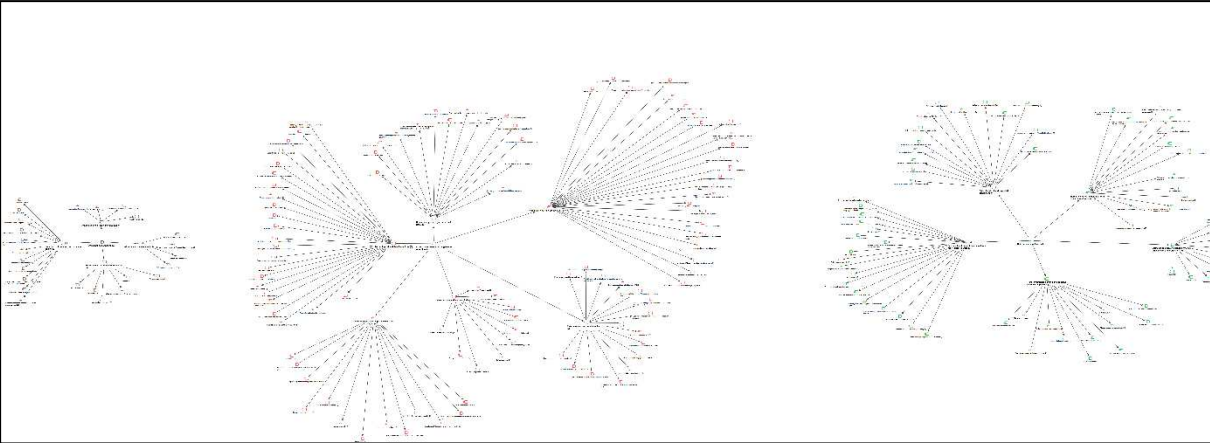
● Reflection and Outlook

1. Considering all these changes, what has been the most significant impact of AI on your work?
2. How do you think the role of leaders will evolve in the future as AI becomes even more integrated?
3. What advice would you give to other leaders preparing to work with AI in their teams or organizations?
4. Is there anything you would like to add about your experiences or views on AI that we have not yet discussed?

