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Me, my role, and (A)I

A qualitative case study on how managers proactively craft their role in response to AI-driven changes in knowledge work

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Artificial intelligence is becoming embedded in knowledge work, reshaping how information is accessed, produced, evaluated, and translated into organizational action. Prior research has examined AI’s implications for expertise, decision-making, and work transformation, but less is known about how managers reshape their role when AI alters the conditions of knowledge work. Drawing on job crafting theory, this thesis examines how managers proactively craft their role amid AI-driven changes in knowledge work. The study adopts a qualitative single-case design at a large multinational technology company, anonymized as TechCo, based on 20 semi-structured interviews with managers across functions, hierarchical levels, and degrees of AI exposure. Findings show that managers engage in selective role crafting rather than uniform AI adoption. Task crafting occurs as managers move AI into first-pass knowledge work, shifting their effort from producing inputs while retaining responsibility for validation, contextualization, and final judgment. Relational crafting occurs around managerial interactions, where AI supports preparation and communication while managers protect trust, empathy, authenticity, and accountability. Cognitive crafting occurs as managers reinterpret their value, moving from producing answers toward validating, translating, enabling, and making knowledge actionable for others. The thesis contributes by showing that AI-driven managerial role crafting unfolds through expansion and protection, relocating rather than reducing managerial value.

Keywords: Artificial Intelligence, Managerial Work, Job Crafting Theory, Knowledge Work, Role Boundaries

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Sincerely,
Rosel Chowdhury & Bilal Ibrahim Ali

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List of Definitions

The following definitions clarify how central concepts are used in the thesis.

Concept	*Definition in this thesis*	*Anchoring literature*
Artificial Intelligence (AI)	Generative, agentic, and embedded AI systems that rely on machine learning techniques to infer patterns from data and perform tasks that usually require human judgment and expertise.	Berente et al. (2021); Shavit et al. (2023); Faraj et al. (2018)
Knowledge work	Work centered on interpretation, judgment, and problem-solving, with outputs that are often hard to assess by technical criteria alone.	Alvesson (2001); Bailey & Barley (2020)
AI-driven changes in knowledge work	Changes in how knowledge is accessed, produced, structured, evaluated, communicated, and used as AI becomes embedded in work.	Lebovitz et al. (2022); Waardenburg et al. (2022); Pakarinen & Huising (2025)
Managerial role	Responsibilities through which managers coordinate people, interpret information, set priorities, exercise judgment, and translate inputs into action.	Mintzberg (1973); Hales (1986); Katz (1955)
Managerial role crafting	Managers' self-initiated reshaping of what they do, how they relate to others, or how they understand their role, adapted from job crafting theory.	Adapted from Wrzesniewski & Dutton (2001); Berg et al. (2010); Zhang & Parker (2019)
Forms of crafting	Task crafting changes what work is done and how; relational crafting changes work-related interactions; cognitive crafting changes how the role is understood.	Wrzesniewski & Dutton (2001); Zhang & Parker (2019)
Crafting orientation	Approach-oriented crafting expands resources or opportunities, while avoidance-oriented crafting reduces risks, demands, or threats to key work boundaries.	Bruning & Campion (2018); Zhang & Parker (2019)
Job resources and demands	Resources support goals or development, while demands require effort and may create pressure; in this thesis, AI can be both.	Tims & Bakker (2010); Tims et al., (2012)

1. Introduction

1.1 Background

> *"Once everyone in my team started using AI, it really made me reflect on what I bring to the table as a manager. [...] I had to figure out, what role can I play in all of this?"*
> - **Senior Research Manager (I05)**

The reflection above captures a central question for contemporary managerial work: what role do managers play when the conditions of knowledge work change? For decades, managerial value has rested on a distinctive combination of capabilities: holding information others did not have, translating it into decisions, and setting direction for others to follow (Mintzberg, 1973; Katz, 1955; Hales, 1986). Artificial intelligence (AI) is changing this combination. Once treated largely as experimental or future-oriented, AI is increasingly embedded in everyday organizational work, as companies move beyond isolated pilots toward broader efforts to redesign workflows and operating models around AI-enabled forms of work (Microsoft, 2025; Singla et al., 2025). This wave of AI also differs from earlier waves of digitalization. While earlier automation primarily targeted routine and standardized tasks, generative AI and, increasingly, agentic systems enter more cognitively demanding forms of work that involve interpreting, producing and coordinating knowledge (Alavi & Westerman, 2023; Yee et al., 2025). AI is therefore no longer only a peripheral digital tool, but part of the conditions under which knowledge work is organized and performed (Bailey & Barley, 2020).

These developments carry particular weight for managers, and for two reasons that compound each other. Managerial work has long involved interpersonal, informational, and decisional responsibilities through which managers coordinate people, interpret information, set priorities, and translate dispersed inputs into collective action (Mintzberg, 1973; Hales, 1986; Katz, 1955). Managers occupy a distinctive position in knowledge work: they not only produce or consume knowledge, but also help determine how knowledge is interpreted, prioritized, and made actionable across teams and organizational processes. When AI becomes embedded in precisely those informational and analytical parts of work, managers face a double exposure. They navigate AI as part of their own managerial work, where it increasingly supports how they access information, prepare decisions, and structure analysis. At the same time, they navigate AI as a condition of the work they coordinate, legitimate, and make accountable to others. This double exposure is sharpened further in organizations where AI adoption is not merely available but expected, and where managers are encouraged to role-model adoption, build AI literacy in their teams, and demonstrate AI engagement as part of their leadership responsibility. Research suggests that AI does not simply replace managerial activities but recomposes them, making some tasks more AI-supported while rendering responsibilities related to judgment, validation, coordination, and accountability more salient in the managerial role (Huang et al., 2019; Raisch & Krakowski, 2021).

This leads us back to the question that the senior manager posed above. When AI takes on more of the informational and analytical work that once defined managerial value, the question is not whether the managerial role disappears, but what it becomes: what managers continue to own, what they delegate, what shifts toward oversight and judgment rather than production, and how they actively work out the boundaries of their own contribution in a context where those boundaries are no longer given. It is that question, posed at the level of the managerial role rather than at the level of tool adoption, that this study takes as its starting point.

1.2 Problem Discussion

The question raised in the preceding section does not have a ready answer in existing research. Recent AI research provides important insight into how AI reshapes the conditions of knowledge work. Studies show, for example, that AI can challenge professional expertise by producing outputs that workers must interpret, verify, and translate into situated practice (Lebovitz et al., 2022; Waardenburg et al., 2022; Pakarinen & Huising, 2025). Other research highlights how AI-supported decision-making creates new demands around evaluation, justification, and accountability, particularly when algorithmic outputs influence decisions that remain organizationally consequential (Raisch & Krakowski, 2021; Shrestha et al., 2019). Research focused more specifically on managerial work similarly suggests that AI may alter analytical tasks, decision processes, monitoring, and task allocation, while increasing the importance of human judgment, coordination, oversight, and legitimacy (Huang et al., 2019; Van Doorn et al., 2023; Hoffmann et al., 2025). Yet, taken together, these streams of literature tell us more about how AI changes work and managerial responsibilities than about how managers interpret these changes as changes to their own role. This omission matters because formal managers occupy a dual position: they are both affected by AI in their own work and responsible for translating AI-driven change into everyday organizational practice. Their responses are therefore shaped not only by personal tool use, but by the broader responsibilities of the managerial role itself, including coordination, validation, judgment, and accountability. This makes the managerial role a particularly important site for studying AI-driven change at the level of everyday professional practice, in line with calls to move AI research closer to micro-level interactions and behaviors (Bailey & Barley, 2020; Sarala et al., 2025), and with the still limited empirical attention paid to managers' own perspectives on AI-related change (Cao et al., 2021).

This gap calls for a theoretical lens that captures how managers proactively adjust the boundaries and meaning of their role, rather than treating AI adoption as the main phenomenon. Job crafting offers such a lens. It explains how individuals proactively alter what they do, how they relate to others, and how they understand the meaning of their work in response to changing work conditions (Wrzesniewski & Dutton, 2001; Zhang & Parker, 2019). Applied to managers in an AI-enabled context, job crafting makes it possible to examine how AI-driven changes become connected to adjustments in managerial tasks, relationships, responsibilities, and role meaning. It therefore provides the analytical foundation for studying how managers craft their role as AI becomes embedded in knowledge work.

1.3 Purpose and Research Question

The purpose of this study is to explore how managers proactively craft their managerial role as AI changes the conditions of knowledge work. Rather than examining AI adoption or tool use as outcomes in themselves, the study focuses on managers' role-level responses to AI-driven change. Using job crafting as a sensitizing analytical lens, it examines how managers reshape the task, relational, and cognitive boundaries of their role: what they do, how they relate to others, and how they understand the value of managerial work. In doing so, the study seeks to understand how managers respond to the changing demands, resources, and expectations that emerge as AI becomes increasingly embedded in knowledge-intensive organizational work. To fulfill this purpose, the study is guided by the following research question:

- *How do managers proactively craft their managerial role in response to AI-driven changes in knowledge work?*

1.4 Delimitations

This study focuses on formal managers and their role-level responses to AI-driven changes in knowledge work. Rather than examining AI as a technical system to be evaluated for performance, adoption rates, or implementation outcomes, AI is treated as an organizational condition that shapes how managerial work is experienced, interpreted, and enacted. Objective outcomes such as productivity or efficiency gains fall outside the scope of the study, as do knowledge workers who do not hold formal managerial responsibility.

The study is further delimited to managers' own accounts of how AI relates to their work and role, rather than direct observation of managerial behavior or AI use. It therefore examines perceived and narrated role crafting, not objectively measured role change. The study is conducted as a qualitative single-case study at a large multinational ICT incumbent, prioritizing contextual depth over broad empirical generalization across organizations, industries, or national contexts.

1.5 Expected Contribution

This study contributes to theory and practice. Theoretically, it shows how AI-driven change in managerial work is interpreted and enacted at the level of managers' everyday role adjustments. While prior research examines how AI reshapes knowledge work, expertise, decision-making, and organizational processes, less is known about how managers interpret these changes as changes to their role. By applying job crafting as a theoretical lens, this study examines AI-driven change from managers' own perspective, focusing on how they proactively reshape the task, relational, and cognitive boundaries of their role. In doing so, it moves beyond questions of AI adoption or task automation toward a role-level understanding of how AI-driven change is interpreted and enacted in managerial practice.

Practically, the study aims to generate insight into how organizations can better support managers during AI transformation. As managers are expected to use AI, role-model adoption, build AI literacy, and guide AI-related change, their role becomes central to how AI is translated into organizational practice. By highlighting managers' experiences of AI-related role change, the study may help organizations approach AI transformation not only as tool access or technical training, but as a managerial work-design issue involving role expectations, validation practices, judgment, relationships, and accountability.

2. Theory

This chapter provides the reader with an understanding of previous research (2.1). Based on this review, the research gap is then identified (2.2), followed by a presentation of the study's theoretical framework (2.3).

2.1 Literature Review

2.1.1 Artificial Intelligence in Knowledge Work

Knowledge work is often associated with analysis, judgment, and problem-solving, but it is rarely a purely technical activity. Alvesson (2001) argues that knowledge work is difficult to define and evaluate because both competence and outputs are often ambiguous. In such settings, knowledge depends not only on expertise, but also on interpretation, credibility, and social processes through which knowledge claims become accepted. This makes AI particularly consequential in knowledge work, because it enters domains where expertise, judgment, and legitimacy are already socially and organizationally mediated.

AI should therefore be understood not only as a technical tool, but as an organizational phenomenon. Berente et al. (2021) argue that AI is characterized by autonomy, learning, and inscrutability, while Bailey & Barley (2020) emphasize that intelligent technologies must be studied in relation to broader organizational dynamics, including power, variation, ideology, and institutions. From this perspective, AI matters not only because of what it can automate, but because it changes the conditions under which knowledge is produced, interpreted, governed, and acted upon. This is especially important in knowledge-intensive settings, where decisions often depend on judgment, accountability, and coordination across actors.

Empirical studies support this view by showing that AI often reorganizes rather than replaces human expertise. In their study of machine learning in hiring, van den Broek et al. (2021) show that AI did not eliminate the need for domain experts, but instead created hybrid forms of human-AI knowledge production. Similarly, Lebovitz et al. (2022) show that professionals using AI in medical decision-making must engage in additional interpretive work to assess opaque AI recommendations. Waardenburg et al. (2022) further show that algorithmic predictions create a need for knowledge-broker roles that translate AI outputs between technical and organizational communities. Pakarinen & Huising (2025) extend this argument by conceptualizing expertise as relationally constituted, meaning that AI raises not only technical questions of accuracy, but also organizational questions of explainability, legitimacy, and accountability.

Recent developments in generative and agentic AI broaden these issues further. Generative AI extends AI's use beyond prediction and optimization into drafting, summarization, synthesis, and decision preparation, while agentic AI points toward more workflow-embedded and goal-directed forms of support (Krakowski, 2025; Shavit et al., 2023). Early evidence suggests that these technologies are moving into less structured and more judgment-intensive activities, where their implications cannot be reduced to efficiency or substitution alone (Brynjolfsson et al., 2025; Krakowski, 2025). Prior research also suggests that AI may affect authority, evaluation, role understanding, and the conditions under which knowledge claims are trusted and acted upon in organizations (Strich et al., 2021; Scarbrough et al., 2025; Monod et al., 2024). Taken together, this literature suggests that AI in knowledge work is best understood as a process of recomposition, where human expertise, AI-generated outputs, and organizational judgment become increasingly interdependent. This makes managerial work especially relevant, because managers are often responsible not only for using knowledge, but for interpreting, prioritizing, legitimizing, and translating knowledge into coordinated action.

2.1.2 The managerial role and AI-driven task recomposition

Managerial work has long been characterized as fragmented, interaction-heavy, and oriented toward integrating people, information, and action rather than executing isolated technical tasks. Mintzberg's (1973) classic account depicts managerial work as fast-paced, reactive, and reliant on verbal interaction, with managers operating through interpersonal, informational, and decisional roles. Later observational studies reinforce this pattern, showing continuity in the time-pressured and interaction-intensive nature of managerial work (Kurke & Aldrich, 1983; Tengblad, 2006). Hales (1986) similarly emphasizes liaison, information handling, coordination, negotiation, and problem handling as central managerial activities, while Katz (1955) argues that managerial effectiveness depends not only on technical skills, but also on human and conceptual skills that enable managers to work through others. Taken together, these accounts position managerial work as fundamentally integrative, with value created through coordination, judgment, and influence rather than stand-alone technical expertise.