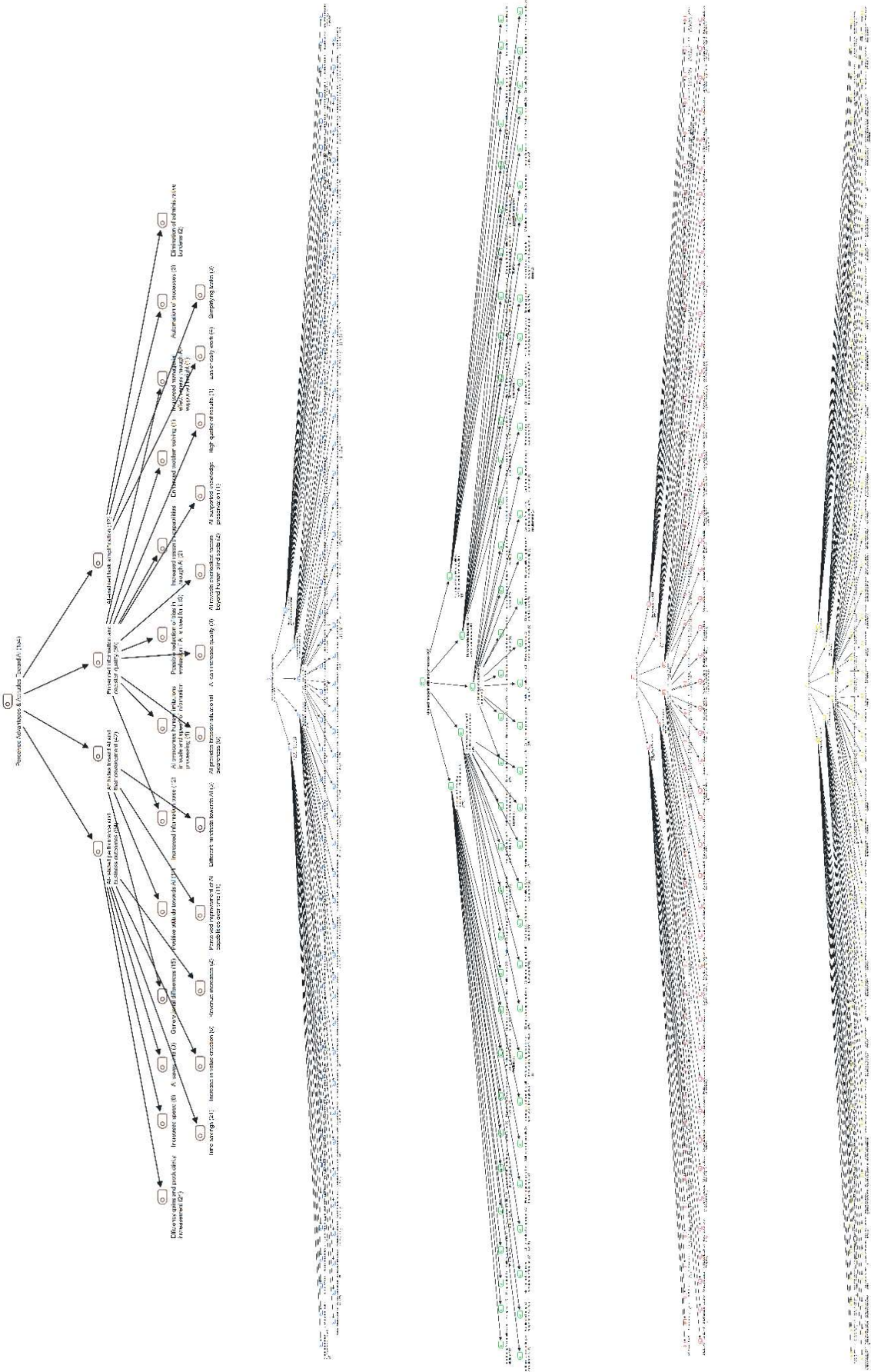


**THANK YOU VERY MUCH
FOR YOUR SUPPORT!**

Appendix 5 Preliminary Coding Structure



Appendix 6 Theme Maps in Order of Appearance



Appendix 7 Table of Themes & Sub-Themes

Theme	Sub-Themes	Definition
Perceived Advantages & Attitudes Toward AI	<p>Attitudes toward AI and their development</p> <p>AI-enabled task simplification</p> <p>Enhanced information and decision quality</p> <p>AI-related performance and business outcomes</p>	<p>This theme covers perceived advantages and attitudes towards AI in the context of managerial work. It includes general views and expectations about the development, as well as expected benefits of usage. Overall, it provides the context for understanding later findings on changes happening due to AI adoption.</p>
Transformation of managerial work and responsibilities through AI	<p>AI-driven transformation of managerial value creation</p> <p>AI-enabled automation and redistribution of tasks</p> <p>Emerging human oversight and AI-collaboration roles</p> <p>Organizational, structural and leadership role transformation</p> <p>Shift toward strategic, interpretive and sense-making work patterns</p>	<p>This theme describes how AI changes the substance and focus of managerial work. It includes a redistribution of preparational, administrative, and analytical tasks, which enables managers to concentrate more on evaluative, interpretive, and human-centered responsibilities. Managerial value shifts toward judgement, guidance, and responsible AI use. Existing role descriptions no longer fully reflect these evolving demands. Overall, the theme highlights how AI reshapes managerial work in practice.</p>
AI-related managerial skills and competencies	<p>Critical, ethical and expert AI judgement</p> <p>Human-centered leadership in AI-driven transformation</p> <p>Strategic and creative capabilities for AI-driven work transformation</p> <p>Technical and prompting competencies for AI-enabled work</p> <p>Transformational learning and adaptive change competencies</p>	<p>This theme outlines what managers need to work effectively in AI-enabled environments. It includes critical and ethical judgement, domain expertise for validating AI outputs, and human-centered leadership skills that support employees through changing ways of working. Furthermore it covers strategic and creative abilities for interpreting AI-generated input, as well as prompting and adaptive learning competencies. Overall, the theme defines the competencies managers need in AI-supported environments.</p>
Risks and Barriers to Managerial AI Adoption	<p>Ethical, legal and compliance risks</p> <p>Human competencies and skill risks</p> <p>Organizational and process barriers</p> <p>Overreliance and misuse of AI</p> <p>Psychological and emotional barriers</p> <p>Technological and data-related limitations</p>	<p>This theme captures the contextual restraints that frame how managers and employees engage with AI. It includes ethical, legal, and data-related risks, gaps, and organizational obstacles. Furthermore, it contains psychological and emotional barriers, as well as risks from unreliable output or overreliance. Overall, the theme provides the boundary conditions that accompany AI adoption and helps explain the challenges that managers must navigate.</p>