As AI extends into analytical and informational tasks, it may alter which aspects of managerial work become most central. Huang et al. (2019) argue that as AI expands from mechanical tasks toward analytical "thinking" tasks, the relative importance of interpersonal and empathetic "feeling" tasks increases, including communication, coordination, and relationship maintenance. Applied to managers, this suggests that managerial value may become more concentrated in interpreting, contextualizing, and mobilizing action around AI-supported outputs. A similar distinction is made by Van Doorn et al. (2023), who argue that the effects of digital transformation depend on task characteristics and managers' role embeddedness. Formal-rational tasks, which are codified and more readily automated, differ from substantive-rational tasks, which rely on tacit knowledge, contextual interpretation, and human monitoring. Together, these perspectives suggest that AI may shift managerial emphasis away from codifiable tasks and toward activities embedded in context, coordination, and judgment.

However, a simple substitution narrative does not capture AI's implications for managerial work. Raisch & Krakowski (2021) argue that automation and augmentation are interdependent in management, creating an automation-augmentation paradox where automating parts of work also generates new demands for goal specification, evaluation, and accountability. Shrestha et al. (2019) similarly show that human-AI decision-making can take different forms, including delegation, sequential hybrids, and aggregated arrangements, each requiring decisions about how human and AI contributions should be combined. Related research on algorithms and work further suggests that AI can reshape coordination and control. Faraj et al. (2018) show how black-boxed performance and anticipatory quantification affect the organization and evaluation of work, while Kellogg et al. (2020) demonstrate that algorithmic control can reconfigure direction, evaluation, and governance. Rather than simply removing work from managers, AI may therefore increase the importance of framing decision processes, overseeing AI-supported work, and remaining accountable for outcomes when the basis for action is not fully transparent.

Recent evidence from generative AI makes this recomposition of managerial work more visible. Hoffmann et al. (2025) find that access to GitHub Copilot shifts task allocation toward core production work and away from non-core project management, while also changing interaction patterns and exploratory behavior. They further suggest that generative AI may enable more hands-on management by allowing managers who have moved away from core tasks to reconnect more directly with their teams, potentially flattening aspects of hierarchy. Overall, the literature points not to the disappearance of managerial work, but to its recomposition. As analytical and informational activities become increasingly AI-supported, managerial value may become less tied to producing analysis alone and more tied to framing objectives, interpreting outputs, coordinating action, sustaining legitimacy, and remaining accountable. This makes it important to examine how managers respond to such changes in the composition and meaning of their role, which the next section approaches through the job crafting literature.

2.1.3. Job Crafting

Organizational research has historically approached job design from a top-down perspective, predominantly conceptualizing employees as passive recipients of standardized roles (Wrzesniewski & Dutton, 2001). In contrast, the concept of job crafting positions employees as proactive "everyday job designers" who exert individual agency to reshape the structural and social parameters of their work (Wrzesniewski & Dutton, 2001; Tims & Bakker, 2010). Fundamentally, job crafting has been defined as the "physical and cognitive changes individuals make in the task or relational boundaries of their work" (Wrzesniewski & Dutton, 2001). This definition conceptualizes the construct as a self-initiated process through which employees deliberately alter the execution of tasks, the nature of their interpersonal work interactions, or the mental framing of their work's purpose (Wrzesniewski & Dutton, 2001; Bruning & Campion, 2018). Building upon this foundation, subsequent literature has further refined the construct by defining it as the proactive "changes that employees may make to their job demands and job resources" to align the job with their personal abilities, needs, and preferences (Tims & Bakker, 2010; Tims et al., 2012). Across these theoretical developments, job crafting is consistently characterized as a bottom-up, proactive behavior initiated by the employee, rather than a top-down response to organizational requirements (Tims & Bakker, 2010; Tims et al., 2012; Bruning & Campion, 2018).

Contemporary developments of job crafting theory

Job crafting literature has predominantly progressed along two primary theoretical trajectories: the role-based perspective and the resource-based perspective (Bruning & Campion, 2018; Zhang & Parker, 2019). The role-based perspective, originating from the seminal work of Wrzesniewski & Dutton (2001), conceptualizes job crafting as a process of altering and shaping identity and meaning. It focuses on how individuals psychologically and physically redraw the task and relational boundaries of their work to align their roles with their personal values and professional purpose (Wrzesniewski & Dutton, 2001; Bruning & Campion, 2018). In contrast, the resource-based perspective, rooted in the Job Demands-Resources model presented by Tims & Bakker (2010) views crafting as a behavioral strategy to optimize the work environment. Under this perspective, the primary objective is to maintain a balance between job demands (the pressures of the role) and job resources (the support systems available) to ensure high engagement and person-job fit (Tims et al., 2012; Zhang & Parker, 2019).

To address the theoretical fragmentation within the field, recent scholars have sought to bridge the role-identity and job demands-resources perspectives through integrative frameworks that account for both the content and the psychological orientation of crafting behavior (Zhang & Parker, 2019). Two prominent contributions in this regard are the "role-resource approach-avoidance" model by Bruning & Campion (2018) and the hierarchical structure of job crafting proposed by Zhang & Parker (2019). Both frameworks move beyond the singular focus of earlier models by synthesizing the "what" of job crafting (tasks and resources) with the "why" (underlying psychological motivation), yet they differ in their structural categorization and conceptual reach.

Job crafting in the context of organizational hierarchy and rank

Job crafting does not occur in a structural vacuum, and cannot be understood independently of employees' position in the organizational hierarchy. Berg et al. (2010) show that organizational rank shapes how employees enact job crafting. Higher-rank employees typically possess greater autonomy, discretion, and formal authority, which can enable more expansive forms of crafting, such as redefining priorities, delegating tasks, or adopting new work practices (Berg et al., 2010; Bruning & Campion, 2018; Rudolph et al., 2017). In contrast, lower-rank employees more often face externally imposed constraints such as prescribed tasks, supervisory expectations, and limited control over work methods.

Furthermore, higher-rank employees tend to experience crafting challenges as located in their own expectations, priorities, and use of time, while lower-rank employees tend to locate challenges in the expectations and behaviors of others (Berg et al., 2010). Consequently, lower-rank employees' adaptive responses frequently involve attempting to change the expectations and behaviors of others to actively create opportunities to job craft. In contrast, because higher-rank employees tend to locate their challenges within their own expectations, priorities, and use of time, they must engage in adaptive moves that alter their own behaviors rather than attempting to change those of others (Berg et al., 2010).

However, a higher rank does not automatically imply unlimited freedom to craft. Berg et al. (2010) show that, although senior employees have more formal autonomy, their crafting may be constrained by accountability, interdependence, and visibility within the broader organization.

This distinction is particularly relevant when studying managers. Because individuals at different levels of the organizational hierarchy face distinct sets of constraints and affordances, their approaches to redefining their work inherently diverge, making certain crafting activities more or less relevant to different segments of the workforce (Bruning & Campion, 2018). As managers often occupy higher-rank positions, they may have greater latitude to alter their tasks, relationships, and role boundaries, while also being constrained by interdependence, responsibility for others, and expectations attached to their managerial context. Consequently, exploring job crafting through the lens of organizational rank provides a necessary contextual understanding of how managerial roles are shaped and constrained.

Job crafting in the era of artificial intelligence

The introduction of artificial intelligence into knowledge work creates a particularly relevant context for job crafting. Recent scholars suggest that AI can reshape not only how tasks are performed, but also task boundaries, role expectations, and the meaning attached to professional roles, thereby creating new pressures for employees to reinterpret and adjust their work (Law & Varanasi, 2025; Mayer et al., 2025; Perez et al., 2024). From a job crafting perspective, AI-driven change can therefore be understood as a potential source of renewed person-job fit concerns, where established tasks, skills, and role meanings may no longer fully align with changing work conditions. Employees may respond by proactively reshaping their work to restore alignment between their role, capabilities, and professional values (Lu et al., 2014; Tims & Bakker, 2010). At the same time, AI may function as a job resource by supporting knowledge-intensive work, expanding access to information, and enabling new ways of completing tasks (Tarafdar & Saunders, 2022), while also creating new demands related to validation, oversight, learning, and accountability (Freise et al., 2025; Law & Varanasi, 2025). This dual role makes AI especially relevant for job crafting theory, as employees may respond through different forms of role adjustment aimed either at pursuing new opportunities or managing emerging demands (Bruning & Campion, 2018; Zhang & Parker, 2019). For managers, this is particularly important because AI-related changes may affect not only their own tasks, but also their responsibility for coordinating others' work, validating outputs, and interpreting the value of their role.

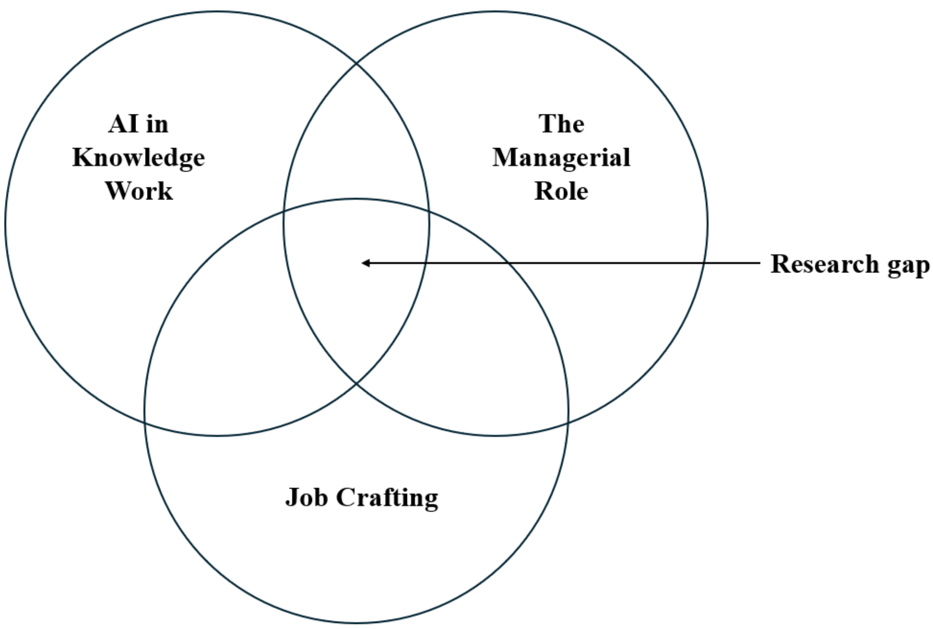
2.2 Research Gap

The literature reviewed above shows that AI is changing knowledge work by reconfiguring how expertise, interpretation, accountability, and knowledge claims are produced and made actionable in organizations (Bailey & Barley, 2020; Berente et al., 2021; van den Broek et al., 2021; Lebovitz et al., 2022; Waardenburg et al., 2022; Pakarinen & Huising, 2025). Research on managerial work further suggests that managers are central to these changes, since their role is rooted in coordinating people, interpreting information, exercising judgment, and translating inputs into collective action (Mintzberg, 1973; Hales, 1986; Katz, 1955). Recent AI research also indicates that AI may recompose managerial work by altering analytical tasks, decision processes, coordination, oversight, and accountability rather than simply replacing managerial activity (Huang et al., 2019; Shrestha et al., 2019; Raisch & Krakowski, 2021; Van Doorn et al., 2023; Hoffmann et al., 2025). However, this literature primarily explains AI-driven change as a structural, technological, or task-level phenomenon. It offers less insight into how managers themselves interpret such changes as role-level issues and adjust their own managerial role in response.

Job crafting provides a useful lens for addressing this missing role-level perspective because it conceptualizes individuals as proactive shapers of their work rather than passive recipients of changing job conditions. It makes it possible to analyze how managers adjust task boundaries, relational boundaries, and role meaning under changing work conditions (Wrzesniewski & Dutton, 2001; Berg et al., 2010; Bruning & Campion, 2018; Zhang & Parker, 2019). This is particularly relevant in an AI-enabled knowledge-work context, where AI may simultaneously create resources, such as faster access to information and improved preparation, and demands, such as validation, oversight, learning, and accountability. However, emerging research connecting AI and job crafting has mainly examined broader work transformation, early-career professionals, or specialist professional contexts, rather than formal managers whose crafting is shaped by responsibility for others' work, coordination, judgment, and accountability (Law & Varanasi, 2025; Mayer et al., 2025; Perez et al., 2024).

The gap addressed in this thesis is therefore not simply whether managers use AI, but how AI-driven changes in knowledge work become connected to managerial role crafting. In particular, limited empirical insight exists into when AI remains a practical work support and when it becomes part of how managers reshape what they do, how they relate to others, what they take responsibility for, and how they understand the value of their role. Addressing this gap responds to calls for AI research to move closer to situated professional practice and micro-level behavior (Bailey & Barley, 2020; Sarala et al., 2025), as well as to calls for greater attention to managers' own perspectives on AI-related role change (Cao et al., 2021).

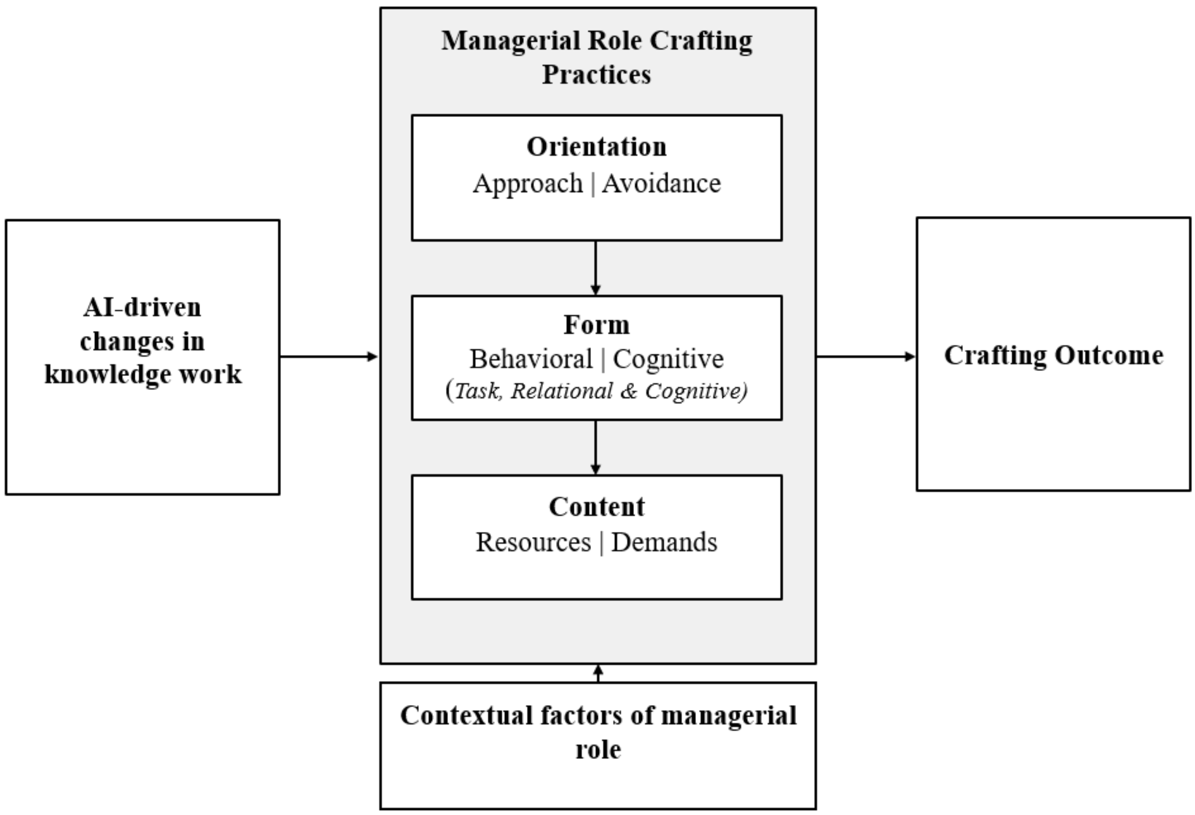
Figure 1 - Research gap



2.3 Theoretical Framework

To address the identified research gap, this study develops an integrative theoretical framework for analyzing AI-driven managerial role crafting (see Figure 2). The framework is inspired by Zhang & Parker's (2019) hierarchical structure of job crafting, but adapts it to the specific context of this thesis by incorporating AI-driven changes in knowledge work and contextual factors of the managerial role. Zhang & Parker's (2019) framework is suitable as a foundation because it integrates two central branches of job crafting research: the role-based perspective, which emphasizes task, relational, and cognitive boundary changes and their implications for meaning and identity (Wrzesniewski & Dutton, 2001), and the job demands-resources perspective, which conceptualizes job crafting as employees' proactive modification of job demands and resources (Tims & Bakker, 2010; Tims et al., 2012). However, because this thesis examines managers' response to AI-driven changes in knowledge work, the framework is extended beyond job crafting itself to account for the technological trigger (AI-driven changes in knowledge work) and the managerial context in which crafting occurs.

Figure 2 - Theoretical Framework (inspired by Zhang & Parker (2019))



The starting point of the framework is AI-driven changes in knowledge work, which this thesis treats as the contextual trigger that creates new opportunities, demands, and uncertainties in the managerial role. Rather than focusing on AI use as a technical practice in itself, the framework examines how managers respond to AI-driven change by reshaping the tasks, relationships, demands, resources, and meanings that constitute their managerial role.

The central part of the framework captures job crafting practices, structured around three analytical levels inspired by Zhang & Parker (2019): orientation, form, and content. The first level is crafting orientation, which distinguishes between approach-oriented and avoidance-oriented crafting (Zhang & Parker, 2019). This level helps interpret the underlying direction of managers' responses to AI. Drawing on Bruning & Campion (2018), approach crafting can be understood as efforts to expand role boundaries, pursue positive outcomes, or develop new resources, while avoidance crafting refers to efforts to reduce, limit, or protect against negative aspects of work.

The second level of job crafting practices concerns crafting form, referring to whether crafting occurs behaviorally or cognitively (Zhang & Parker, 2019). Behavioral crafting captures concrete changes in how work is enacted; this is reflected in task crafting and relational crafting: task crafting involves changes in, for example, the scope or execution of tasks, while relational crafting involves changes in the type or quantity of interactions at work (Wrzesniewski & Dutton, 2001). Cognitive crafting, by contrast, concerns changes in how individuals interpret the meaning, purpose, or significance of their work (Wrzesniewski & Dutton, 2001; Zhang & Parker, 2019). In this thesis, task and relational crafting are therefore treated as behavioral expressions of managerial role crafting, while cognitive crafting captures changes in how managers understand the meaning and value of their role. This adaptation is necessary because the research question concerns how managers craft their managerial role in practice.

The third level concerns crafting content, or what is being crafted. Drawing on the JD-R perspective, Zhang & Parker (2019) distinguish between crafting job resources and job demands. This level enables analysis of whether AI is experienced as a resource that supports managerial work, a challenge demand that requires learning and experimentation, or a hindering demand that creates uncertainty, strain, or accountability concerns (Tims & Bakker, 2010; Tims et al., 2012; Zhang & Parker, 2019). This is particularly relevant because AI may simultaneously support managerial work and introduce new responsibilities related to validation, oversight, pace, quality, and responsible use (Freise et al., 2025; Law & Varanasi, 2025).

The framework further treats the managerial role as a contextual condition shaping how job crafting unfolds. Managers are not generic job crafters; their crafting is shaped by the structural and relational conditions, constraints, and responsibilities attached to managerial work.

Collectively, the framework provides an appropriate lens for the scope of this study. It preserves Zhang and Parker's (2019) core hierarchical logic, while extending it to fit the empirical focus of the thesis. In this study, managerial role crafting refers to managers' self-initiated reshaping of what they do, how they relate to others, and how they understand their role, adapted from job crafting theory. By adding AI-driven changes in knowledge work as the trigger, contextual factors of the managerial role as shaping conditions, and crafting outcomes as the result of role reconfiguration, the framework supports the study's central aim: to examine how managers proactively reshape their roles in response to AI-driven changes in the conditions of knowledge work. Moreover, the framework informs the methodological approach of the study. It functions as a sensitizing lens for data collection and analysis, helping structure the examination of managers' crafting practices, contextual conditions, and emerging role outcomes. The next chapter, therefore, outlines how a qualitative case study was designed to examine this phenomenon empirically.

3. Methodology

The chapter describes the methodological approach of this study. First, the research design and approach (3.1). Second, a description of the data collection process (3.2), and third, the data analysis method (3.3). Lastly, we also discuss the ethical considerations, along with quality considerations (3.4).

3.1 Research Design and Approach

3.1.1 Research design

This study adopts a qualitative, abductive research design grounded in an interpretivist epistemology. A qualitative approach is appropriate because the study seeks to understand how managers interpret and respond to AI-driven changes in knowledge work, rather than to measure the objective effects of AI on managerial work. Since the study focuses on managers' experiences, interpretations, and meaning-making, an interpretivist stance is suitable. From this perspective, managerial role change is not treated as an objective phenomenon that can be observed independently of those experiencing it, but as something understood through the meanings managers assign to their work and organizational context (Orlikowski & Baroudi, 1991; Klein & Myers, 1999).

An abductive approach was chosen because the study addresses a domain where prior theory is relevant but incomplete (Edmondson & McManus, 2007). Existing literature provides important insight into AI-driven changes in knowledge work and into job crafting as a form of proactive role adjustment, but limited research has examined how managers specifically craft their managerial role in response to AI. The study, therefore, does not seek to test a predetermined model deductively, nor to generate theory entirely from the ground up. Instead, it aims to elaborate existing theoretical foundations while remaining open to emergent empirical patterns.

In practical terms, the research process followed the principle of systematic combining, where theory, empirical material, and analysis evolve iteratively through continuous movement between them (Dubois & Gadde, 2002). This allowed the initial conceptual framework to inform data collection and interpretation while also being refined in light of recurring patterns and unexpected empirical insights (Ahrens & Chapman, 2006). Job crafting was therefore treated as a sensitizing lens rather than a fixed coding template. This enabled the analysis to examine how managers interpreted and adjusted their role in relation to AI-driven changes, while still remaining open to accounts of limited AI use, practical constraints, and experiences that did not fully fit the initial framework.

3.1.2 Case Study

This study adopts a single-case study design. A case study is appropriate when the aim is to develop an in-depth understanding of a contemporary phenomenon in its real-life setting, particularly when contextual conditions are central to the phenomenon under investigation (Flyvbjerg, 2006; Yin, 2003; Yin, 2009). In this study, the phenomenon concerns how AI-driven changes in knowledge work relate to the content, coordination, and conditions of managerial work, and how managers shape their role in response within an organizational setting. A single-case design was therefore considered suitable because it enables close examination of managers' experiences and interpretations in the context in which those experiences are formed. This is consistent with prior arguments that case studies are valuable for generating rich insight into complex phenomena and for examining how context shapes perceptions and practices (Darke, Shanks & Broadbent, 1998). In line with Dyer & Wilkins (1991), the choice of a single case also reflects a prioritization of depth over breadth, as a multi-case design would likely have limited the contextual understanding this study seeks to achieve.

The case is a large global incumbent in the ICT industry characterized by active and strategically prioritized AI implementation, broad access to generative and agentic AI tools, and strong organizational expectations around AI use. These conditions make the case analytically relevant because managers operate in an environment where AI is not only available as an individual work tool, but increasingly embedded in organizational workflows, leadership expectations, and transformation initiatives. Although the study includes managers from different functions, hierarchical levels, and degrees of AI exposure, it is treated as a single case because respondents are situated within a shared organizational AI context marked by common strategic priorities, governance conditions, and tool infrastructure. Since the study seeks contextual depth and theory elaboration rather than statistical generalization, a single-case design is considered appropriate (Easton, 1995). To preserve confidentiality, the organization is henceforth referred to as "**TechCo**".

3.2 Data Collection

Prior to the interviews, supplementary contextual material was reviewed to develop an initial understanding of the case setting. This included internal documentation related to TechCo's AI strategy, available AI tools, and broader organizational initiatives connected to AI use. The purpose of this material was to establish familiarity with the organizational AI context and to frame the interview protocol more effectively, thereby reducing the need to spend interview time on broader contextual clarification. This helped to situate managers' accounts within the broader organizational environment in which AI tools were used, promoted and governed.

3.2.1 Interview Sample

A purposive sampling strategy was used to select interviewees, prioritizing relevance to the research question over representativeness of a broader population (Braun & Clarke, 2013; Flick, 2009). Since the study focuses on how managers experience and shape their roles in relation to AI-driven changes in knowledge work, formal managers were considered the most relevant respondents. Suitable interviewees were identified through an internal people database containing employees in the case organization. From this database, only employees holding formal managerial roles were selected. Interviewees were then purposively chosen to ensure variation across organizational areas, managerial levels, functional contexts, and degrees of AI exposure. The sample includes both managers with broader organizational responsibility, such as managers of other managers, and managers with responsibility for individual contributors. This variation was important because AI-related role crafting may differ depending on organizational position, functional context, proximity to AI-intensive work, and scope for role adaptation.

In total, 20 interviews were conducted (see *Table 1*). Although participants differed in function, seniority, and organizational location, they were all situated within the same overall organizational context, characterized by active AI implementation, broad access to AI tools, and shared organizational expectations around AI use. This provided both comparability across interviewees and sufficient variation to generate rich empirical insights relevant to the study's purpose. The number of interviews was not fixed in advance, but guided by theoretical saturation, understood here as the point at which additional interviews no longer contributed meaningfully to new patterns or variations relevant to the developing analysis (Bowen, 2008).

Table 1 - Interview Sample

Participant	Managerial Role	Organizational Area	Managerial Scope	Date	Duration
I01	Manager, Strategy & Technology	Strategy & Technology	Manager of Individuals	2026-03-25	55 min
I02	Technical Manager, Network Software Development	Network Software Development	Manager of Managers	2026-03-25	55 min
I03	Line Manager	Network & AI Analytics	Manager of Individuals	2026-03-27	50 min
I04	Head of Intelligent Automation	Product Engineering & Automation	Manager of Managers	2026-03-30	55 min
I05	Senior Research Manager, AI & Machine Learning	AI & Machine Learning Research	Manager of Managers	2026-03-31	60 min
I06	Head of Sales & Commercial Management	Sales & Commercial Operations	Manager of Managers	2026-04-01	60 min
I07	Senior Research Manager, R&D	Research & Development	Manager of Managers	2026-04-01	60 min
I08	Line Manager	AI Platform Engineering	Manager of Individuals	2026-04-01	60 min
I09	Line Manager	Software Development	Manager of Individuals	2026-04-02	40 min
I10	Line Manager	Research & Development	Manager of Individuals	2026-04-02	45 min
I11	Head of AI & Automation	Analytics Delivery & Business Operations	Manager of Individuals	2026-04-08	50 min
I12	Section Manager, Engineering Automation	Engineering Automation	Manager of Individuals	2026-04-08	75 min
I13	Head of Group Accounting	Global Finance	Manager of Managers	2026-04-08	53 min
I14	Head of People	Regional People / HR Function	Manager of Managers	2026-04-09	30 min
I15	Head of Radio Architecture	Research & Development	Manager of Managers	2026-04-09	60 min
I16	Head of Sourcing Strategy	Global Sourcing	Manager of Managers	2026-04-09	45 min
I17	Head of Legal	Regional Legal Function	Manager of Managers	2026-04-28	45 min
I18	Customer Delivery Manager	Customer Operations	Manager of Individuals	2026-04-28	40 min
I19	Line Manager	Software Development	Manager of Individuals	2026-04-28	50 min
I20	Compliance Manager	Risk & Compliance	Manager of Managers	2026-04-28	55 min

3.2.2 Interview process

The interviews were conducted digitally through Microsoft Teams, which was considered appropriate given the geographical and practical complexity of accessing managers across a large international organization. This format made it possible to reach respondents in different parts of the organization while still enabling in-depth conversations centered on their experiences and interpretations. Prior qualitative research suggests that video-based interviews can constitute a viable alternative to physical interviews when the aim is to generate rich empirical material through dialogue and reflection (Deakin & Wakefield, 2014; Nehls, Smith & Schneider, 2015).