Managerial Actions Enabling AI Adoption	<p>Supportive communication and psychological safety for AI use</p> <p>AI-related learning and capability development</p> <p>AI-driven culture and team empowerment</p> <p>AI infrastructure and resource access</p> <p>AI strategy and governance</p> <p>Experimentation and safe AI exploration</p>	<p>This theme describes the leadership practices that support effective AI adoption. It includes clear communication, psychological safety, and practical guidance that encourage employees to engage with AI. Furthermore, it contains aspects such as access to training, reliable tools, and internal expertise and covers cultural and strategic actions, as for example normalizing AI use, establishing governance structures, and enabling low-risk experimentation. Overall, the theme highlights how managers actively shape the conditions for responsible and successful AI use.</p>
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Appendix 8 Full List of Codes

Code	Frequency
Code system	2017
Perceived Advantages & Attitudes Toward AI	
Attitudes toward AI and their development	
Different mindsets towards AI	5
Generational differences	15
Perceived improvement of AI capabilities over time	11
Positive attitude towards AI	11
AI-enabled task simplification	
Automation of processes	3
Easier daily work	4
Elimination of administrative burdens	2
Simplifying tasks	3
Enhanced information and decision quality	
AI can increase quality	3
AI overcomes human limitations in scale and speed of information processing	4
AI provides broader situational awareness	6
AI reveals overlooked factors beyond human blind spots	2
AI-supported knowledge preservation	1
Enhanced problem solving	1
High quality of results	1
Increased information base	12
Increased managerial effectiveness through AI-supported insight	1
Increased research capabilities through AI	2
Possible reduction of bias in evaluation if AI is used for it	3
AI-related performance and business outcomes	
AI saves time	3
Efficiency gains and productivity increase	24
Increase in value creation	6
Increased speed	8
Revenue increases	2
Time savings	21
Transformation of managerial work and responsibilities through AI	
AI-driven transformation of managerial value creation	
AI cross-sector relevant	3
AI influences all aspects of work	6
AI-assisted analytical support for managerial decisions	38
AI-assisted scenario simulation and predictive analysis for decisions	5
AI-supported competitive intelligence	2
Declining relevance of efficiency as leadership differentiator	1
Increase in value creation	8
Increased importance of human critical judgement in value creation	3
Possibility of reduced workload	1
Shift from output-based to input-based goal setting due to AI uncertainty	1
Shift in value creation	4
Untapped potential for AI-driven efficiency in managerial tasks	2
Shift in value creation (more time for larger scale projects)	1
AI-enabled automation and redistribution of tasks	
Increased time invest in AI-related tasks	4
AI automation in development tasks (IT)	1
AI automation of simple data processing tasks	8
AI can be used for research	13
AI can take over simple tasks	6
AI enables quick information access	11
AI for content creation (layout and video)	5
AI for data analysis	11