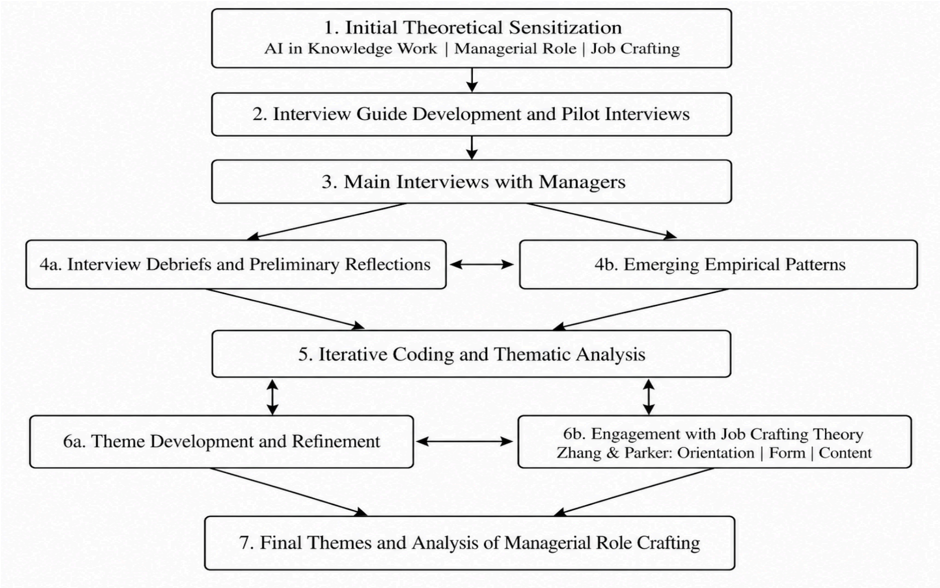
All interviews were conducted individually to give respondents space to speak freely about their experiences of AI, managerial work, and role change without the influence of group dynamics (Frey & Fontana, 1991). The interviews lasted approximately 60 minutes and were recorded with the permission of the participants. The recordings and transcripts were treated confidentially to protect participant anonymity. Both authors attended each interview, which supported joint observation, immediate reflection, and comparison of interpretations during and after the conversations (Belk, Wallendorf & Sherry, 1989). In line with the abductive research design, reflections from earlier interviews were carried into later stages of data collection, allowing subsequent interviews to become progressively more focused while remaining open to unanticipated themes.

3.2.3 Interview design

A semi-structured interview design was adopted, as this was considered appropriate for generating rich and reflective accounts of the focal phenomenon. Semi-structured interviews provide a balance between consistency and flexibility, allowing researchers to maintain a common focus across interviews while giving respondents space to elaborate on experiences, interpretations, and examples in their own terms (Kvale & Brinkmann, 2014; Braun & Clarke, 2013). This was particularly suitable given the interpretivist and abductive research design of the study, where the aim was not to confirm predetermined categories, but to understand how managers described AI-related changes in their work and role.

An interview guide was developed to support this process. The guide was informed by the study's purpose and initial theoretical framing, while remaining open enough to capture unanticipated empirical insights. In this sense, it helped orient the interviews toward relevant issues without requiring respondents to speak in predefined theoretical categories. Questions were formulated in an open-ended and conversational manner, allowing respondents to reflect on their managerial role, their use of AI tools, and whether and how AI had affected their work. Follow-up questions were asked based on the respondents' answers, and each interview ended with an open-ended prompt inviting participants to raise additional issues they considered important. In line with the abductive approach, the guide was gradually refined throughout the data collection process as recurring themes and surprising insights emerged from earlier interviews (Dubois & Gadde, 2002). To identify weaknesses in the design before the main data collection began, two pilot interviews were conducted, allowing wording, sequence, and focus to be adjusted so that subsequent interviews could generate richer and more relevant material.

Figure 3 - Overview of the Research Process



3.3 Data Analysis

The analysis of the interview material followed an abductive logic, in which empirical material, prior literature, and the analytical framework were related iteratively throughout the research process (Dubois & Gadde, 2002; Ahrens & Chapman, 2006). Analysis began during data collection rather than only after all interviews had been completed. Notes were taken during each interview, followed by an immediate debrief in which preliminary reflections, recurring patterns, and emerging analytical questions were discussed. These early reflections informed subsequent interviews by helping to sharpen attention toward both recurring and unexpected issues relevant to the developing analysis (Linneberg & Korsgaard, 2019).

All interviews were recorded and transcribed in full, after which the material was reviewed and coded manually. Both authors first engaged with the transcripts individually to identify relevant excerpts and initial codes that remained close to the interviewees' own language and descriptions of how their managerial work related to AI. These initial codes were then compared and discussed jointly, allowing the analysis to move from interview-level observations toward broader empirical patterns across the dataset. The coding process was systematic and iterative, broadly inspired by thematic analysis in that it involved repeated movement between the full dataset, initial codes, developing themes, and the broader argument of the study (Braun & Clarke, 2006).

Figure 4 - Example of Data Analysis

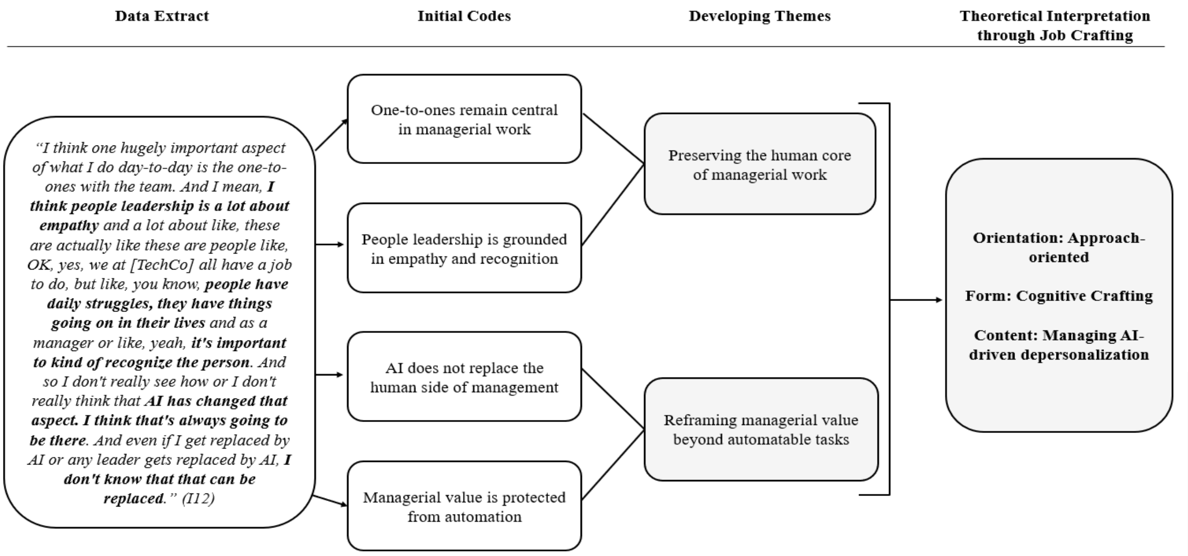


Figure 4 illustrates how the coding process moved from empirical material to theoretical interpretation. The example shows how a selected interview extract was first coded close to the participant's own wording, then grouped into developing themes, and finally interpreted through the job crafting lens. Together with *Figure 3*, which presents the broader abductive research process, *Figure 4* helps show how the analysis developed from data collection and initial coding into the empirical themes and theoretical interpretations presented in the following chapters.

In later stages, the material was interpreted more explicitly through the lens of job crafting. Job crafting was not treated as a rigid coding template from the outset, but as a sensitizing analytical lens that helped structure and deepen the interpretation of emerging patterns. This allowed the analysis to examine how AI-related changes became connected to task, relational, and cognitive forms of managerial role crafting, while still remaining open to empirical material that did not fully fit the framework. Accounts in which managers described AI as useful but not role-changing, or where AI use was limited by practical, relational, or organizational constraints, were retained as analytically important rather than excluded. This made it possible to interpret the material in dialogue with existing theory while preserving the abductive openness of the study. A consolidated overview of the theme development process is provided in Appendix A.

3.4 Quality and Ethical Considerations

The trustworthiness of the study was strengthened through alignment between the research question, empirical material, and iterative research process, guided by Lincoln & Guba's (1985) criteria of credibility, transferability, dependability, and confirmability. Credibility was supported by the abductive design, where parallel data collection and analysis allowed emerging interpretations to be revisited and refined. This was particularly important given that managers reflected on ongoing AI-related changes in their roles. Transferability was addressed through a contextually grounded account of managerial role crafting in a large incumbent organization undergoing active AI implementation, enabling readers to assess the relevance of the findings in similar settings. Dependability and confirmability were supported through transparent documentation of the research process, full transcription of interviews, manual coding, and the involvement of both authors throughout data collection, coding, and interpretation. Given the authors' proximity to the case and the contemporary salience of AI, reflexivity was also important throughout the research process. This was addressed through continuous discussion of assumptions, comparison of interpretations, and retention of material that complicated the emerging argument rather than only confirming it.

Ethical considerations were closely intertwined with these quality dimensions. Given that the study concerns managers' reflections on AI adoption and role change within an ongoing organizational setting, confidentiality was essential both ethically and for enabling candid responses. Participants were informed in advance about the purpose of the study and that the interviews would be recorded, and explicit consent was obtained before each session. Participation was voluntary, with the right to decline questions or withdraw at any point. Both the case company and interviewees are anonymized, and all research material was handled in accordance with SSE guidelines and used solely for this thesis. These measures align with established principles of ethical research practice regarding informed consent, confidentiality, and responsible handling of empirical material (Bryman & Bell, 2022).

4. Empirical Findings

This chapter presents the empirical findings of the study. It begins by introducing TechCo and the organizational AI context in which the managers were situated (4.1). The chapter then presents four empirical themes derived from the interviews: AI-supported task recomposition (4.2), AI around managerial interactions (4.3), changing meaning of the managerial role (4.4), and increased expectations around AI use (4.5). Table 2 provides an overview of these themes before they are presented in detail.

Table 2 - Overview of Empirical Themes

Empirical theme	Core empirical pattern	Illustrative empirical examples
AI-supported task recomposition	Managers described AI as entering recurring informational, administrative, analytical, and preparatory parts of managerial work, while human review and judgment remained necessary.	Summarizing meetings, extracting action points, drafting texts, comparing documents, searching for information, preparing goals, structuring presentations, and reviewing AI-generated outputs.
AI around managerial interactions	Managers described AI as supporting the work surrounding interactions, particularly preparation, coordination, communication, and follow-up, while relational work itself remained human-centered.	Preparing for meetings, summarizing communication, supporting stakeholder alignment, preparing feedback or coaching conversations, and following up on discussions.
Changing meaning of the managerial role	Managers described their contribution as increasingly tied to judgment, interpretation, coordination, accountability, and human presence rather than direct production of outputs alone.	Validating AI outputs, applying critical judgment, translating information into action, coaching employees, maintaining accountability, and preserving empathy and trust.
Increased expectations around AI use	Managers described growing expectations to understand, use, govern, and enable AI within their teams and work contexts.	Building AI literacy, role-modeling AI use, encouraging experimentation, following up on adoption, managing security concerns, and enabling employees to use AI.

4.1 The Case Study: TechCo and the Organizational AI Context

4.1.1 TechCo as a Knowledge-Intensive Case Organization

TechCo is a large international incumbent in the ICT industry, characterized by organizational complexity, global presence, and knowledge-intensive work. Operating in a mature and competitive market, the organization faced increasing demands for productivity, efficiency, and renewed value creation, making AI adoption part of broader efforts to transform work. AI had become a strategic priority, reflected in company-wide objectives, leadership communication, and cross-functional initiatives encouraging active engagement with AI. AI competence was also incorporated into leadership development priorities, signaling that AI adoption was increasingly treated not only as an individual skill but as a managerial capability. At the same time, managerial AI use was shaped by organizational governance.

Policies on data classification, confidentiality, and the use of external models with internal information affected what managers could use AI for and how confidently they could incorporate it into their work. AI engagement was therefore encouraged, but bounded by security and governance constraints. The interviewed managers operated across different levels of scope, from managers of individual contributors to managers of managers, and across areas including strategy, software development, AI platform engineering, sales, finance, HR, sourcing, legal, customer operations, product management, and compliance.

4.1.2 The AI Tooling Landscape and Uneven Adoption

Managers described a broad range of AI-enabled tools entering their work environments, including internal generative AI platforms, Microsoft Copilot, AI-powered enterprise search applications, domain-specific assistants, and agentic or coding-related tools in more technical contexts. AI most commonly appeared in work related to analysis, communication, coordination, information retrieval, and decision preparation. However, these tools differed in maturity, integration, reliability, and fit with existing workflows, shaping how confidently managers could incorporate them into recurring work. Adoption was uneven. Some managers had embedded AI deeply into daily routines, while others used it mainly for selected activities such as summaries, drafting, or knowledge search. A smaller group described AI primarily as future potential rather than current reality, often due to role context, data sensitivity, local regulations, tool maturity, or distance from AI-intensive work. This variation reflected differences in role proximity to AI-intensive work, individual AI familiarity, data and policy boundaries, and the organizational culture surrounding experimentation. These conditions help explain why some managers described AI as affecting how they worked and understood their contribution, while others described it as a useful productivity support with more limited perceived role implications.

4.2 Managers Route Task Preparation Through AI

AI appeared most consistently in task-related and preparatory parts of managerial work. Managers used AI to reduce manual effort in administrative routines, move from unstructured input toward more organized starting points, and access knowledge before engaging with specialized or unfamiliar material. Rather than replacing managerial responsibility, AI shifted where effort was concentrated: preparation, drafting, searching, and structuring became more

AI-supported, while deciding, contextualizing, and taking responsibility remained with the manager.

4.2.1 Reducing Administrative Work

Managers described AI as useful for reducing the manual effort involved in recurring administrative and information-heavy parts of managerial work. This included preparing goals, summarizing performance feedback, structuring annual wrap-ups, reviewing requirements, compiling input from others, preparing presentations, and documenting meetings. Across these routines, AI helped managers move from dispersed or unstructured material toward more organized outputs that could be reviewed, adapted, and used.

One recurring example concerned goal-setting and performance management. Several managers described using AI to turn initial managerial input into clearer and more structured employee goals. One manager described building a custom GPT to support this process:

> *"I created a goal-setting GPT for myself [...] I used the SMART methodology [...] and then what I do is input the developer, their role, their job stage [...] and out comes a very clearly defined goal for them. [...] Obviously, I have to refine that slightly, but it saves like 95% of my job in creating goals."* (**I08**)

This illustrates how AI entered administrative work closely tied to managerial responsibility. The manager still discussed goals with employees and refined the output, but AI reduced the time spent turning those discussions into structured formulations. Similar patterns appeared in annual employee wrap-ups, performance feedback, requirements review, and preparation of presentation material. For example, one manager used AI to identify key requirements from long business documents and summarize stakeholder feedback for performance management:

> *"Sometimes the business requirements are coming through a very elaborative document, like a 60, 70 pager document. So using [TechCo Chat tool] to help identify what are the key requirements [...] Then from people perspective, [I] use it to summarize [...] performance management feedback."* (**I11**)

Meeting-related work formed part of the same pattern. Managers described AI-generated transcripts, summaries, and action points as reducing the need to manually document discussions. However, AI did not remove the administrative responsibility entirely. Managers still had to refine outputs, assess relevance, adapt material to context, and decide how it should be used.

4.2.2 Creating Structured Starting Points

Beyond recurring administrative routines, managers used AI in more open-ended tasks where the challenge was not only to complete work faster, but to establish direction, structure, or an initial argument. This was especially visible when managers prepared strategy documents, communication, slides, or longer written material before involving others.

One manager described using AI when working on a strategy document, not to produce the document on their behalf, but to develop and improve the approach:

> *"I'm working on a strategy document, and I use GenAI quite a lot for that, but more to give me ideas and to try to find a good approach to it. I didn't start with generative AI, but I used it to enhance the document."* (**I01**)

Similar uses appeared across several interviews. Managers used AI to organize thoughts, test formulations, summarize longer material, structure arguments, compare sources, and prepare material for communication or decision-making. In these situations, AI helped managers move from a blank page or fragmented input toward a more developed draft or structure. The material still had to be adapted to the task, audience, and organizational context.

4.2.3 Expanding Knowledge Access and Validation

AI also changed how managers accessed knowledge before engaging with specialized or unfamiliar material. Several managers used AI to search across internal documents, summarize requirements, prepare for stakeholder discussions, or understand topics outside their immediate expertise. This was particularly visible in roles where managers needed to engage with complex technical, financial, legal, or organizational material without being the primary domain expert.

In finance-related work, one manager described an internal AI assistant built on accounting standards, internal policies, and domain-specific knowledge:

> *"When our finance people have an accounting issue, instead of starting to read through a lot of directives, they can prompt this in the tool itself and get*

> *[TechCo] accounting instructions. [...] It can populate an accounting assessment: what is the background, what is the issue, what does the standard say, and what is the conclusion."* (**I13**)

This made specialized knowledge more accessible and helped employees and managers arrive with more developed initial assessments. However, broader access did not remove the need for human review. The same manager emphasized that the output still had to be checked:

> *"It is not 100%, but it is rather good. And then you put a pair of eyes on it."* (**I13**)

This need for critical review appeared across interviews. Managers generally did not treat AI-generated material as automatically reliable or context-ready. One manager described this boundary clearly:

> *"You cannot just take whatever AI says to you and use that as the truth. You need to have critical eyes on it [...] If you just take whatever from there, then you are in really bad shape."* (**I01**)

A similar pattern appeared in technical work, where AI accelerated code generation but increased the need for checking, documentation, and guidelines:

> *"We write code now very, very fast, but checking it and verifying it takes so much time. [...] We need to find out how to use this new person in the team that is writing code much faster than we can."* (**I03**)

AI therefore broadened access to information and expertise, but it also made the need for checking more visible. Managers could engage with more material, understand unfamiliar topics more quickly, and arrive better prepared for discussions. At the same time, they repeatedly emphasized that AI-supported outputs had to be reviewed before being used, especially when the material concerned technical, financial, legal, or organizationally sensitive issues.

4.3 Managers Use AI Around Human Interaction

Compared with task-related uses, managers described AI's influence on human interaction as more indirect. AI was not presented as replacing managerial relationships, but as supporting the work around them: preparing for conversations, structuring feedback, tailoring communication, or creating a more informed basis for discussion. The interaction itself remained dependent on managerial judgment, presence, and trust.

4.3.1 Preparing for Interactions

Managers most often described AI as useful before interactions took place. It helped them gather background, identify discussion points, and structure their thoughts before engaging with employees or stakeholders. This was particularly visible when managers used AI to prepare for sensitive or difficult conversations:

> *"I have used generative AI as a way to brainstorm: what should I do, what should I say to this person, how could they react? [...] It becomes a coach to me before I coach someone else."* (**I08**)

AI offered a second perspective before the manager acted, while responsibility for tone, judgment, and delivery remained with the manager. Similar patterns appeared in stakeholder interactions, especially in technically complex settings. One manager explained how AI helped clarify unfamiliar topics after discussions:

> *"I can go back to my computer and write down my thoughts or the parts that I didn't understand, and get a quick understanding of what that person was actually describing. In the past, you had to either ignore it or ask someone else."* (**I05**)

AI therefore helped managers enter conversations better prepared, particularly when they had to engage with specialized knowledge outside their immediate expertise.

4.3.2 AI-Supported Feedback and Communication

AI was also used to structure feedback and written communication. Several managers described using AI to summarize unstructured input, improve wording, or tailor messages to the recipient. This was especially visible in feedback-related work, where managers had to synthesize input from multiple sources:

> *"I can just write down my thoughts and then ask AI to summarize it, make it clear, and also challenge me. [...] It gives me suggestions: these are aspects that you might have missed."* (**I05**)

In some cases, AI-generated material became a third reference point in communication. The clearest example came from a manager who used AI to summarize peer feedback and managerial input before discussing the interpretation with an employee:

> *"We can use AI as the bad guy. [...] This is how AI has interpreted the feedback from your colleagues, your peers, and my input. It says that you can improve in these areas, and these are your strengths. What do you think?"* (**I05**)

This was the most explicit example, but similar dynamics appeared when managers used AI as a sounding board, tested how a message might be received, or turned fragmented input into a more neutral basis for discussion. At the same time, managers were aware that AI-supported communication could become too polished or impersonal. One manager described the risk directly:

> *"You get to read all these perfectly drafted emails, and that is taking out the personality of the communication."* (**I17**)

AI-supported communication therefore appeared ambivalent. It helped managers structure feedback and prepare communication, but also raised concerns about authenticity, personal voice, and what should remain recognizably human.

4.3.3 Human Interaction Remains Central

Although AI supported preparation, feedback, and communication, managers generally did not describe the human side of leadership as replaceable. Several accounts emphasized that managerial work still depended on trust, empathy, presence, and personal judgment. One manager connected this directly to the core value of management:

> *"The value of a manager is to be a human. AI will not see the human in that way. [...] It is about how you look at people, how you understand how they are feeling,*

and not so much about if AI can summarize what tasks they have done or should do." (**I03**)

Similar views appeared in accounts of coaching, employee development, and one-to-one conversations. Managers used AI to prepare and communicate more effectively, but continued to define the interaction itself as dependent on human presence, emotional judgment, and trust.

4.4 Managers Reinterpret Their Value

Beyond tasks and interactions, several managers reflected on what their role involved in an AI-enabled workplace. Some described AI as prompting a broader reconsideration of managerial value, especially where AI made information, analysis, or technical support more accessible to employees. In these accounts, managerial value was described less around personally holding knowledge and more around connection, translation, coaching, clarity, judgment, and enabling others to use AI meaningfully. This reinterpretation was not uniform. Other managers saw AI mainly as a productivity tool or future potential, with more limited implications for how they understood their role.

4.4.1 From Expert to Translator

Several managers described their role as becoming less centered on personally holding knowledge or producing answers. As AI tools made information and expertise more accessible, these managers emphasized connecting people, translating complexity, prioritizing resources, and creating clarity. One manager contrasted the traditional image of the manager as expert with a more enabling and connective role:

> *"The idea of a manager before was maybe that the manager is the person who knows everything, like a specialist. I think now the shift is towards someone more generalist, someone who is able to connect things and relate to different people. [...] This is also reflected in our recent recruitments of managers."* (**I01**)

This account illustrates how AI was associated with a shift in the perceived basis of managerial value. If information and knowledge became easier to access, the manager's contribution was less about personally holding knowledge and more about helping others use knowledge meaningfully. Others similarly described clarity creation as a central managerial responsibility, particularly the ability to translate complex or ambiguous information into something others could understand and act on. One manager noted that AI could create uncertainty because employees and specialists could also use AI to progress quickly:

> *"Managers are fearing that they are no longer at the top of the technology anymore, so they have to reevaluate what kind of value they actually contribute with."* (**I05**)

These reflections suggest that managerial value was not described as disappearing, but as moving toward alignment, translation, coaching, contextual judgment, and helping others act on increasingly available information.

4.4.2 AI Literacy and Role Modeling

Several managers also described AI use as something they needed to learn, demonstrate, and encourage in others. AI literacy was not only an individual skill, but something managers helped make part of everyday work. This was especially visible among managers leading technical or AI-intensive teams, where the managerial responsibility was framed less around personal productivity and more around enabling broader adoption:

> *"For me, as a leader, it is more about getting others to use it than myself. If I can get all my 80 developers to use it, the effect of that is more than if I spend the time using it myself."* (**I04**)

Other managers similarly described AI competence as something that had to be translated into team routines and concrete development goals. In some cases, this was connected to a broader expectation that teams should challenge established ways of working. One manager described AI adoption not only as tool use, but as part of a mindset shift around process improvement:

> *"We are expected to scrutinize how we work, automate as much as we can, and bring AI into as much of the work as we can. [...] I want them to challenge: why are we doing this? Could we do it in a different way?"* (**I14**)

In these cases, AI literacy and adoption became part of managerial responsibility. Managers did not only use AI themselves; they encouraged experimentation, translated organizational expectations into team routines, and helped employees understand where AI could be useful.

4.4.3 Uneven and Selective Role Change

The reinterpretation of managerial value was uneven across the sample. Some managers described AI as meaningfully affecting how they understood their contribution, while others framed it as useful but limited. A few were still learning how to use available tools or saw AI mainly as future potential, often due to role context, data sensitivity, tool maturity, or distance from AI-intensive work. One manager working close to AI research explained that, at the managerial level, the role had not changed dramatically, even though AI supported efficiency in specific activities:

> *"On my level, it hasn't changed that much to be honest. [...] It's a lot of new tools to figure out and how to handle. I will for sure say that AI has made my meetings more efficient [...] but the challenges I face is the same."* (**I05**)

Another manager similarly described AI as promising but not yet deeply embedded in their own managerial work:

> *"As of now, it doesn't really impact my work, at least not to the extent that it should. [...] I'm not using it to the full potential, but I've seen the potential of it. Maybe I'm just a late adopter."* (**I04**)

This unevenness shows that AI-related role reinterpretation was not automatic. It appeared strongest where managers had sufficient exposure to AI-supported work, confidence in the tools, and perceived usefulness to connect AI use to broader questions of managerial value. Where these conditions were weaker, AI remained useful but peripheral: it supported tasks without substantially changing how managers understood their role.

4.5 AI Reshapes Managerial Demands

While managers described AI as useful in task preparation, interactional support, and role enablement, they also associated it with changing expectations around pace, scope, quality, and responsibility. AI was therefore not experienced only as workload reduction. It also affected what managers felt expected to handle, how quickly they were expected to respond, and how carefully they had to assess AI-supported outputs.

4.5.1 Faster Work, Faster Decisions

One form of increased expectation concerned pace. As AI made it easier to access information, summarize material, and prepare decisions, some managers described a corresponding expectation that managerial responses should happen faster. One manager connected AI-enabled productivity to a higher decision tempo:

> *"With the rise of productivity [...] people are coming to leaders with more questions, and decisions need to be taken faster because things are happening faster."* (**I12**)

This acceleration was also visible in strategy work. One manager rejected the idea that AI simply created more time for people management, arguing instead that AI increased the speed at which managerial work had to adapt:

> *"I don't think I got more time for people [...] AI is moving so fast. We need to be faster in how we develop, how we think, how we plan strategies."* (**I03**)

The same manager noted that strategies could become outdated more quickly than before. AI-supported work therefore appeared to compress managerial time horizons. Managers described not only faster access to information, but also faster expectations around response, decision-making, and strategic adjustment.

4.5.2 Saved Time, Broader Scope

Managers also described AI-enabled efficiency as expanding the scope of what they could handle or were expected to handle. Rather than freeing time in a straightforward way, saved time was often absorbed into deeper involvement, broader coverage, or higher expectations for output quality. One manager described this directly:

> *"I still have to do everything I did in the past. It is just easier and more efficient. And that is the challenge, because then I can take on and dive more deeply into things."* (**I05**)

Other managers described similar effects when AI helped them prepare more thoroughly, review longer documents, or arrive with more developed proposals. Several also connected AI use to higher expectations of quality. Since AI could help produce more polished drafts, summaries, and analyses, the threshold for acceptable managerial output appeared to rise. However, this depended on the manager's ability to judge what AI produced:

> *"We need to be even more competent to judge what comes out from the AI tools, if it is valuable, if it is of any use, or if it is even correct."* (**I10**)

Efficiency gains were therefore often absorbed back into managerial work. Rather than simply reducing workload, AI-enabled time savings allowed or encouraged managers to cover more material, prepare more thoroughly, engage more deeply, or meet higher expectations for the quality of outputs.

4.5.3 Practical Limits on AI Use

Managers also pointed to practical conditions that limited what AI could realistically deliver, including data quality, security rules, tool maturity, and integration with existing systems. Several described a gap between expectations of AI-enabled efficiency and the work required to make AI useful. One manager explained this in relation to data quality:

> *"Everyone feels like, now you have AI, now you can deliver that much faster. But we don't have the data quality in place. [...] If the data is not in the right format, this is not something that we can just do."* (**I03**)

Similar concerns appeared when managers avoided external tools due to confidentiality rules, or described internal tools as useful but limited by fragmented systems and uncertain reliability. These limits help explain why AI did not enter managerial work uniformly. Expectations of faster and better output were not always matched by available data, tools, or organizational conditions.