AI for forecasting	2
AI for generating educational materials	1
AI replacing junior-level analytical tasks	1
AI support content adaption and translation	6
AI support content creation	18
AI supports meeting preparation	8
AI supports simple development tasks	1
AI takes over administrative tasks	5
AI taking over analytical dashboard routines	1
AI-assisted resource identification	1
AI-enabled automatic suggestion	9
AI-enabled suggestions	1
AI-supported documentation (minutes, summaries, transcripts)	21
AI-supported identification of suitable existing solutions	1
AI partially replacing expert knowledge (data research)	4
Automation in development tasks	1
Automation of processes	5
Change in overall task volume due to AI	3
Efficiency gains enable different fulfilment of tasks	1
Efficiency gains and improved time management	2
Elimination of low-value tasks	4
Foundational analytical work becomes automated	2
Increased use of AI for research related information retrieval	4
Increased work pace	3
Job substitution in low level jobs	4
More concise communication through AI assistance	1
Partial task substitution by AI	9
Prompting effort	1
Prompting effort negligible	1
Reduced manual data preparation due to AI	2
Reduction of manual information generation	7
Substitution of low level jobs	3
Time savings through AI	1
Emerging human oversight and AI-collaboration roles	
Lower verification requirement for low-stakes tasks	1
AI as additional consultation source and support mechanism	3
AI as additional consultation source in discussions	2
AI as analytical tool	1
AI as coach	8
AI as decision-maker / AI taking over decision authority	2
AI as first point of contact	6
AI as quality control	4
AI as sparring partner	4
AI as supportive tool	2
AI should not be used as a goal in itself but integrated only when useful	2
Expert roles still needed	10
Final check through AI	1
Human accountability can not be delegated to AI	13
Human employees shift into supervisory roles	4
Human follow-up may be necessary	1
Human oversight and validation role	57
Human pattern-recognition becomes core leadership value	1
Human-AI translation / interface role	4
Need to provide sufficient contextual input for AI outputs	2
Shift from data collector to quality assessors	2
Shift from delegation of analytical tasks to AI-enabled self-analysis	2
Shift from human / expert validation towards AI-supported validation	5
Shift of human work toward crisis intervention in AI-managed processes	1

Shift toward AI-transformation leadership responsibilities	7
Shift toward leaders acting as ethical safeguards in AI use	3
Shift towards quality control	3
Organizational, structural and leadership role transformation	
AI as large-scale change	10
AI affects organizational foundations / deep cultural impact	3
AI as team member	5
AI assigned defined job roles / AI receives formal job profiles	1
AI teams	2
AI-supported design and workflow creation	2
Accelerated reskilling requirements due to AI	1
Building a culture of AI-supported ideation	2
Change driven environment	5
Change towards learning culture	5
Changing job profiles	9
Content shift within stable leadership roles due to AI	6
Cross-functional AI implementation teams	2
Disruption of entry-level roles	1
Feedback practices influenced by AI	2
Fundamental changes	2
Generational differences in AI usage	2
Gradual shift towards AI use	9
Higher-level roles change less in their core tasks	10
Increased expectation of employee self-leadership	2
Increased workload through upskilling	8
Increasing importance of person-job fit	1
Increasing integration of AI into work routines	8
Need for flexible structures	4
Normalization of AI in daily work	5
Organizational change	3
Organizational redesign	2
Performance requirements remain unchanged despite AI	1
Reduction of traditional leadership roles	1
Restructuring: Dissolve separation between IT and business units	1
Shift from expert authority to coaching-oriented leadership	6
Shift from operational management toward strategic mentorship	1
Shift in how tasks are executed due to AI	5
Shift in leadership focus toward strategy and people development	1
Shift of responsibility from managers to employees	1
Shift to bottom-up AI ideation	3
Shift toward bottom-up AI innovation as dominant model	2
Shift toward empowering employee autonomy	1
Shift toward more human-centered leadership roles	11
Shift toward process-oriented organization	3
Stability of interpersonal leadership responsibilities	5
Stable formal responsibilities	7
Strategic workforce restructuring due to AI	4
Structural changes	2
Transition from task-oriented to project-oriented work	1
Unchanged contractual responsibilities	1
Upskilling	8
Shift only in training content	1
Workflow change due to AI (Agentic AI)	5
Shift toward strategic, interpretive and sense-making work patterns	
Shift of tasks toward training and supported app development	1
Shift in time allocation towards training and exploration of tools	1
Shift in time allocation (still high effort to receive good results)	1
Shift in time allocation	3