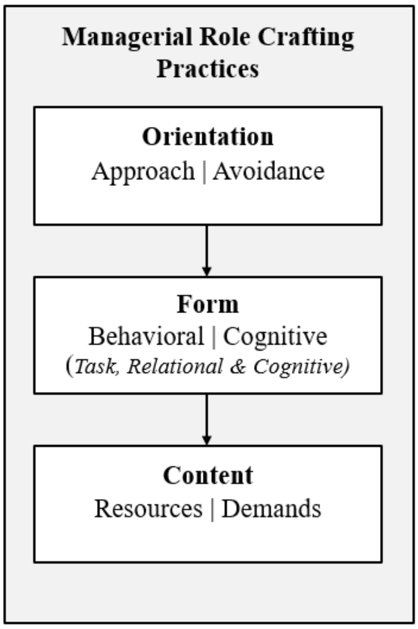
4.6 Summary of Empirical Findings

To summarize the empirical findings, the above sections show that AI entered managerial work in selective and uneven ways. The interviewed managers at TechCo described AI as most visible in preparatory and informational work, where it supported summarization, drafting, knowledge access, documentation, and structuring. However, AI was rarely described as replacing managerial tasks outright. Instead, it helped managers reach more developed starting points, while responsibility for interpretation, validation, and contextualization remained with them. AI also affected the work surrounding managerial interactions, as managers used it to prepare conversations, structure feedback, improve communication, and support coordination. Yet they continued to emphasize trust, empathy, authenticity, and human judgment as central to managerial work. Finally, AI was experienced not only as a resource, but also as a source of new expectations around pace, scope, quality, validation, and responsible use. The following chapter analyzes and interprets these empirical patterns using the Job Crafting framework.

5. Analysis

This chapter analyzes the empirical findings through the theoretical framework developed in Chapter 2. The analysis proceeds according to the three forms of job crafting, examining how managers crafted the task boundary of their role (5.1), the relational boundary of managerial work (5.2), and the meaning of the managerial role (5.3). The chapter then considers the orientation and content of these crafting practices (5.4), before synthesizing the analysis into an adapted framework of AI-driven managerial role crafting (5.5).

Figure 5 - Illustration of Theoretical Framework



5.1 Crafting the Task Boundary

Managers crafted the task boundary of their role when AI changed not only how tasks were supported, but where managerial effort and responsibility were located. Routine use of AI for summaries, drafts, or search did not in itself constitute task crafting. It became analytically relevant when managers used AI to alter the sequence of task work, shifting effort from manual compilation and first-pass production toward framing, reviewing, adapting, and deciding how AI-supported material should be used. Through the lens of job crafting, this represents behavioral task crafting, as managers changed how task-related work was carried out and how the boundary between AI-supported preparation and managerial responsibility was drawn (Wrzesniewski & Dutton, 2001; Zhang & Parker, 2019).

5.1.1 AI-Supported Task Recomposition

The findings show that AI changed the starting point of several managerial tasks. Instead of beginning from fragmented information, long documents, empty pages, or manually compiled notes, managers could begin from AI-generated summaries, drafts, comparisons, or structured proposals. The managerial task did not disappear, but its sequence changed. Work that previously required manual compilation could begin from a more developed input, which managers then had to assess, refine, and contextualize.

This represents an approach-oriented form of task crafting. Managers incorporated AI to expand their capacity for preparation, improve the quality of initial material, and engage with more information than they otherwise could have handled. However, the task boundary was not simply expanded outward. Time saved through AI was often reinvested into deeper preparation, broader scope, or higher expectations for output quality. AI, therefore, created capacity, but that capacity was frequently absorbed back into the managerial role.

Task recomposition, therefore, is concerned less with a reduction of managerial work than a redistribution of effort. Managers moved away from some manual preparation and first-pass production, while becoming more involved in framing, refinement, and deciding how AI-supported outputs should enter organizational action.

5.1.2 Validation as Managerial Boundary Work

The same task recomposition that made AI useful also created a new layer of managerial work around validation. As preparation, drafting, search, and knowledge retrieval became more AI-supported, managers had to determine where AI's contribution ended and where managerial responsibility began. Validation, therefore, became a central mechanism through which the task boundary was crafted.

This extends task crafting under AI conditions. In the original job crafting literature, task crafting concerns changes in the number, scope, or type of tasks performed (Wrzesniewski & Dutton, 2001). In this study, managers not only changed how tasks were performed; they constructed a boundary around AI-supported outputs by making review, contextualization, and accountability part of their task responsibility. This created what can be understood as a validation burden. While AI reduced the effort required to produce first drafts, summaries, comparisons, and structured inputs, it also shifted managerial effort toward assessing whether these outputs were accurate, relevant, contextually appropriate, confidentially safe, and organizationally usable. The task was therefore not simply reduced, but redistributed from first-pass production toward second-pass judgment.

This finding connects to prior AI research on interpretation, translation, and verification of algorithmic outputs, but locates such work specifically within the managerial role (Lebovitz et al., 2022; Waardenburg et al., 2022; Pakarinen & Huising, 2025). Managers were not only users of AI-supported outputs; they remained responsible for deciding whether these outputs were legitimate enough to guide communication, decisions, or action. Validation thus functioned as managerial boundary work: managers expanded AI-supported preparation while protecting the boundary around accountability and final judgment. Task crafting, therefore, involved both incorporating AI into managerial work and preserving managerial responsibility for the consequences of its use.

5.2 Crafting the Relational Boundary

Managers crafted the relational boundary of their role by incorporating AI into the preparation and support work surrounding interactions, while maintaining limits around the interaction itself. AI was used to prepare for conversations, structure feedback, refine communication, and understand stakeholder perspectives. However, managers generally did not describe AI as replacing the relational core of leadership. Instead, AI entered the preparatory layer of relational work, while judgment, empathy, trust, and responsibility remained human.

5.2.1 AI Around Interaction

The findings show that AI supported managers in preparing for relational situations before they occurred. This included using AI to anticipate reactions, structure feedback, clarify unfamiliar topics, and improve the wording of messages. Through a job crafting lens, this represents relational crafting because managers adjusted the conditions of work-related interaction, even when the interaction itself remained human. AI therefore affected relational work indirectly: it shaped how managers entered, framed, and prepared for interactions rather than replacing the relational encounter.

This form of crafting was approach-oriented. Managers used AI to improve the quality of interactions by entering conversations better prepared, with clearer language or a more structured understanding of the issue at hand. AI therefore expanded managers' relational preparation capacity. However, the interaction itself remained dependent on the manager's ability to interpret the situation, judge tone, read context, and respond appropriately. In this sense, AI changed the conditions around relational work rather than substituting for relational work itself. The relational boundary was crafted by separating what could be prepared with AI from what had to be enacted by the manager.

5.2.2 Protecting the Human Core of Leadership

At the same time, managers crafted relational boundaries by identifying what should not be delegated to AI. Several accounts emphasized that coaching, trust-building, emotional judgment, and sensitive conversations required human presence. This suggests that avoidance-oriented crafting did not appear mainly as resistance to AI or withdrawal from work. Rather, it appeared as active boundary-setting around parts of the managerial role that managers considered too relational, sensitive, or accountability-laden to automate.

This finding extends how avoidance crafting can be understood in AI-enabled managerial work. In job crafting theory, avoidance-oriented crafting is often associated with reducing demands or protecting oneself from strain (Bruning & Campion, 2018; Zhang & Parker, 2019). In this study, avoidance crafting was not only about reducing unwanted demands. It was also about protecting the quality and legitimacy of managerial relationships. Managers used AI where it could support preparation or communication, but drew boundaries around authenticity, empathy, and responsibility.

Relational crafting under AI conditions therefore involved both expansion and protection. Managers expanded the preparatory resources available for interaction, while protecting the human elements they considered central to leadership. This distinction is important because it shows that managerial resistance to certain AI uses was not necessarily reluctance or low adoption. In many cases, it reflected an active judgment about where AI support ended and where human relational responsibility had to remain.

5.3 Crafting the Meaning of the Managerial Role

Managers also crafted the cognitive boundary of their role by reconsidering what made their managerial contribution valuable in an AI-enabled work context. This form of crafting was more uneven than task and relational crafting. Some managers interpreted AI as changing where managerial value was located, while others saw AI mainly as a useful support tool with limited implications for how they understood their role. Cognitive crafting therefore depended not on tool availability alone, but on whether managers connected AI to broader questions of contribution, responsibility, and role meaning.

5.3.1 Reframing Managerial Value

For some managers, AI made knowledge and information more accessible to employees, prompting a reconsideration of what managers contribute when answers, drafts, and analysis are easier to generate. Their role was not described as disappearing, but as becoming less centered on producing answers themselves and more centered on helping others interpret, prioritize, contextualize, and act on knowledge. Through a job crafting lens, this represents cognitive crafting because managers reinterpreted the meaning and purpose of their role in relation to changing work conditions (Wrzesniewski & Dutton, 2001; Zhang & Parker, 2019).

This reframing was visible in a shift from manager-as-answer-provider toward manager-as-translator, connector, and contextual judge. AI did not remove the need for managerial expertise, but changed how that expertise was expressed. Rather than being valuable primarily because they could produce or possess answers, managers described value in translating complexity, creating clarity, aligning people, coaching employees, and exercising contextual judgment. Managerial expertise was therefore reframed from owning knowledge toward mobilizing knowledge in context.

5.3.2 AI Literacy as Managerial Responsibility

Cognitive crafting was also visible when managers began to understand AI literacy and experimentation as part of their managerial responsibility. For these managers, AI use was not only a matter of personal productivity. It became connected to role modeling, enabling team adoption, and helping employees understand how AI could be used meaningfully in their work.

This was particularly visible among managers closer to AI-intensive or technical work, where the effect of enabling others often outweighed the effect of personal AI use. In these cases, managers crafted their role by expanding what they considered part of managerial contribution: not only coordinating work, but also encouraging experimentation, translating organizational expectations into team routines, and building confidence around AI use. AI literacy therefore became cognitive crafting when managers began to see enabling others' AI use as part of their own managerial value.

5.3.3 The Uneven Reach of Cognitive Crafting

At the same time, cognitive crafting did not appear uniformly across the interviews. Some managers described AI as improving efficiency in specific activities without changing the underlying meaning of their managerial role. Others viewed AI as promising but not yet sufficiently integrated, reliable, or relevant to their own work to prompt deeper role reinterpretation.

This unevenness is analytically important. It shows that AI-driven cognitive crafting was not triggered by tool availability alone. It depended on whether managers connected AI to broader questions of role value, responsibility, and contribution. Where AI remained peripheral, immature, or limited to isolated productivity gains, managers were less likely to reinterpret the meaning of their role. Where AI affected the work managers oversaw, the knowledge their teams used, or their responsibility for enabling others, cognitive crafting became more visible.

Cognitive crafting under AI conditions was therefore conditional rather than automatic. Managers reinterpreted their role most clearly when AI challenged or changed what they understood themselves to contribute: not simply doing more with AI, but redefining where managerial value lies when knowledge work becomes increasingly AI-supported.

5.4 Orientation and Content of AI-Driven Managerial Role Crafting

The analysis of task, relational, and cognitive crafting shows that managers' responses to AI were not only about what form of role boundary was adjusted, but also about the direction and content of that adjustment. Across the three forms, managers used AI both to expand their work and to protect important role boundaries. AI also appeared both as a resource that supported managerial work and as a demand that created new expectations around validation, learning, pace, and accountability.

5.4.1 Approach and Avoidance as Expansion and Protection

Managers' AI-related crafting combined approach- and avoidance-oriented responses. Approach-oriented crafting was visible when managers used AI to improve preparation, access information more quickly, structure material, increase output quality, or enable their teams to experiment with new ways of working. In these cases, AI was incorporated as a way to expand the resources available for managerial work and increase managers' capacity to act.

At the same time, managers also engaged in avoidance-oriented crafting by setting boundaries around what AI should not do. This was visible in their reluctance to delegate sensitive relational work, their emphasis on validating AI-generated outputs, and their concern for authenticity, confidentiality, and accountability. However, avoidance crafting did not primarily appear as withdrawal or resistance. Rather, it appeared as protection: managers used AI where it was useful, while actively preserving aspects of the role they considered central to managerial value.

This suggests that approach and avoidance were not separate or opposing responses. Managers often expanded AI-supported work and protected human-centered role boundaries at the same time. Under AI conditions, crafting was therefore not simply a matter of increasing or reducing job demands and resources, but of deciding where AI could extend managerial work and where managerial judgment, responsibility, and relational presence needed to remain.

5.4.2 AI as Resource and Demand

The content of managers' crafting also reflected AI's dual character as both a resource and a demand. AI functioned as a resource when it supported preparation, reduced manual effort, improved access to knowledge, structured communication, or helped managers arrive at more developed starting points. These uses allowed managers to engage with more material, prepare more thoroughly, and support their teams more effectively.

However, AI also created new demands. Managers had to learn how to use tools, assess their reliability, validate outputs, protect confidential information, and manage rising expectations around speed and quality. This was particularly visible in the validation burden created by AI-supported work. Time saved in first-pass production was often partly reabsorbed by the need to review, contextualize, and take responsibility for outputs before they could be used. In this sense, AI did not simply reduce workload. It changed where managerial effort was located, shifting part of the role from producing material toward evaluating whether AI-supported material was good enough, safe enough, and relevant enough to enter organizational action.

This duality helps explain why managers' role crafting was selective rather than uniform. AI became valuable where it could be incorporated into existing managerial responsibilities in ways that improved preparation, coordination, or enablement. Yet its usefulness was limited where tool maturity, data quality, security rules, or relational sensitivity made AI difficult to trust or apply. Managers' crafting, therefore, involved not only adopting AI, but continuously judging where AI created useful resources and where it introduced new demands that had to be managed.

5.5 Analytical Synthesis: AI-Driven Managerial Role Crafting

Taken together, the analysis shows that managers' responses to AI can be understood as AI-driven managerial role crafting when AI use becomes connected to role boundaries, responsibilities, and role meaning. The analytical threshold is therefore not tool use in itself, but whether managers interpret AI-related opportunities, demands, or limitations as relevant to what they do, how they relate to others, what they remain accountable for, and where managerial value lies. Across the analysis, managers crafted their task boundary by incorporating AI into preparation while retaining responsibility for validation, crafted their relational boundary by using AI around interaction while protecting human judgment and trust, and crafted the meaning of their role by reconsidering where managerial value lies in AI-enabled knowledge work.

The central pattern across these forms was selective expansion and protection. Managers expanded the AI-supported parts of their role by using AI to increase preparation capacity, structure information, draft material, access knowledge, and support others' AI use. At the same time, they protected boundaries around judgment, accountability, confidentiality, authenticity, empathy, and trust. AI-driven managerial role crafting was therefore not a linear movement toward automation, nor a simple resistance to AI. Rather, managers incorporated

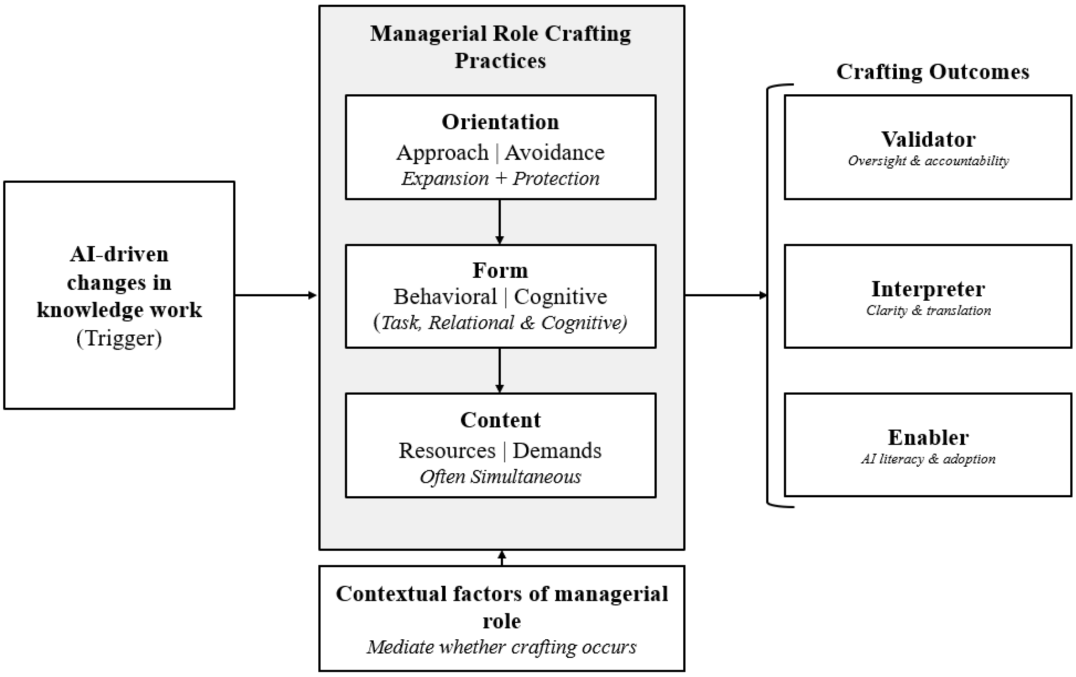
AI where it strengthened their ability to act, while preserving the parts of the role they perceived as central to responsible managerial work.

Figure 6 synthesizes this pattern into an adapted framework of AI-driven managerial role crafting. The framework illustrates how AI-driven changes in knowledge work create new opportunities and demands that managers respond to through task, relational, and cognitive crafting. These responses are shaped by both expansion and protection and result in three crafted role positions: the manager as *validator*, *interpreter*, and *enabler*. The *validator* position was most visible when AI-supported outputs entered accountability-laden work, such as feedback, strategic communication, financial or legal assessments, or customer-facing material. The *interpreter* position was most visible when managers translated AI-supported knowledge across expertise, hierarchy, or stakeholder boundaries. The *enabler* position was most visible when managers were responsible for developing others' AI use or embedding AI into team routines.

These positions should not be read as fixed manager types, but as overlapping ways in which managers crafted their role under different conditions. A manager could act as a *validator* when reviewing AI-generated material, as an *interpreter* when translating AI-supported insights into organizational action, and as an *enabler* when helping others develop AI-related capabilities. In this sense, the *validator* position is most closely linked to task crafting, while the *interpreter* and *enabler* positions show how relational and cognitive crafting combine in AI-enabled managerial work. The framework should therefore be understood as an analytical synthesis rather than a causal model. It shows how AI became role-relevant not simply by entering managerial work, but by prompting managers to redraw boundaries around responsibility, interaction, and value.

This synthesis provides the basis for the discussion chapter. It shows that AI-driven changes in knowledge work do not automatically redefine the managerial role. Instead, managers actively craft their role through selective decisions about where AI should be incorporated, where human judgment should remain central, and how managerial value should be reinterpreted in an AI-enabled organization.

Figure 6 - Adapted theoretical framework



6. Discussion

This chapter returns to the research question and discusses what the findings imply for theory and practice. It first presents the study's answer to how managers proactively craft their managerial role in response to AI-driven changes in knowledge work (6.1). It then discusses the study's theoretical contributions (6.2) and practical implications for organizations and managers (6.3), before outlining limitations (6.4) and suggestions for future research (6.5).

6.1 Managers' Response: Selective Role Crafting Around AI

We conclude that managers proactively craft their role through selective expansion and protection around AI. Rather than simply adopting AI tools into existing routines, managers interpreted AI-related opportunities, demands, and limitations in relation to what they do, how they relate to others, what they remain accountable for, and where they understand managerial value to lie. AI-driven role crafting was therefore not a uniform response to technology adoption, but a situated process shaped by role context, AI proximity, tool maturity, and perceived responsibility for others' work.

This selective role crafting appeared across three interconnected boundaries of managerial work. In relation to the task boundary, managers expanded AI-supported work by incorporating AI into preparation, knowledge access, drafting, structuring, summarization, and administrative support. However, this did not remove managerial responsibility. Managers retained responsibility for validating outputs, interpreting relevance, contextualizing information, and deciding whether AI-supported material could be used in communication, decisions, or action.

In relation to the relational boundary, managers used AI around human interaction, for example, to prepare feedback, structure communication, or follow up on meetings. Yet they also protected trust, authenticity, empathy, confidentiality, and human judgment as aspects of managerial work that should not be replaced by AI. In relation to the cognitive boundary, managers reconsidered where their value lies when knowledge work becomes increasingly AI-supported. For some, this meant moving from personally holding or producing knowledge toward translating, validating, enabling, and making knowledge actionable for others.

In conclusion, the central answer to the research question is that managers craft their role by expanding AI-supported work where it improves preparation, access, quality, and enablement, while protecting judgment, accountability, confidentiality, authenticity, and human interaction. Where AI remained peripheral, immature, or limited to isolated productivity gains, it was less likely to prompt deeper role reinterpretation. AI-driven managerial role crafting is therefore best understood as selective rather than uniform: managers craft around AI when they connect it to their responsibilities, relationships, and contribution (see Figure 6). This answer forms the basis for the theoretical contributions discussed next.

6.2 Theoretical Contributions

This study contributes to research on AI in knowledge work, managerial work, and job crafting by showing how managers proactively craft their role when AI changes the conditions of managerial work. Prior research has already shown that AI can reshape knowledge work by creating new demands around interpretation, verification, translation, and accountability (Lebovitz et al., 2022; Waardenburg et al., 2022; Pakarinen & Huising, 2025). Research on managerial work has similarly suggested that AI may make interpersonal, coordinative, judgment-based, and oversight-oriented aspects of management more important as analytical and informational tasks become increasingly AI-supported (Huang et al., 2019; Raisch & Krakowski, 2021; Van Doorn et al., 2023; Hoffmann et al., 2025). The contribution of this thesis is therefore not to show that AI changes managerial work, but to explain how managers interpret these changes as role-level issues and proactively reshape their managerial role in response.

First, the study contributes a role-level extension of job crafting theory in an AI-enabled managerial context. Job crafting theory explains how individuals proactively reshape the task, relational, and cognitive boundaries of work (Wrzesniewski & Dutton, 2001; Zhang & Parker, 2019), while emerging AI-related job crafting research has begun to examine how workers adapt to AI-driven work transformation (Law & Varanasi, 2025; Mayer et al., 2025; Perez et al., 2024). This study extends that conversation by focusing on formal managers, whose crafting is shaped not only by their own work conditions, but by responsibility for others' work, coordination, judgment, and accountability. It shows that AI-driven managerial role crafting unfolds as boundary work around where AI support ends and managerial responsibility begins. This specifies how task, relational, and cognitive crafting operate when the object being crafted is not only a job, but a managerial role embedded in the work of others.

Second, the study refines the understanding of crafting orientation by showing how expansion and protection operate simultaneously under AI conditions. Prior job crafting research distinguishes between approach-oriented crafting, which expands resources or opportunities, and avoidance-oriented crafting, which reduces demands or protects against undesirable work conditions (Bruning & Campion, 2018; Zhang & Parker, 2019). In this study, managers expanded AI-supported preparation, drafting, knowledge access, communication support, and team experimentation, while also protecting boundaries around accountability, confidentiality, authenticity, judgment, and trust. This shows that protective crafting under AI conditions is not simply resistance or withdrawal. Rather, it can function as active boundary-setting around the parts of managerial work that managers perceive as central to responsible role performance. This also extends the job demands-resources perspective by showing that AI operates as both a resource and a demand: it supports managerial work while creating a validation burden around quality, contextual fit, responsible use, and accountability.

Third, the study contributes to research on managerial work by specifying how managerial value is reworked in practice. Prior literature already suggests that AI may shift managerial attention toward interpersonal, coordinative, and judgment-based responsibilities. This study adds a more fine-grained account of how that shift is enacted through three crafted role positions. As *validators*, managers preserve accountability for AI-supported outputs by reviewing, contextualizing, and deciding whether they are appropriate for use. As *interpreters*, managers translate AI-supported information into situated meaning, communication, and action. As *enablers*, managers support others in using AI meaningfully by modeling experimentation, building AI literacy, and translating organizational expectations into team-level practice. These positions show that AI does not simply reduce or displace managerial value. Instead, managerial value is relocated toward validating, translating, enabling, and making knowledge actionable for others.

Together, these contributions show that AI-driven managerial role crafting is best understood as selective boundary work: managers actively decide where AI should support their role and where human judgment, accountability, and relational presence must remain central. Existing research explains many of the ways AI reshapes knowledge work and managerial work. This study adds a manager-centered account of how those changes are interpreted, negotiated, and incorporated into the managerial role through job crafting. In doing so, it links AI research and job crafting theory by showing how managers expand AI-supported work while protecting the human, relational, and accountability-based dimensions of managerial value.

6.3 Practical Implications

The findings suggest that organizations should treat AI in managerial work as a role- and work-design issue, not only as a tool-adoption issue. Managers' AI use needs to be connected to clearer expectations around responsibility, validation, and accountability. As managers increasingly use AI for preparation, drafting, summarization, communication, and decision support, organizations should clarify when AI-supported outputs require human review, escalation, or additional expertise. This is particularly important in sensitive areas such as performance feedback, strategic communication, legal or financial assessments, and customer-facing work. The practical issue is therefore not only whether managers use AI, but whether they know what AI may support, what remains non-delegable, and how responsible use should be evaluated.

Organizations should also recognize managers as AI enablers, not only as individual AI users. Several managers described their contribution less in terms of personal productivity and more in terms of helping others use AI meaningfully. Leadership development and performance dialogues should therefore acknowledge managers' role in building team AI literacy, modeling responsible experimentation, sharing useful practices across teams, and translating broad AI ambitions into local routines. At the same time, organizations should protect the relational integrity of managerial work by clarifying where AI can support preparation for interaction and where direct human involvement remains necessary. Overall, AI-enabled management requires more than access to tools; it requires clarity around validation, accountability, enablement, and the human boundaries of managerial work.

6.4 Limitations

As with all qualitative single-case studies, the findings should be understood in relation to the context in which the study was conducted. TechCo is a large multinational ICT incumbent with active AI initiatives, broad access to AI tools, and relatively high digital maturity. This made it a relevant setting for studying AI-driven managerial role crafting, but it also limits direct transferability to organizations with lower AI maturity, less developed digital infrastructure, or different industry and regulatory conditions. The sample also included managers with varying proximity to AI-intensive work. While this enriched the analysis, it means that some patterns may be more visible among managers closer to AI-related initiatives, tools, or strategic discussions.

A second limitation concerns the study's reliance on interview-based accounts. The thesis captures how managers interpreted and narrated AI-related changes in their work, rather than directly observing managerial behavior or measuring changes in role performance. This is consistent with the study's interpretivist aim, but it means that the findings reflect managers' own accounts of role crafting and cannot fully capture how these changes are experienced by employees, peers, or senior leaders. Relatedly, the study captures a specific moment in an ongoing AI transformation. As tools mature, governance develops, and agentic AI becomes more integrated into workflows, the forms of role crafting identified here may change. The findings should therefore be read as an account of AI-driven managerial role crafting in an emerging phase of organizational AI use, rather than as a stable or final description of how AI will affect managerial work.

6.5 Future Research

Future studies could apply and refine the adapted framework in other organizational contexts, industries, and levels of AI maturity to examine whether the validator, interpreter, and enabler positions identified in this thesis represent broader patterns of managerial role crafting or whether they are shaped by the specific conditions of a digitally mature ICT incumbent.

Longitudinal research would also be valuable, as AI-driven role crafting may change as AI use becomes more embedded in everyday work. Building on Mayer et al.'s (2025) suggestion that AI-related job crafting may evolve as organizational routines stabilize, future studies could examine whether managerial validation, interpretation, and enablement become absorbed into ordinary routines, reactivated when new capabilities such as agentic workflows emerge, or formalized into leadership expectations around AI literacy and responsible use.

Future research could also explore whether deeper cognitive crafting becomes more widespread as managers gain experience with AI, or whether it remains dependent on role context, AI proximity, tool maturity, and responsibility for others' work. Multi-perspective studies, including employees, peers, and senior leaders, could further examine how managers' AI-supported role crafting is experienced by others, including whether it is perceived as enabling, distancing, legitimizing, or creating new accountability bottlenecks.