AI for ideation creation	8
AI for trend identification	1
AI transforms rough ideas into structured and coherent content	1
AI-assisted strategic decision-making	3
Contextual grounding	1
Innovation and reimagining remain leadership tasks	1
Shift from input work to interpretive work	8
Shift from reactive problem-solving to proactive leadership action	2
Shift from routine work to high-intensity crisis response	2
Shift from subjective intuition to data-driven perspective expansion	2
Shift from task assignment to purpose- and direction-setting	3
Shift from task execution to question-framing and interpretation	1
Shift in leadership focus toward meaning creation	4
Shift in performance focus	1
Shift in performance focus towards communication and strategy	1
Shift toward strategic framing of AI outputs	1
Shift toward strategic tasks	7
Shift towards strategic tasks	2
Strategic foresight remains human leadership responsibility	1
Transforming AI output in narrative that engages	1
Trend identification	2
AI-related managerial skills and competencies	
Critical, ethical and expert AI judgement	
Assessing AI suitability for domain-specific safety requirements	2
Ability of source verification in AI use	1
Ability to critically validate AI outputs	9
Critical evaluation of AI outputs	23
Critical thinking and judgement	18
Domain knowledge needed to detect AI errors	3
Ethical competence and bias handling	4
Evaluation Competence	5
Increased importance of expert judgement	3
Need for holistic oversight despite automation	1
Preservation of non-AI operational competence	5
Responsibility competence in AI-enabled leadership	3
Risk awareness in AI usage	10
Sensitive awareness of discriminatory factors	1
Skill in oversight and accuracy checking	3
Human-centered leadership in AI-driven transformation	
Ability to reduce AI-related fears through empathetic leadership	6
Ability to translate technical concepts into emotionally accessible language	1
Creating meaning	1
Emotional intelligence in AI-related conversations	3
High demand for interpersonal skill & experience (for all employees)	6
Human-centered leadership competence	20
Increased need for leaders to manage AI-induced psychological stress	2
Managing different abilities more important than high technical skill level	2
Managing generational differences	3
Motivational ability	2
Provide counterpart based on empathy-driven leadership	4
Psychological awareness for team heterogeneity	7
Self reflection and reflective ability in general	3
Strategic and creative capabilities for AI-driven work transformation	
Abstraction ability	1
Control, communication, and strategic thinking as constant	1
Creativity	1
Imagination	1
Increased demand for human creativity	2

Increased solution orientation	1
Problem solving	1
Strategic capabilities	2
Strategic creativity	1
Structural and strategic thinking	4
Technical and prompting competencies for AI-enabled work	
Ability to formulate precise instructions	7
Ability to select the appropriate AI tool	6
Baseline technological competence required	11
Digital intuition	1
Giving context	9
Learning general prompting still necessary in the beginning	1
Multi-tool proficiency and understanding of functions	8
Need for deeper practical AI proficiency	6
Prompt engineering idea has become less central	3
Prompting	14
Prompting may vary depending on AI tool	1
Reduced prompting complexity through natural language function	1
Skill to prompt correctly	2
Skill to refine and improve AI systems based on human feedback	1
Support in solution finding and giving context	3
Technological understanding as basic requirement	15
Understanding AI capabilities and limitations	18
Transformational learning and adaptive change competencies	
Shift from experience-based to learning-based leadership success	1
Ability to encourage change	4
Ability to learn	10
Ability to operate effectively under uncertainty	3
Change leadership competence	23
Continuous learning and self-development	11
Encouraging learning culture	1
Flexibility and adaptation competence	4
Need for balanced adoption mindset	10
Openness to learning / adaptive mindset	21
Persistence in iterative AI problem-solving	2
Proactiveness	2
Resilience and boundaries setting	3
Risks and Barriers to Managerial AI Adoption	
Ethical, legal and compliance risks	
Legal restrictions limiting AI usage	4
AI lacks empathy	5
Boundaries of AI reliability and human oversight	3
Data protection risk	18
Dependency on external regulatory frameworks	5
Ethical uncertainty	1
Human verification required	12
Legal uncertainty as barrier	1
Risk of confidential data leakage to external AI systems	8
Risk of dehumanized leadership through AI dependence	4
Risk of diminished leadership empathy	1
Risk of industrial espionage	2
Risk of private tool use	6
Human competence and skill risks	
Possibility of insufficient human capacity to oversee complex AI-driven processes	1
Difficulty transitioning from administrative to conceptual/strategic work	1
Industry-wide challenge of maintaining expertise under AI automation (especially for juniors)	1
Insufficient ethical awareness	1
Lack of time to engage with AI adoption	2