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8. Appendices

8.1 Appendix A: Consolidated Theme Development Table

This appendix provides a consolidated overview of the theme development process by illustrating how recurring empirical patterns across the interviews were developed into initial codes, broader themes, final empirical themes, and links to the subsequent analysis.

Recurring empirical pattern across interviews	Empirical grounding across interviews	Codes and theme development	Final empirical theme(s)	Link to analysis
Managers described AI as useful for summarizing meetings, extracting action points, and reducing the need to manually document discussions.	*I01, I08, I09, I10, I12,* I14 described AI-supported meeting summaries, transcripts, action points, and follow-up as recurring uses in managerial work.	Initially coded as meeting summaries, action points, automated notes, reduced manual documentation, and better follow-up. These codes were first treated as "AI efficiency" and "meeting support," but were consolidated into a broader pattern of AI changing recurring task-related work.	**AI-supported task recomposition**	Supports the analysis of how managers craft task boundaries by shifting effort from manual documentation toward review, participation, and follow-up.
Managers used AI to draft, structure, and prepare written outputs, including strategy documents, presentations, emails, and other managerial material.	*I01, I10, I13, I15, I16* described AI as useful for generating ideas, structuring text, preparing first drafts, refining communication, and improving presentation material.	Initially coded as drafting support, text structuring, first-draft generation, idea generation, presentation preparation, and conciseness. These examples were first treated partly as communication support, but were refined as task recomposition because they concerned how managerial outputs were initiated and prepared.	**AI-supported task recomposition**	Supports the analysis of how AI changes the starting point of managerial output production, while managers remain responsible for refinement, contextualization, and approval.
Managers used AI to compare documents, synthesize information, search internal material, and identify relevant differences across large amounts of information.	*I01, I06, I13, I14, I15, I16* described AI-supported search, document comparison, internal knowledge retrieval, policy comparison, and synthesis across multiple sources.	Initially coded as document comparison, information search, synthesis, extracting differences, navigating internal sources, and structuring knowledge. These scattered examples were developed into a broader theme about AI changing how managers access and structure knowledge.	**AI-supported task recomposition**	Supports the analysis of AI as a resource for task-related work, while also increasing the importance of deciding what information is relevant and actionable.
Managers used AI in formal people-management routines such as goal drafting, onboarding, performance input summaries, and preparation of employee-related material.	*I08, I11, I13, I16* described using AI to prepare SMART goals, summarize performance input, create onboarding plans, and prepare employee-related material.	Initially coded as goal drafting, SMART goals, onboarding preparation, performance summaries, and employee-related preparation. These examples were retained within task recomposition because managers described AI as supporting formal preparation and documentation rather than replacing the relational or evaluative act itself.	**AI-supported task recomposition**	Supports the analysis of how AI enters people-management tasks while evaluative, relational, and contextual responsibility remains with the manager.
Managers used AI to prepare, structure, communicate, coordinate, and follow up around managerial interactions.	*I03, I05, I08, I12, I14, I16, I18, I19* described using AI to prepare for discussions, understand unfamiliar topics, summarize communication, structure feedback, follow up on meetings, and coordinate across stakeholders.	Initially coded as meeting preparation, topic understanding, background knowledge, feedback preparation, communication structuring, email summarization, stakeholder coordination, and follow-up support. These codes were consolidated into a broader theme because they concerned the work surrounding interactions rather than replacing the interaction itself.	**AI around managerial interactions**	Supports the analysis of how AI changes the conditions around managerial interaction by improving preparation, coordination, and communication, while leaving the interaction itself dependent on human judgment.
Managers emphasized that AI-supported outputs required validation, critical review, and final human judgment before use.	*I01, I05, I07, I13, I15, I18* emphasized the need for critical review, validation, and human assessment before AI-supported outputs could be relied on or acted upon.	Initially coded as critical review, validation, checking output, not accepting AI as truth, human assessment, second opinion, and trust concerns. This was initially considered as a separate "trust in AI" theme, but was refined into a cross-cutting mechanism connected to task recomposition, validation work, and role meaning.	**AI-supported task recomposition / Changing meaning of the managerial role**	Supports the analysis of validation as managerial boundary work, where managers draw the line between AI-supported preparation and managerial accountability.
Managers described AI as useful around informational work, but not as a replacement for coaching, empathy, trust, authenticity, or human support.	*I08, I12, I14, I17, I19* emphasized one-to-one interaction, open dialogue, empathy, motivation, coaching, trust, and personal communication as central parts of the managerial role.	Initially coded as human support, empathy, coaching, open dialogue, relational judgment, authenticity, trust, and motivation. These codes were first grouped as "human leadership," then consolidated into role meaning because participants used them to describe what remained central in their role.	**Changing meaning of the managerial role**	Supports the analysis of cognitive and relational crafting, where managers protect and redefine their value around human, interpretive, and relational work.
Managers described their role as increasingly focused on alignment, coordination, people development, translation, and turning information into action.	**I01, I06, I08, I14, I16, I19** described managerial work as steering, aligning, filtering information, translating market or technical realities, creating clarity, coaching, and helping others deliver.	Initially coded as alignment, coaching, steering, translating information, filtering information, helping others deliver, creating clarity, and sensemaking. These codes were developed from baseline role descriptions and AI-related reflections into a theme about how managers understood their contribution under AI-enabled conditions.	**Changing meaning of the managerial role**	Supports the analysis of how AI makes coordination, interpretation, sensemaking, and judgment more central to managerial value.
Managers treated AI literacy, role modelling, and enabling others' experimentation as emerging managerial responsibilities.	*I04, I07, I11, I14, I16, I20* described learning AI tools, encouraging team members to use AI, running pilots, following up on use, cascading AI competence, and seeing greater impact from enabling employees than from individual use alone.	Initially coded as AI literacy, learning tools, understanding tool potential, knowing enough to lead, enabling others, encouraging experimentation, adoption follow-up, team AI use, and scaling pilots. These codes were first separated as individual learning and AI adoption, but were combined because managers connected AI literacy to role modelling, team enablement, and managerial responsibility.	**Changing meaning of the managerial role / Increased expectations around AI use**	Supports the analysis of AI literacy as managerial responsibility and the enabler position, where managers craft their role by legitimizing, guiding, and supporting others' AI use.
Managers described AI as creating new expectations around pace, scope, quality, governance, and responsible use.	*I04, I05, I10, I11, I12, I14, I16, I20* described faster decision cycles, broader scope, higher quality expectations, adoption pressure, governance concerns, data quality issues, security boundaries, and responsible AI use.	Initially coded as faster decisions, increased pace, broader scope, higher standards, adoption pressure, efficiency expectations, governance, security, responsible use, legal boundaries, and productization. These codes were developed into a broader theme about AI as both opportunity and responsibility.	**Increased expectations around AI use**	Supports the analysis of AI as both a resource and a demand in managerial role crafting, where efficiency gains may also create additional validation, learning, and accountability work.
Some managers described AI as useful but not yet fundamentally role-changing, or as unevenly relevant depending on function, access, maturity, and context.	*I04, I05, I15, I17, I18* described AI as promising but not yet fully changing their own managerial role, while others emphasized that impact varied across tools, functions, data access, organizational maturity, and proximity to AI-intensive work.	Initially coded as limited role change, uneven adoption, context dependence, tool maturity, data limitations, functional variation, and AI proximity. These accounts were retained as a qualifying pattern rather than excluded, preventing the analysis from overstating AI's impact or treating role crafting as uniform across managers.	**Cross-cutting qualification**	Supports a more nuanced analysis of AI-driven managerial role crafting as selective, uneven, emerging, and dependent on organizational and role-specific conditions.

8.2 Appendix B: Interview guide

Topic	**Question**
Background and baseline role construction	• Can you briefly describe your background and current role at TechCo? • What does your role as a manager entail? • What does a typical working week look like for you as a manager?
AI exposure and current use	• Do you use any AI tools or AI-supported systems in your work? • How, if at all, do you use AI in your managerial work? • Can you walk me through a concrete example of a recent situation where you used AI? • Are there areas where you choose not to use AI? Why?
Task, relational, and cognitive crafting	• Can you describe a recent situation where generative or agentic AI affected how you worked as a manager? • Can you describe a task that you now approach differently because of AI? How would you have approached it before? • Have you changed how you interact with other people as part of your managerial role? • Has AI changed the way you think about and view your managerial role? • Has AI changed what you now see as your contribution as a manager? • Has AI changed what skills or capabilities you need as a manager?
Resources and demands	• What resources have become more important for you to do your job under these changes? • Have the demands on you as a manager changed because of AI?
Agency, boundaries, and risks	• To what extent have you felt that you could shape your role yourself, and to what extent have the changes been imposed on you? • Are there areas where AI has had no effect on your managerial role? • Is there any part of your managerial role that you try to protect or preserve as AI becomes more embedded in your work? • Are there limitations to how AI can affect your work? • What risks do you associate with using AI as a manager? • Is there anything about AI and your managerial role that you would like to highlight?

8.3 Appendix C: E-mail template used in interview invitations

Subject: SSE x TechCo - Invitation to Participate in Master's Thesis Interview on AI and Managerial Work

Hi [Interviewee's name],

We hope you are doing well.

We are Rosel Chowdhury and Bilal Ibrahim, Master's thesis students at TechCo and currently completing our final semester in Business and Management at the Stockholm School of Economics.

Our research examines how AI is impacting managerial work. As part of a case study at TechCo, we are conducting interviews with managers who can offer relevant perspectives on this topic.

We think you might have some relevant insights on this topic, and we would greatly appreciate the opportunity to interview you for 60 minutes online. If you are available in the coming weeks, please reply with a few suitable time slots, and we will handle the scheduling. If the coming weeks are not convenient, please let us know, and we will adjust accordingly.

The interview will cover:

1. Your background and role at TechCo
2. The impact of AI on managerial work
3. If/How managers are adapting their work/role

Your participation will be anonymous, and all information shared will be treated confidentially and used only for this research.

Thank you for your time and consideration. We look forward to hearing from you.

Best regards,
Rosel Chowdhury & Bilal Ibrahim
Master's Thesis Students, Stockholm School of Economics

8.4 Appendix D: Use of AI in the thesis

What AI tools have been used and how?

- AI-based transcription tools, such as Microsoft Teams transcription, were used to support the handling of interview material.
    - These tools produced initial transcripts of interview recordings.
    - The transcripts were used as working documents for reviewing the empirical material.
    - The transcripts were checked against the recordings and corrected when necessary to ensure that the interviewees' statements were represented accurately.
- ChatGPT, Gemini, and Claude were used as support tools for structuring, reviewing, and refining the thesis.
    - Supported critical review of draft text by identifying unclear arguments, repetition, suboptimal transitions, and areas where claims needed further development.
    - Helped generate alternative formulations and revision suggestions, especially when improving flow, concision, and academic tone.
    - Used as discussion partners when working through theoretical connections.
- AI tools were used in a limited way for literature and reference support.
    - Supported the organization and comparison of academic articles.
    - Used to assist with reference formatting.

In what ways have these tools contributed to increasing the quality of the thesis?

- Improved the handling of empirical material.
    - Transcription tools made it possible to access and review interview material more efficiently. This created more time for interpretation, comparison, and analysis of the empirical data. Manual transcript checking helped ensure that efficiency gains did not come at the expense of accuracy.
- Improved the linguistic quality of the thesis.
    - Language-support tools helped identify unclear, overly long, or grammatically weak sentences. This contributed to a more consistent academic tone and

improved readability. The tools were particularly useful in the final stages of refining the text.

- Strengthened the structure and coherence of the thesis.
    - ChatGPT helped test different ways of organizing complex material. It supported clearer links between the research question, literature review, theoretical framework, findings, analysis, and discussion. It also helped identify overlaps and sections where the argument needed clearer transitions.
- Supported critical revision.
    - ChatGPT was used to challenge draft sections and highlight possible weaknesses in logic, argumentation, and conceptual consistency. This encouraged more careful reflection on whether claims were sufficiently supported and clearly connected to the thesis' purpose.
- They made the writing process more iterative and efficient.
    - AI tools supported restructuring, revising, proofreading, and formatting. This allowed the authors to test alternative formulations and section structures more quickly. The increased efficiency made it possible to spend more time on interpretation, theoretical refinement, and analytical consistency.

What potential risks were found using AI and what measures were taken to reduce these risks?

- Risk: transcription errors or loss of nuance
    - AI-generated transcripts may mishear words, omit details, or fail to capture meaning accurately.
    - Measure taken: Transcripts were reviewed against the recordings and corrected where necessary.
- Risk: inaccurate or unsupported content
    - AI tools can make claims that appear convincing but are inaccurate or not supported by academic literature.
    - Measure taken: All source-based claims were checked against the original articles before being included in the thesis.
- Risk: incorrect interpretation of theory
    - AI may simplify or misrepresent nuanced theoretical concepts.

    - Measure taken: AI suggestions were checked against the relevant literature and revised to preserve theoretical precision.
- Risk: confidentiality and data protection
    - Empirical material may contain sensitive or identifiable information.
    - Measure taken: Interview material was anonymized and handled carefully. Identifiable or sensitive information was not used in ways that could compromise confidentiality.
- Risk: generic or context-insensitive recommendations
    - AI may provide broad suggestions that do not fit the specific thesis topic, case, or theoretical framework.
    - Measure taken: All suggestions were critically assessed and adapted to the research question, empirical material, and academic requirements of the thesis.

What are the insights gained from using AI tools in the thesis writing process?

- AI was most useful when used for supporting revision, reflection, and structure
- The use of AI showed that efficiency gains are possible, especially in transcription, proofreading, outlining, and revising, but these gains require careful human control.
- AI tools were particularly helpful for identifying unclear reasoning, suggesting alternative formulations, and making complex arguments easier to communicate.
- AI could not replace the authors' responsibility for interpreting literature and analyzing empirical material.
- A central insight was that AI works best when the authors already understand a topic and use AI to improve how the author's own ideas/arguments are expressed.
- AI contributed positively to the thesis process, however, its usefulness depended on manual verification and continued authorial responsibility throughout the research and writing process.