Learning constructive use	1
Limited depth of AI use / extended search engine mindset	1
Limits of upskilling older generations	1
Loss of gradual professional onboarding (decrease junior level)	1
Reduced experimental learning	2
Risk of loss of skills	8
Skill mismatch due to outdated qualifications	1
Systematic underestimation of AI capabilities	1
Understanding of capabilities of the different tools	1
Organizational and process barriers	
Absence of leadership endorsement as barrier	2
Challenges of reskilling employees	2
Challenges of upskilling existing workforce	2
Cultural adaptation challenge	1
Discrepancy between private vs. professional AI usage	7
Disruption of traditional career paths	1
Increased and additional time invest in AI-related tasks	3
Increasing complexity increases uncertainty	4
Individualized AI use limits collective value creation	2
Lack of clear AI performance metrics	5
Legacy deficits amplify AI adoption challenges	2
Mismatch between existing employee skills and new AI-driven role requirements	2
Operational time pressure leads to decreased adoption	1
Organizational failure to provide adequate AI tools	1
Organizational mistrust toward AI	3
Organizational unpreparedness for AI adoption	6
Reluctance to use AI for high-stakes or complex decisions	2
Restrictive communication discourages AI use	2
Restrictive managerial communication discourages AI use	4
Risk of falling behind	5
Superficial AI adoption without strategic purpose	1
Time savings not realized yet	1
Uncertainty about measurable AI impact	9
Underestimation of cultural consulting support	1
Overreliance and misuse of AI	
AI used as superficial search tool	2
Critical use of AI	2
Emerging dependency on AI	1
Lack of reflective AI use among employees	5
Risk of losing critical thinking	7
Risk of not getting the full picture	1
Risk of overestimating AI output	10
Risk of overreliance on AI	24
Risk of uncritical acceptance of AI outputs	6
Underestimating AI usefulness	3
Psychological and emotional barriers	
Psychological diversity as organizational challenge	1
Risk of employee disengagement due to surveillance	1
Fear	3
Fear of replacement due to AI	10
Heterogeneous team attitudes toward AI	10
Hype-driven AI actionism (FOMO-induced adoption pressure)	2
Increased psychological stress due to AI-driven work intensification	3
Initial activation barrier to AI use	6
Loss of meaning through excessive monitoring	1
Loss of professional identity due to AI	3
Loss of routine and fast pace as emerging stressor	2
Older generation sticking to traditional way of working	5

Perceived inability to match AI-generated performance	1
Persistence on established routines	5
Possibility of work overload and increased performance pressure	2
Resistance due to long-established work identity	3
Risk of employee engagement decline	2
Stress-induced abandonment of AI use	2
Technological and data-related limitations	
AI does not reveal bias by itself	2
AI lacks creativity and future orientation	2
AI limitations due to biased training data	3
AI limitations due to reliance on historical data	1
AI limited to recombination, not true innovation	1
Deep fake and authenticity concerns	1
Dependence of AI benefits on data quality and infrastructure	3
Fragmented data infrastructure as barrier	4
Lack of digital infrastructure as barrier to AI adoption	2
Limitations of AI in complexity	8
Limited functions and possibilities	6
Limited metacognitive enhancement through AI	1
Need for customized solutions	1
Restricted access level	1
Restricted database access limits AI functionality	1
Risk of hallucinations	15
Risk of inaccurate AI information	6
Risk of training internal AI on wrong data	1
Technical restrictions	6
Unreliable output	8
Usability of tools sometimes limited	2
Managerial Actions Enabling AI Adoption	
Communication and psychological safety	
AI needs to be communicated as tool for every level	1
Active encouragement	8
Active exchange and checking team attitudes toward AI	3
Avoiding pressure linked to AI	1
Avoiding productivity pressure linked to AI	2
Breaking barriers and building trust	4
Building trust	10
Communication of change is important	4
Early encouragement to adopt AI	1
Encouragement	16
Encouraging a constructive error culture	7
Entertaining podcast format	1
Fostering positive AI experiences / success stories	18
Openness toward AI depends on enabling conditions	1
Providing explicit permission and psychological safety for AI use	8
Raise awareness among staff	3
Reducing fear	8
Roadshows	1
Strategic framing of AI as supportive tool	5
Talk open about fears	1
Transparency	9
AI-related learning and capability development	
AI training plan	2
Compliance trainings	8
Encouraging continuous training	4
Fostering critical AI use	2
Fostering knowledge exchange about how to use AI meaningfully	6
Improving trust through trainings	1

Need for reskilling existing workforce	5
On-demand training	1
Promoting balanced AI learning (possibilities + limitations)	2
Promoting critical and reflective AI culture	1
Prompt libraries	1
Prompting Training	2
Prompting trainings to solve hallucination issue	1
Providing AI capability and limitations training	7
Providing concrete AI use-case examples	4
Teaching critical AI reflection (training)	1
Training and Upskilling	9
Training required	16
AI infrastructure and resource access	
Employees demand access to effective AI tools to secure job performance	1
AI center of excellence	1
AI-supported validation mechanisms	2
Centralized AI use-case intake and evaluation center	1
Centralized development of reusable AI tools	1
Dedicated AI team	8
Early AI pilot user role	1
Establishing internal AI experts	6
Facilitating quick access to AI insights	1
Facilitating quick access to tech-savvy peers	1
Organizational responsibility to provide adequate AI tools	1
Point of contact for AI related questions (AI experts)	2
Possible need for external consulting support	1
Possible need for technological consulting support	1
Providing accessible AI resources	2
Provision of secure internal AI tools	5
Working Groups	1
AI strategy and governance	
Tracking of adoption rates	2
Strategic top-down framing to build AI trust and enhance usage	3
AI should not be used as a goal in itself but integrated only when useful	2
Adopting a problem-first approach to AI implementation	6
Cost savings as relevant metric	4
Cross-functional involvement in AI governance	5
Defining clear legal boundaries for use	5
Development of AI policies and governance structures	9
Documentation of process time to understand if AI use is efficient	3
Evaluation framework adjusted based on AI adoption	1
Focusing AI adoption on measurable business value	8
Formulation of goals directly related to AI	4
Monitor and track training	2
Need for flexibility in job profiles	1
Need for organizational restructuring for AI adoption	3
Official authorization of AI use / enabling conditions	9
Organizational rollout / formal introduction	10
Permission-based governance instead of restrictive rules	2
Policy decisions enabling safe use	3
Recognizing new AI-enabled use cases for existing materials	3
Reduction of bureaucratic barriers to AI usage	1
Responsible use	3
Shift from tool-driven adoption to strategic value-driven AI use	5
Tie adoption to targets	4
Time savings as relevant metric	5
Unified measurement framework for assessing AI impact across operational and functional contexts	2

Validating AI necessity before project initiation	2
Viewing AI adoption as ongoing organizational change process	9
AI-driven culture and team empowerment	
Need for cultural leadership to maintain engagement	3
Creating spaces for authentic human interaction	2
Active enabling use of AI through projects	8
Actively balancing AI refusal and overuse within the team	3
Advocating for AI adoption / pushing for implementation	2
Balancing top-down and bottom-up in AI adoption	4
Challenges to inspire engagement	1
Creating space for regular knowledge sharing (meetings)	3
Enabling environment increases adoption potential	9
Encouraging bottom-up AI ideas and initiatives	9
Enhancing team motivation through visibility and recognition	1
Fostering AI-inspired creative thinking in teams	1
Informal knowledge sharing	1
Leadership endorsement increases AI adoption	9
Leadership responsibility to convey AI adoption mindset	3
Normalization of AI use in daily work	2
Promoting team-based AI use instead of isolated individual usage	1
Reinforcing AI initiatives through positive feedback	2
Use of multipliers to support team adoption	6
Experimentation and safe AI exploration	
Applying hands-on AI-driven change management	3
Demonstrating AI benefits to increase adoption	4
Enabling experimentation culture	12
Enabling experimentation through incentives	2
Encouragement through experimentation	1
Encouragement through incentives	4
Encouraging exchange and feedback	2
Exchange forums	1
Experimentation with AI in training settings	4
Hackathons	3
Introducing AI via staged testing and gradual validation	4
Knowledge sharing and peer-to-peer learning	7
Learn-and-share sessions	1
Lunch-and-learn sessions	1
Personal exchange (1:1) with team members	1
Positive Incentives	1
Recognizing and legitimizing AI-related experimentation	1
Showcasing practical AI use cases & quick-win success experiences	12
Space for experimentation	2
Workshops	1